# A PROBABILISTIC DECISION ANALYTICAL APPROACH FOR WATERSHED PLANNING: A MERCURY TOTAL MAXIMUM DAILY LOAD CASE STUDY

A DISSERTATION

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DOCTOR OF PHILOSOPHY

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# ABSTRACT

This work develops a decision analytical approach to water quality management at the watershed scale through a mercury Total Maximum Daily Load (TMDL) development case study. This approach treats the key environmental variables as causally-related random variables that may be influenced through mitigation actions (interventions) to an uncertain degree. Starting from the perspective that water quality management falls under the rubric of "decision-making under uncertainty", I explore the application of state of the art probabilistic tools for decision support. This work goes beyond the current deterministic paradigm in which conservative modeling choices are used to deal with predictive uncertainty. The proposed decision model frames the TMDL setting process as a set of regulatory decisions that may involve large uncertainties (limited data bases and incomplete knowledge) subject to tight regulatory deadlines and small decision process budgets.

Probabilistic source analysis and linkage analysis models based on the available data, standard environmental science and engineering theory, and mercury biogeochemistry expertise were created for the case study mercury TMDL decision situation. Discrete conditional probability distributions based on these models and expertise were incorporated in a Bayesian network model, a tool for solving prediction and inference queries. In conjunction with a parametric value model, this mercury Bayesian network serves as the basis of a mercury TMDL decision model for the case study. This decision model demonstrates a formal context for considering the importance of uncertainty in TMDL decisions, for prioritizing information collecting activities, for considering trade-offs between compliance uncertainty and mitigation costs, and for considering and representing hypotheses within a TMDL decision-modeling framework. Sensitivity analysis using the Bayesian network is used to demonstrate approaches for prioritizing information collection activities and for estimating the value of perfect information on variables of interest. As demonstrated, future information activities should be based on preliminary models of the uncertain

relationships between possible interventions and environmental targets. Very importantly, the Bayesian perspective of decision analysis allows decision participants to interpret new information (monitoring and knowledge) in light of previous information and knowledge, which is a good basis for an adaptive management framework.

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# DEDICATION

I dedicate this dissertation to my wife, Rochelle, for her constant, sustaining, and indispensable support. I would also like to share the dedication with my family and friends for their much-needed guidance and inspiration through the years.

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GLOSSARY OF ACRONYMS, SYMBOLS, UNITS

| | |
|---|---|
| $\equiv$ | Defined as |
| $\{S_1,...\}$ | Set of states for a variable, S. |
| $\Pi_i(x_i)$ | Product over a set of indexed variables, $x_i$. |
| cfs | Cubic feet per second |
| DOC | Dissolved organic carbon |
| EPA | Environmental Protection Agency |
| $Hg_T$ | Total mercury concentration in water, including dissolved and particulate fractions |
| $Hg_T$/TSS | The ratio of the total mercury concentration in water to the total suspended solids concentration |
| log | Logarithm (base 10) |
| ln | Natural logarithm (base e) |
| MA | Microbial activity |
| maf | Million acre-feet |
| mdf | Mean daily flow |
| $MeHg_T$ | Total monomethylmercury ($CH_3Hg^+$) concentration in water, including dissolved and particulate fractions |
| mg/L | Milligrams per liter |
| µm | Micrometer |
| ng/L | Nanograms per liter |
| NPS | Nonpoint source |
| ppm | Parts per million |
| PRHg | Percent reactive mercury in $Hg_T$/TSS |
| RWQCB | Regional Water Quality Control Board |
| TMDL | Total maximum daily load |
| TSS | Total suspended solids |

# CHAPTER 1: MOTIVATION, OBJECTIVES, AND BACKGROUND

## 1.1 MOTIVATION

States list surface waterbodies as impaired under § 303(d) of the Clean Water Act when, although in compliance with surface water point source discharge regulations, they cannot meet their designated beneficial uses, such as providing potable water supply, aquatic habitat for wildlife, and recreational opportunities, due to contamination. In such cases, nonpoint source (diffuse) water pollution is often the source of the impairment[1]. When nonpoint water pollution sources are significant sources, impaired waterbodies are addressed through the creation of a Total Maximum Daily Load (TMDL) regulation that is designed to restore the beneficial use by sufficiently reducing contaminant sources. Examples of contaminants that have been addressed by TMDLs include mercury, copper, sediment, and polyaromatic hydrocarbons (PAHs). In practice, TMDL decisions are often made under large uncertainties due to severe data limitations and gaps in understanding of the linkages between the controls being considered and the environmental targets of interest.

Modeling plays a central role in the TMDL planning and setting process (Reckhow, 1999; NRC, 2001; Lung, 2001; USEPA, 2002). Whether the models are empirical (statistical) or mechanistic, they represent the best scientific understanding of how contaminant loadings relate to water body impairment of designated beneficial uses (NRC, 2001). Once a waterbody is listed as impaired, predictive models are used to assess the relative contributions of various pollution sources, to predict the total load reduction required to meet ambient water quality standards, and to predict the relationships between specific control measures (e.g., point source load reductions)

[1] For some contaminants, atmospheric deposition may also contribute to surface water impairment. In most watersheds (Benoit et al. (GET CITE)), atmospheric deposition is the dominant input of mercury. In this case study, run-off from mine wastes and geothermal spring inputs are the dominant sources of mercury (RWQCB-CV, 2004).

and water quality targets (e.g., ambient water concentration of a particular pollutant) in the load allocation process.

Decision-making related to TMDL planning and implementation requires one to answer questions related to determining the reasons for non-attainment of beneficial use and evaluating strategies for mitigating those determined causes. Neither of these questions can be answered with certainty. Uncertainty in model predictions can be large and, when explicitly considered, can confound interpretation of results in terms of the decisions that need to be made. Uncertainty is, however, often treated superficially in water quality management decisions, which can be a major source of contention between stakeholders and regulatory agencies (Houck 2002; Ortolano 1997a). Regardless of the quality of knowledge and data bases, current TMDLs are almost always addressed using deterministic models of linkages between sources and environmental endpoints.

Uncertainty, whether the source is incomplete knowledge about the physical, chemical, and biological processes that control contaminant transport and fate, a lack of data about variables that are known to be important, or the stochastic variability inherent in natural systems (e.g., future stream flow), is a reality that any water quality management decision framework must recognize, assess, and, when possible, reduce. The consideration of uncertainty in TMDLs is constrained by the regulatory requirements for the use of a Margin of Safety (MOS) and thus most discussions of uncertainty in TMDL decisions take the MOS as a starting point. From this perspective, an uncertainty analysis of the relevant (deterministic) models can be performed (in theory) and, from this uncertainty analysis, the choice of an appropriate MOS in the TMDL target can be made. The use of conservative modeling assumptions, or even conservative mitigation goals, as "the MOS" is another strategy in use. From a decision analytical point of view, the *choice* of "how conservative" the MOS should be is *itself* a decision of fundamental importance. To leave this choice as a scientific/engineering judgment ignores the fact that this involves risk management and value judgments.

The National Research Council (NRC 2001) and the US Environmental Protection Agency (USEPA 1999) suggest the use of adaptive management to deal with the significant uncertainty involved in TMDL decisions. The decision analytical approach proposed in this work could be used as the planning basis for developing an adaptive management strategy for TMDL development and implementation (Cook et al. 2004; USEPA 1999). The information collection prioritization methodology shown in later chapters could be used to choose the mitigation/response hypotheses to be tested. Since the proposed model is Bayesian in nature, interpreting the meaning of the results from future monitoring could be done through Bayesian updating using both prior and new information. Bayesian approaches for interpreting new data in the face of previous data and knowledge have the advantage of being flexible and general[2], which allow them to cope with very complex problems (Gelman et al. 1995). Current adaptive management strategies tend to use deterministic models and intuition to design mitigation/response hypotheses. Learning from future evidence is not modeled formally in common current practice.

This research focuses on a particular mercury TMDL situation in Northern California. Water quality impairment due to high mercury fish tissue concentrations and high mercury aqueous concentrations is a widespread problem in several sub-watersheds that are major sources of mercury to the San Francisco Bay . Several mercury Total Maximum Daily Load regulations are currently being developed to address this problem. Decisions about control strategies are being made despite very large uncertainties about current mercury loading behavior, relationships between total mercury loading and methylmercury formation, and relationships between potential controls, total mercury and methylmercury loads, and fish tissue mercury burdens.

[2] The ability to create complex models using Bayesian methods comes from their ability to provide a simple framework for dealing with multiple, potentially correlated and/or uncertain, parameters (Gelman et al., 1995).

## THE MEANING OF UNCERTAINTY IN TMDL SETTING

The meaning of uncertainty is important in the TMDL setting context. Scientists and engineers often interpret uncertainty as a property of the natural world and distinguish events with uncertainties that are "knowable" (i.e., those with a definable population of possible events) from events that do not. As Morgan and Henrion (1990) point out, this attitude renders probability theory and tools irrelevant to most decision-making situations, especially those involving complex systems. From the Bayesian point of view adopted in the modern decision sciences, uncertainty is expressed in terms of probabilities, where the probabilities represent degrees of belief about events in the world. These degrees of belief are a property of the current state of information (Howard 1984; Luce and Raiffa 1989; Morgan and Henrion 1990; Pearl 2000). This shifts the burden from the intractable technical problem of defining the sample space for the future state of a partially understood complex system to the much more tractable problem of expressing the uncertainty in that future state as a probability distribution that is conditioned on what is currently known about the behavior of the complex system and other relevant factors. From the Bayesian decision analytical perspective, the role of environmental science and engineering expertise in decision support is to help decision-makers express what is currently known about the uncertain causal relationships between the interventions that could be made (alternatives) and the multitude of possible future consequences of those interventions (outcomes).

## CAUSALITY

It is noted that the definition of causality used in this work is also different from that often used by modern science and engineering practitioners. While there is an on-going wide-ranging interdisciplinary debate about the precise definition of causality in a variety of contexts (including scientific contexts), causality is used by many scientists and engineers to mean that a prior set of circumstances can be used to predict a future set of circumstances based on physical laws (Ellis 2005; Galavotti et al. 2001; Pearl 2000; Sowa 2000). Uncertainty is then a reflection of the quality of the prediction and, in practice, is usually not explicitly represented in causal (mechanistic) scientific models. Leaving the intellectual underpinnings of this tradition unexamined, for many (if not most) environmental problems of interest to decision-makers, it is incomplete. In the context of decisions about manipulating complex environmental systems, partial understanding of the interactions between the physical, chemical, and biological components of the system, incomplete information on boundary conditions when mechanisms are understood, incomplete data sets needed for calibrating existing models of system behavior, uncertainty in the appropriateness of the chosen models, the counterfactual nature of environmental interventions[3], and other significant sources of uncertainty all promote the use of a definition of causality that explicitly incorporates these uncertainties (Heckerman and Shachter 1995; Pearl 2000; Reckhow 1999; Spirtes et al. 2000). The probabilistic definition of uncertain causal relations used in this work comes from a relatively new body of work, including Pearl (2000), Heckerman and Shachter (1995), Spirtes et al. (2000), and others, and is described in more detail in Chapter 3.

## TMDL Decision Analytical Approach

The approach proposed in this work starts from a decision analytical paradigm precisely because it allows us to think about the uncertain causal connections in complex environmental decisions in terms of a comprehensive (spans the possible outcomes) yet comprehensible set of discrete possible outcomes. These discrete outcomes are chosen such that a discrete probability distribution defined over them adequately approximates the continuous probability distribution over the range of possible outcomes for a particular intervention. In the proposed approach, the model of the uncertain causal relations between possible interventions (mitigation alternatives), environmental components (described by variables), and environmental

[3] Environmental interventions, i.e., steps taken to alter a complex environmental system to change it in some "desirable way", are counterfactual in the sense that, once the intervention is made, there is rigorous no way to determine the degree to which the intervention *caused* the observed changes. In other words, since interventions on complex environmental systems are unique events, there is no

endpoints of concern (described by targets) can be used to predict the probability distribution over decision outcomes. While the decision model will provide these predictions, *the real purpose of a decision analytical approach is to determine the best course of action from a set of alternatives given our state of current information and our preferences.*

Since current environmental scientific and engineering practice usually does not frame environmental mitigation predictions using the concepts of uncertain outcomes and uncertain causality, there is a role for another type of expert in environmental decision technical support, namely the environmental decision analyst. The environmental decision analyst works with decision participants (decision-makers, stakeholders, and domain/subject matter experts from the relevant scientific and engineering disciplines) to build probabilistic (causal) conceptual models that aid them in developing a deeper understanding of the important uncertainties that make their decision situation difficult. The probabilistic conceptual model may be created as an *influence diagram*, which can be used as a graphical communication tool that organizes and represents the many uncertainties that make a particular set of decisions hard. The influence diagram represents these uncertainties in terms of the their relevance to meeting decision-maker goals and targets for individual strategies (Howard 1990; Howard and Matheson 1984). In the literature, an influence diagram can either be a graph of a decision tree or a *probabilistic (Bayesian) network model* that includes algorithms that can be used to evaluate a decision problem, perform inferences, and to make predictions (Jensen 2001; Pearl 1988; Shachter 1988). At the conceptual model development phase of defining the environmental decision problem, the graphical interpretation may be used. The probabilistic conceptual model then consists of assertions of causal relationships and/or conditional independence between variables, with no numerical specification of probability distributions over possible future events. In the decision sciences literature, this initial form of the influence

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way to test the hypothesis that the intervention had a particular effect and no ability to reproduce the experiment in a controlled manner. See, e.g., Pearl (2000) or Heckerman and Shachter (1995).

diagram is referred to as an unspecified influence diagram (Shachter 1988). Even with no further work on the influence diagram, decision participants may find that the unspecified influence diagram of their decision problem helps them in communicating about possible strategies and in thinking about information collection strategies.

If further information for identifying the best strategy is desired, the environmental decision analyst may then work with decision participants to evolve this conceptual model by assessing the needed conditional probability distributions that describe the uncertain causal relationships between alternatives, environmental variables, and environmental targets. Once this required probabilistic information has been assessed, the influence diagram may be implemented as a Bayesian network for generating useful decision analytical insights.

## 1.2 BACKGROUND ON THE DECISION PROBLEM AND RESEARCH OBJECTIVES

This research uses a detailed case study to illustrate the development and application of a Bayesian network-based decision model for addressing watershed-scale management decisions. The case study involves Sulphur Creek, a small mercury-impacted watershed in Northern California (RWQCB-CV 2004b). The decision-makers are the Central Valley Regional Water Quality Control Board and its staff, who are faced with managing on-going mercury contamination problems in several watersheds that contribute to the Sacramento River and the Bay Delta, including Sulphur Creek, Cache Creek, and Harley Gulch. For typical mercury-impacted watersheds, the environmental targets of primary interest are elevated fish tissue levels and methylmercury concentrations in sediment and water. In mercury and gold mine-impacted watersheds, total mercury concentrations in water (including particulate and dissolved fractions) are also an endpoint of concern.

In the Sulphur Creek watershed, fish rarely occur because of poor water quality associated with local geothermal activity. Accordingly, instead of mercury fish tissue targets, decision-makers are using the annual methylmercury load exported from the watershed as the water quality target of primary concern (RWQCB-CV 2004b). The total mercury load exported to Lower Bear Creek is also a target of interest, because of its potential effects on downstream methylmercury production. The compliance actions being considered are related to reducing total mercury concentrations in water and sediment in several areas of the watershed. The uncertainty associated with the predicted changes in methylmercury concentration trends due to total mercury reduction efforts (interventions) is very large. In fact, whether or not methylmercury is controllable through mine-related mitigation in this watershed is not a foregone conclusion. The anthropogenic mercury contamination problem is complicated by the presence of high background mercury loadings (and other water quality factors) related to long-term local geothermal spring inputs (Churchill and Clinkenbeard 2005). For this reason, geothermal spring discharges adjacent to Sulphur Creek are also being considered for remediation, but this may prove difficult to achieve (Rytuba 2005a).

This case study involves a real-world regulatory decision situation, one involving Federal, State, and local agencies and stakeholders, potentially including non-governmental organizations, impacted regulated interests, and the interested public. The approach proposed in this research is an integrated decision analytical framework (decision framework) designed for watershed group decision-making, focusing on the uncertainty in meeting targets, a methodology for considering the desirability of the possible outcomes without consensus, and methods for aiding decision-makers in considering trade-offs in a complex and highly uncertain decision situation. This research tracked the actual Sulphur Creek mercury Total Maximum Daily Load regulatory development process, but was not associated with the real decision-making process in any formal way. To some degree, comparisons can be made between the decision insights generated by this research and the actual decisions made, but it should be kept in mind that the more general purpose of this research is to demonstrate the feasibility of a decision analytical approach to watershed-scale water quality mitigation decision support.

## 1.3 STRUCTURE OF THIS DISSERTATION

The first four chapters of this dissertation provide the introductory material necessary for understanding the decision problem and the mathematical and analytical tools used in later chapters. Chapter 2 describes the decision situation in more detail and provides the starting point for developing the *decision frame* (or decision context), which serves as the foundation for building the decision model in terms of the alternatives being evaluated, the information being used in the decision, and decision participant preferences over possible outcomes from the decision. Collectively, the alternatives, information, and preferences for a decision are referred to as the *decision basis*. The decision context provided in Chapter 2 includes a description of the decision-makers and their stakeholders, the the regulatory (Total Maximum Daily Load) framework, and the water quality problem they are addressing.

Part of the initial framing process for this decision involves identifying the goals and objectives of the decision-makers (as influenced by the regulatory context and stakeholder values). In regulatory situations, many of the decision participants may argue that the regulatory framework imposes the goals and objectives for the decision problem but, in practice, State agencies and their stakeholders exercise considerable discretion in prioritizing nonpoint[4] source water pollution problems and in evaluating alternatives for addressing them (Boyd 2000; Houck 2002). Chapter 4 discusses a process of identifying and structuring goals and objectives in detail using a related regulatory decision example. Once identified, the objectives are associated with tangible *environmental targets* that decision-makers want to (or are required to) meet. In the Sulphur Creek mercury case study, the environmental targets were inferred from the documentation developed by the decision-makers, from public meetings, and from consultation with the decision-makers (RWQCB-CV 2004b). The

[4] EPA defines a nonpoint source as "any source from which pollution is discharged which is not identified as a point source, including, but not limited to urban, agricultural, or silvicultural runoff. Nonpoint source (NPS) pollution occurs when rainfall, snowmelt, or irrigation water runs over land, or through the ground, and picks up pollutants and deposits them into lakes, rivers and groundwater" (online glossary at: http://yosemite.epa.gov/R10/WATER.NSF/0/2f53bb35da337053882569-f1005ecf17?OpenDocument).

decision participants' *preferences* over decision outcomes can then be considered in terms of meeting the environmental targets and the costs associated with the alternative.

Background on the *alternatives* being considered for controlling total mercury and methylmercury levels in Sulphur Creek is discussed in Chapters 2. The last part of the decision basis, *information*, is the focus of Chapters 5 and 6. In decision analysis, "information" refers to what is known about the various uncertainties that are relevant to the decision value. In the environmental decision problem used in this research, the informational part of the decision basis refers to what is known about the uncertain causal relationships between the possible mitigation strategies and the targets of interest, total mercury load and methylmercury load exported from Sulphur Creek. Chapter 5 provides relevant background on mercury biogeochemistry and discusses the available hydrological and water quality data. A conceptual model of the sources, fate, transport, and potential controllability of mercury in this watershed is also presented. This conceptual model is developed as a causal network that can express what we know about the causal relationships between system variables, with explicit representation of uncertainty. Causal networks and other Bayesian networks are introduced in Chapter 3. Assessing the needed probabilistic information from existing data, models, and the available expertise is a large part of this research. Chapter 6 discusses the simulation and expert elicitation methods used to assess the needed probability tables to fully specify this causal network.

A significant part of this research involves the development of a methodology for ordering and valuing outcomes in a group decision setting in which consensus is not expected, but in which cooperation[5] is expected. Chapter 4 describes several

[5] This means that while decision participants may not agree on the values assigned to the various possible outcomes, they are honest about their beliefs and are interested into coming to consensus about which uncertainties are important and which experts and data to use to estimate probability distributions over the uncertainties. In addition, "cooperation" implies that consensus is needed on which alternatives should be evaluated. Ultimately, the goal is to achieve a common consensus-based understanding on the information and alternatives aspects of the decision basis. The methodology is designed only to deal with a lack of consensus on preferences over outcomes.

methods for dealing with this situation. A parametric value model, based on non-compliance penalties for missed targets and the costs associated with mitigation, is introduced in Chapter 7. In decision analysis, a "penalty function" is a tool that can be used to constrain targeted variables for the purposes of exploring the trade-offs between violating targets and expending resources to meet them. In this context, a penalty does not refer to a legal fine that will be imposed upon the decision-makers by a regulatory agency, but rather reflects the "cost" of violating the target in the following sense. The penalty value takes into consideration the probability of non-compliance (predicted from the causal network) and the unknown social cost of non-compliance (treated as a parameter). By treating the social cost of non-compliance as a parameter, decision analysis can be performed and decision analytical insights can be generated without consensus on preferences. This methodology results in the creation of two or three dimensional "decision maps" that allow decision participants to consider natural system uncertainties separately from the consideration of disagreements over preferences. Chapter 7 presents the decision analytical results for the case study and discusses some insights generated by this approach. Chapter 8 offers conclusions from this research and suggests future research.

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# CHAPTER 2: SULPHUR CREEK MERCURY TMDL DECISION PROBLEM

This chapter provides background on the Federal and California state Total Maximum Daily Load regulatory programs and the Sulphur Creek mercury TMDL situation. It ends by describing the mercury mitigation actions being considered by the Central Valley Regional Water Quality Control Board for addressing the Sulphur Creek mercury problem.

## 2.1 BACKGROUND ON TOTAL MAXIMUM DAILY LOAD (TMDL) REGULATIONS

Under section 303(d) of the Clean Water Act, States, Territories, and Tribes with program delegation[6] ("States") are required to develop lists of impaired waterbodies (Percival et al. 2000). In the context of the 303(d) lists, impaired waterbodies refer to waters that do not meet ambient water quality standards[7], but that are in compliance with the NPDES program[8] (USEPA 2005). The Clean Water Act requires that States establish priority rankings for listed waterbodies and develop TMDLs for these waters. Appendix A provides some additional historical background on the adoption of and need for an ambient water quality approach like the TMDL program.

"TMDL" is often used in two senses . First, it refers to the planning process States use for determining how to achieve ambient water quality standards subject to the Section 303d of the Clean Water Act. The second sense is more quantitative and refers to the actual loads that are predicted to result in compliance with ambient water

[6] Program delegation refers to the fact that the Clean Water Act authorizes USEPA to delegate to States, Terrorities, and authorized Tribes responsibility for administering and enforcing clean water programs (Percival et al. 2000).

[7] States, Territories, and Tribes set ambient water quality standards for a given waterbody in terms of "beneficial uses" that they identify. For example, drinking water supply, contact recreation (swimming), and wildlife habitat support are common beneficial uses (USEPA, 2005).

[8] In other words, point source controls are in place that meet NPDES requirements, but the waterbody is being impaired by the combination of point and nonpoint sources.

quality standards. Specifically, this second definition a TMDL is: 1) a calculation of the maximum pollutant load that a waterbody can receive and still meet ambient water quality standards for the designated beneficial uses of that waterbody; and 2) an allocation of that maximum load among the various pollutant sources in the watershed, including point and nonpoint sources. The USEPA requires that a margin of safety be used to account for uncertainty and that seasonal variability be considered .

It is recognized that ambient water quality strategies (like TMDLs) are difficult to develop and implement because of uncertainties demonstrating causal relationships between sources (point[9] and nonpoint[10]) and downstream water quality problems. The TMDL setting and implementation processes may require extensive stakeholder dialogues and, in many cases, collaborative decision processes not traditionally used in the implementation of the Clean Water Act. The use of collaborative decision-making in a complex situation that affects stakeholders with potentially diverse values points to the need for tools that provide decision clarity.

This research builds on the idea that the suggested TMDL decision analytic process is a natural formulation of the watershed approach, in the sense described by (Haith 2003). Haith describes the watershed approach as the logical conclusion of the systems analysis for waste load allocation, emphasizing the relationships between community participation, water quality management goals, watershed activities impacting water quality, and decision-maker/expert understanding of the responses of the natural system. While traditional systems analysis techniques (e.g, waste load

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[9] EPA defines a point source as: "any discernible, confined, and discrete conveyance, including but not limited to any pipe, ditch, channel, tunnel, conduit, well, discrete fixture, container, rolling stock, concentrated animal feeding operation, landfill leachate collection system, vessel, or other floating craft from which pollutants are or may be discharged." (online glossary at: http://cfpub.epa.gov/npdes/glossary.cfm)

[10] EPA defines a nonpoint source as "any source from which pollution is discharged which is not identified as a point source, including, but not limited to urban, agricultural, or silvicultural runoff. Nonpoint source (NPS) pollution occurs when rainfall, snowmelt, or irrigation water runs over land, or through the ground, and picks up pollutants and deposits them into lakes, rivers and groundwater." (online glossary at: http://cfpub.epa.gov/npdes/glossary.cfm)

allocation optimization subject to water quality and budgetary constraints) and/or economic approaches like cost-effectiveness analysis or cost-benefit analysis have been suggested for waste load allocation decisions (Burn and Lence 1992; Churchman 1968; Thomann 1974), a watershed decision analytic framework can integrate the analytical power of such techniques with the community participation and group decision-making aspects of the watershed approach. Thus, a decision analytical process can be viewed as an informed compromise between a purely technical/analytical approach and a purely political/negotiation approach to decision-making.

## 2.2 BACKGROUND ON THE SULPHUR CREEK MERCURY TMDL

The example presented here is based on the Sulphur Creek mercury TMDL setting process. Sulphur Creek is a 6,500 acre watershed in Colusa County in northern California (Figure 2-1) with several significant local mercury sources (Figure 2-2). The Sulphur Creek watershed is part of the California Coast Range mercury mineral belt and has a mercury (and gold) mining history that dates back to the mid-nineteenth century (Churchill and Clinkenbeard 2003). Sulphur Creek, Cache Creek, and other creeks within the Cache Creek watershed are on the Central Valley Regional Water Quality Control Board's (RWQCB) list of impaired water bodies due to elevated mercury levels in water and fish[11] (RWQCB-CV 2004a; RWQCB-CV 2004b). These watersheds are impacted by total and methylmercury loadings from local hydrothermal sources, erosion of soils with high background mercury concentrations and other background sources, and runoff from legacy mine wastes. The principal local stakeholders in the Sulphur Creek mercury TMDL are the private landowners of legacy mines, the Wilbur Hot Springs resort, Colusa County, and the major land-

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[11] As noted in Chapter 1, the available evidence suggests that Sulphur Creek has very few fish and does not provide suitable fish habitat because of water quality issues related to geothermal springs (RWQCB-CV 2004b). No large fish have been reported. In a recent (April 2004) fish survey (electroshock), no fish were observed. In 2000, a single California roach was collected. The RWQCB has determined that non-fish mercury endpoints are more appropriate for a Sulphur Creek mercury TMDL, since fish appear to be rare in Sulphur Creek.

Figure 2-1. Sulphur Creek within Cache Creek watershed. From RWQCB-CV (2004a).

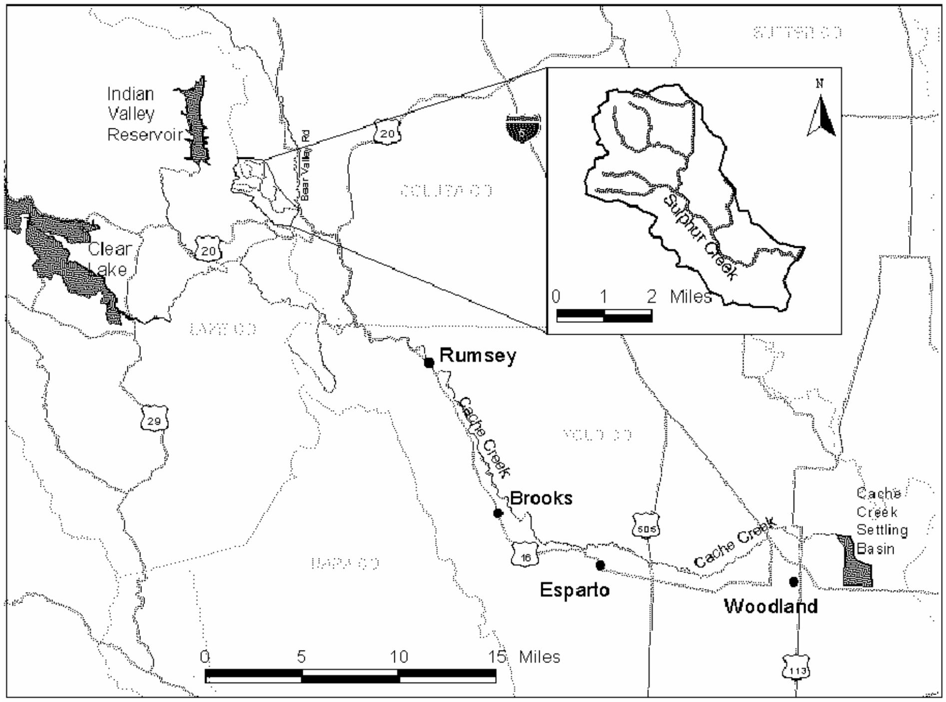
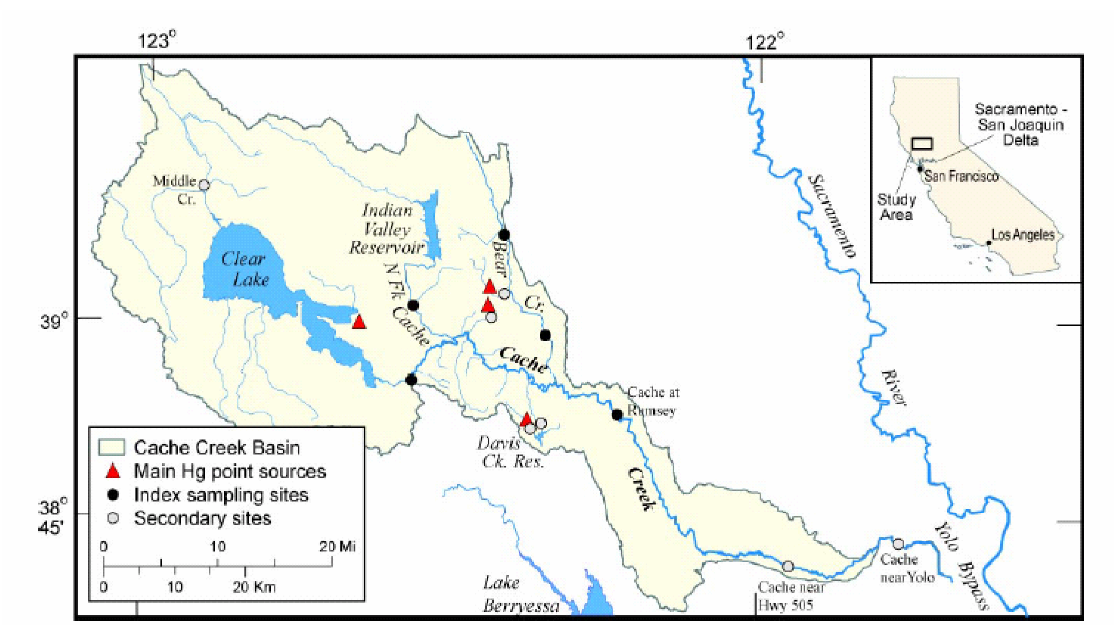



Figure 2-2. Map of the Cache Creek watershed (Suchanek et al. 2004). Mercury sampling sites and USGS flow gage stations correspond to the "index sampling sites" and "secondary sites" shown.



holder in the area, the US Bureau of Land Management. Figure 2-3 shows a map of the Sulphur Creek watershed that includes the locations of the mercury mines and geothermal springs.

The Cache Creek watershed is a major source of mercury to the San Francisco Bay, which is also listed as impaired due to mercury contamination . Elevated mercury fish tissue levels, high concentrations of mercury in the water column, and large loadings of total mercury and methylmercury have been observed in several parts of the Cache Creek watershed.

Since 2000, the Sulphur Creek TMDL workgroup has been collecting information relevant to the setting of the mercury TMDL target and for determining a proposed source allocation scheme. In addition, the CALFED Bay Delta Program, a Federal/California State partnership with the mission of developing and implementing a long-term comprehensive plan that will restore ecological health and improve water management for beneficial uses of the San Francisco Bay-Delta System, has supported several relevant research projects. The results of these studies are summarized in the November 2004 draft Sulphur Creek mercury TMDL report and the various CALFED final reports (available on-line at http://loer.tamug.tamu.edu/calfed/ FinalReports.htm).

Figure 2-3. Map of the Sulphur Creek watershed, showing mine sites and geothermal springs.

## DATA AND RESOURCE LIMITATIONS

Predicting total mercury and methylmercury loadings in mine- and geothermal source-impacted watersheds is an inherently difficult problem. Since most of the total mercury mass is transported with the suspended sediment load, the many difficulties of modeling sediment transport apply. Unfortunately, even larger uncertainties are involved in modeling the relationship between stream segment methylmercury concentrations and total mercury concentrations. While several relevant and useful studies have been conducted, the available data are sparse relative to the complexity of the modeling problem and the very large uncertainties involved (Churchill and Clinkenbeard 2003; Domagalski et al. 2003; Rytuba 2005a; Suchanek et al. 2004). Details about the available relevant water flow and water quality data for Sulphur Creek and their implications for mitigation feasibility are discussed in Chapters 5 and 6.

In general, data collection budgets for TMDL development are very limited relative to the complexity of the situation (Ruffolo 1999). Other important considerations are the large costs associated with the mitigation efforts being considered and recent evidence that strongly suggests that background total mercury and methylmercury loadings may be much larger than previously thought in the Bear Creek and Sulphur Creek watersheds (Rytuba 2005a).

In addition to data and modeling limitations and predictive uncertainty, the California Regional Water Quality Control Boards (RWQCBs) are very limited in number of staff that can be tasked with TMDL development (Ruffolo 1999). Since budgets are limited, the ability to contract outside expertise is also limited. Collectively, these issues point to a need for a decision framework that takes into consideration the very large uncertainties involved and the resource constraints of the State agencies tasked with TMDL development and implementation planning.

## 2.3 MITIGATION ACTIONS BEING CONSIDERED

The Central Valley Regional Water Quality Control Board staff are considering several potential controls for mercury in the Sulphur Creek watershed, including (RWQCB-CV 2004b):

1. Reducing total mercury in run-off from inactive mercury mine sites by removing and/or stabilizing wastes;

2. Remove or otherwise address mercury-contaminated sediments in creek channels and creek banks downstream from mine sites;

3. Reduce erosion of mercury-enriched soils; and

4. If feasible, reducing total mercury and methylmercury loads from geothermal springs.

Once the load allocations have been determined, potential controls will be evaluated during the Basin Plan amendment process. Projects and schedules will be evaluated and chosen subject to the relevant sections of the Porter-Cologne Water Quality Act. Additional monitoring may be performed before choosing projects (RWQCB-CV 2004b). For further background on the Sulphur Creek mercury TMDL, see the Regional Water Quality Control Board report (RWQCB-CV 2004b). Other useful sources of background material from the RWQCB can be found on-line[12].

[12] http://www.waterboards.ca.gov/centralvalley/programs/tmdl/Cache-SulphurCreek/

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# CHAPTER 3: BACKGROUND ON BAYESIAN NETWORKS

## 3.1 DEFINITION AND PROPERTIES OF BAYESIAN NETWORKS

Bayesian networks (belief networks) were developed as a general representation scheme for uncertain knowledge, organizing probabilistic and/or causal relationships between variables of interest as a directed acyclic[13] graph (DAG) (Jensen 1996; Jensen 2001; Pearl 1988; Pearl 2000; Williamson 2001). The network is comprised of nodes and arcs, where the nodes represent the variables of interest and the arcs represent probabilistic relevance[14], which is sometimes described as conditional dependence. If the modeler is willing to make causal assertions about variables within the model, the arcs can be used to represent causal relations (Heckerman and Shachter 1995; Jensen 2001; Pearl 2000). A model may contain several types of variables: chance (or probabilistic) variables represented by ovals, deterministic (functionally determined) variables represented by double ovals, decision variables represented by rectangles, and a value variable represented by a diamond (Figure 3-1). An example of a chance variable is the mean total mercury concentration ($Hg_T$) of a particular stream segment over a particular time period, which for simplicity we will assign three states {Low ≡ $Hg_T < 100$ ng/L, Medium ≡ $100 \leq Hg_T < 1000$ ng/L, High ≡ $Hg_T > 1000$ ng/L}. Associated with this chance variable is a probability distribution over these states,

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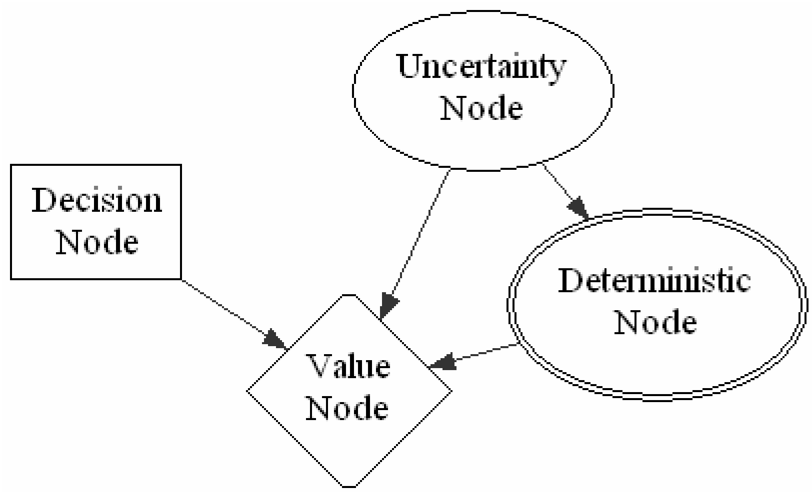
[13] A directed graph is acyclic if there exists no directed path between nodes $A_1 \rightarrow A_2 \rightarrow \ldots \rightarrow A_n$ such that $A_1 = A_n$.

[14] Relevance between chance nodes refers to the relationship between the marginal (prior) probability distribution of the parent and the conditional probability distribution of the child. For example, A→B represents the fact that the conditional distribution for B given A = a ({B|A=a, &}) is not equal to the distribution for B given A ≠ a ({B|A≠a, &}). Relevance is defined in terms of a given state of information and is *not* defined in terms of the events in question. Relevance is a mutual property, i.e., if A→B, then B→A. This property is a result of arc reversal by applying Bayes' Theorem. For more information on the concept of relevance and a proof of mutual relevance, see Howard (1990) and Howard (1996). Some authors refer to this relationship as "conditional dependence" or "probabilistic

Figure 3-1. Types of nodes in a Bayesian network for a decision situation.




perhaps conditioned on another variable. An example of a deterministic variable is the $Hg_T$ load at a particular point in time given the precise values of $Hg_T$ and water flow, since $Hg_T$ load is functionally determined by these values. If there is uncertainty in the state of the predicted $Hg_T$ value for an observed (experimentally determined) flow, then the deterministic variable $Hg_T$ load will be represented by a probability distribution over the possible load states, conditioned on $Hg_T$ and flow. A deterministic variable contains no uncertainty only if the states of its parents are known with certainty. An example of a decision variable is a set of alternatives {Alternative 1, Alternative 2, etc.}, exactly one of which will be chosen by a decision-maker at some point in time. A value variable refers to a table of values (utilities) associated with each of the possible outcomes for each alternative. A utility[15]

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dependence", e.g., Shachter (1986). When the arc is directed into a decision variable, the relationship may be termed "informational dependence" (Howard, 1990; Shachter, 1986; Pearl, 1988).

[15] Utility may be defined in terms of lotteries. When examining a lottery, the decision-maker looks at the possible outcomes for the lottery, in which each outcome has an associated value (v) and a probability of occurrence (p). For example, assume that a two-outcome lottery (Lottery i ≡ $L_i$) has outcomes A and B. The expected value of Lottery i is then computed as $L_i = p_{i,A}*v_{i,A} + p_{i,B}*v_{i,B}$, where $p_{i,j}$ and $v_{i,j}$ refer to the probability and value (in dollars) of outcome "j" in $L_i$. When comparing two lotteries, if the decision-maker prefers $L_1$ to $L_2$ ($L_1$ ► $L_2$), then a number $u(L_i)$ can be assigned to each lottery that describes the strength of the preference for that lottery. If these numbers are defined

represents the strength of the preference placed on that outcome by the decision-maker (Luce and Raiffa 1989). See Chapter 4 for a discussion of using Bayesian networks (influence diagrams) to evaluate alternatives and to perform decision analysis.

Probabilistic relevance between variables is quantified within the network by conditional probability distributions for each variable given every possible combination[16] of values of its parent variables (Jensen, 2001). A variable with no parents is quantified by an unconditional (or marginal) probability distribution. Arcs into non-decision variables represent probabilistic relevance and arcs into decision variables represent the relevant information available at the time the decision is made (Howard 1990; Howard and Matheson 1984; Jensen 2001; Shachter 1986; Shachter 1988). The Bayesian network allows: 1) computation of the posterior probabilities of any subset of the model variables given evidence about any other subset of model variables; 2) determination of the most likely scenario that explains the observed evidence; 3) determination of optimal decisions and value of information and control; and 4) determination of the effects of intervention on variables on interest through causal analysis, if causal assertions can be made (Jensen 2001; Pearl 1988; Pearl 2000; Shachter 1986).

This last use of Bayesian networks is of particular interest for TMDL linkage analysis. In other words, Bayesian networks may be used to make *predictions* about the uncertain response of the natural system to changes in those variables over which the decision-maker has some control. Bayesian networks without decision or value nodes can also be used to model reasoning under uncertainty and may be used as predictive tools in decision situations, e.g., water quality management decision situations (Borsuk et al. 2001; Borsuk et al. 2003; Reckhow 1999; Stow and Borsuk 2003; Varis 1995). One of the advantages of using a Bayesian network approach is

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over the set of lotteries such that $u(L_1) > u(L_2)$ if and only if $L_1 \blacktriangleright L_2$, then a utility function u exists over the lotteries (Luce and Raiffa 1989, p. 29).

[16] For simplicity of presentation, this discussion assumes that the model is based on discrete probability distributions.

that the model evolves as new information is collected, yielding an updated model that reflects the current state of knowledge about the system of interest, synthesizing prior information and new evidence using theoretically sound probabilistic calculus (Jensen 2001; Pearl 1988; Shachter 1988).

While Bayesian network models may be based on empirical probabilistic knowledge of the system of interest, they can also be based on what is known about the *causal relationships* between the variables of interest (Pearl 2000). The introduction of expert knowledge about causal relationships between variables allows natural system processes and behavior to be modeled using Bayesian networks. More importantly, when that causality is only incompletely understood or data-limitations exist, incomplete knowledge about causal relationships can be represented in terms of causal relations between random variables and conditional probabilities that describe these uncertain cause-and-effect relationships. Causal assertions made in Bayesian networks, in effect, provide additional constraints on the flow of information through the network when observations or interventions are made (Pearl 2000). When a variable is observed to be in a particular state, the d-separation[17] properties are different from the situation in which the variable was placed in that state by an intervention. These and other properties of causal networks are described in detail by Pearl (2000). The importance of the decision context for defining causality is described by Heckerman and Shachter (1995).

In the Bayesian network model of the Sulphur Creek mercury TMDL setting decision situation, causal relations and conditional probabilities are based on what is currently known about the relations between HgT sources, HgT loading, MeHg production and the resulting loading, Hg fish-tissue burdens, and other natural-system

[17] D-separation refers to the relationship between evidence introduction and evidence transmission for a given model structure. Two variables are d-separated if, given the evidence entered into the network, no information (changes in belief) may pass between them. Jensen (2001) describes d-separated variables as "structurally independent" to emphasize the blocking of evidence between such variables. If two variables are not d-separated, they are said to be d-connected. The same two variables in a given model structure may be d-separated or d-connected depending on which variables in the structure receive evidence.

variables. The model also includes a probabilistic representation of what is currently known about how mitigation efforts may impact the natural system. The composite effect of predictive uncertainty and natural variability are represented as conditional probability in these models.

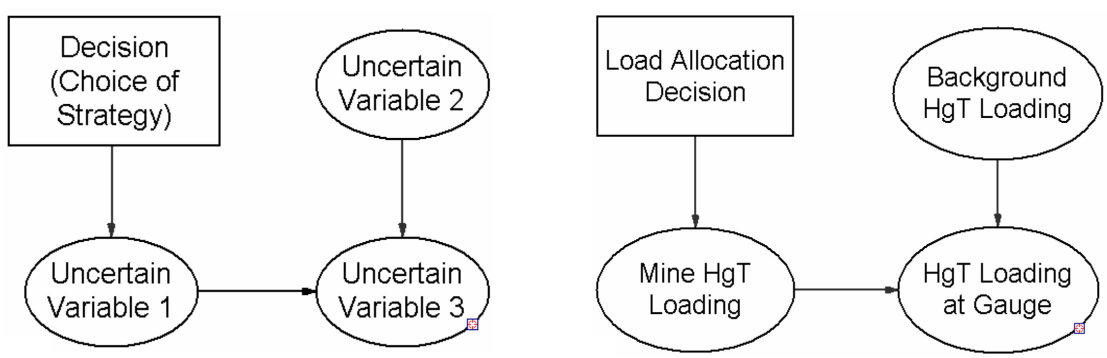
Figure 3-2 shows two related examples of a Bayesian network representation of a decision involving three uncertainties as chance nodes in which the arcs represent causal relationships. The network in (a) of Figure 3-2 is completely generic and is shown to illustrate different kinds of uncertain variables. As shown, this model says that the states of Uncertain Variable 1, 2, and 3 will not be known before the decision is made. In the case of Variable 2, its state is not influenced by the decision. The arc from the decision to Uncertain Variable 1 means that while its state will not be known before the decision, the probability distribution over Uncertain Variable 1 is influenced by the choice of strategy. The path from the decision to Uncertain Variable 3 through the arc from Uncertain Variable 1 to Uncertain Variable 3 means that the decision-maker also has some influence over its state. However, the arc from Uncertain Variable 2 to Uncertain Variable 3 means that Uncertain Variable 3 will also be influenced by something outside of the decision-maker's control (namely Uncertain Variable 2). In this way, uncertain decision-maker influence and uncontrollable uncertainty can be coherently modeled in terms of the available information and the best understanding of the causal behavior of the system being modeled.

Note that the relationships between variables are the same in the causal network shown in (b) of Figure 3-2. The same discussion from (a) holds, but we can now think of these relationships in terms of meaningful variables. In this network, the Load Allocation Decision (a decision about the strategy in reducing future total mercury loadings) has some influence over the future state of "Mine HgT Loading" (total mercury loading from some mercury mine source) over some time period, which will influence the future state of "HgT Loading at Gage" (total mercury loading downstream at a point of compliance) over the same time period. However, HgT

Loading at the Gage is also influenced by "Background HgT Loading" (total mercury loading from all other sources upstream of the gage), which is not under the influence of the decision-makers. In this context, the future state of Background HgT Loading is highly uncertain.

In Bayesian network models, it is often useful to draw relevance relationships in causal directions to increase the intuitiveness of the model (Heckerman and Shachter 1995; Pearl 2000). In this form, relationships between variables in Bayesian network water quality models can be discussed in causal terms for the purposes of evidential reasoning[18], where this causal understanding may be based on knowledge of the specific underlying causal processes involved or based on a statistical aggregation of more complex associations (Reckhow 1999). However, it is emphasized that the general definition of Bayesian networks does not refer to causality and that there is no

Figure 3-2. Bayesian Network Examples. (a) Generic decision involving three uncertain variables as chance nodes. (b) An analogous decision situation for managing mine-related total mercury loadings (Mine HgT Loading).



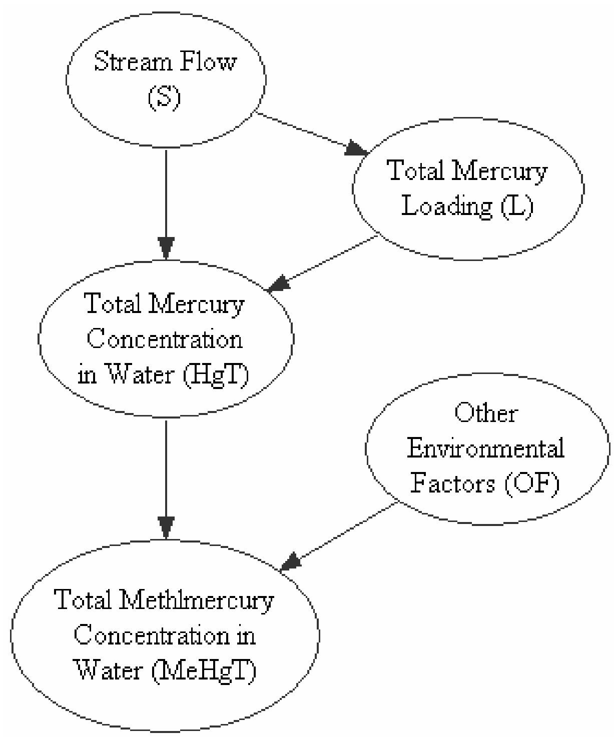

[18] The task of evidential reasoning is to determine the validity of unobservable hypotheses from observable evidence (Heckerman and Shachter 1995). The unobservable hypotheses are the variables of interest to the modeler, with the purpose being to estimate the probability that a particular hypothesis holds true given what has been observed.

requirement that arcs represent causal relationships. The definition of Bayesian networks does, however, require that the d-separation properties implied by the model structure hold for the system being modeled (Jensen 2001). It is often useful in decision analysis to draw arcs in a causal direction for use by decision-makers, but to reverse[19] them for purposes of assessment or evaluation (Shachter 1988).

Causal relationships can be represented using Bayesian networks (Figure 3-3). This figure shows a simple Bayesian network model relating stream flow, total mercury loading, total aqueous mercury concentration, and total (mono)methylmercury concentration in a stream segment over a specific time period. This model asserts that total (unfiltered) methylmercury concentration ($MeHg_T$) is caused by total mercury concentration ($Hg_T$) and "other environmental factors", which may or may not have been observed. In turn, total mercury concentration in water is caused by stream flow and total mercury loading. There are many physical, chemical, and biological processes underlying these causal assertions, but the statements made in this model are accurate based on current understanding (and perhaps even useful to decision-makers, depending on the decision context).

[19] Arc reversal is the application of Bayes' theorem to a Bayesian network and implies appropriate updating of the conditional probability distributions for the variables involved. The rules of and uses for arc reversal are described in, e.g., Howard and Matheson (1984), Shachter (1986), and Heckerman and Shachter (1995).

Figure 3-3. Graphical representation of a Bayesian network for relating mercury loading to methylmercury concentration.




To illustrate one of the points made explicit by the graph, $MeHg_T$ is conditionally independent of stream flow (S) and total mercury loading (L) given the value of $Hg_T$ and the other relevant environmental factors (OF). This conditional independence is represented graphically by the absence of arcs connecting stream flow and total mercury loading to $MeHg_T$, even though there is a path between them through the $Hg_T$ variable. It is emphasized that conditional independence in Bayesian networks refers to the blocking of the transmission of evidence within the network and is *not* the same as complete probabilistic independence (Jensen 2001; Shachter 1998). To illustrate, if the value of total aqueous mercury concentration is not known, evidence concerning total mercury loading (L) may be relevant to $MeHg_T$.

The ability of Bayesian networks to incorporate conditional independence greatly simplifies model development by allowing separate sub-models to be developed for individual conditional relationships, where these sub-models may be based on uncertainty analysis of a mechanistic model, statistical relationships in an empirical model, or probabilistic information elicited from experts (Borsuk et al. 2001; Borsuk et al. 2003). The Bayesian network itself represents a compact representation of a particular factorization of the joint distribution over the model variables (Howard and Matheson, 1984; Jensen, 2001). The factorization for the joint distribution over the universe of variables for the model shown in Figure 3-3 is:

$$\{S, L, Hg_T, OF, MeHg_T\} = \Pi_i\{i|Pa(i)\} = \{S|\&\}\{L|S\&\}\{Hg_T|S,L\&\}\{OF|\&\}\{MeHg_T|Hg_{T,} OF,\&\},$$

where the product is over all of the model variables "i", Pa(i) represents the set of parents for variable "i", and "&" designates the background state of information.

Chance variables can be further sub-divided into hypothesis variables (not directly observable) and information variables, which may provide evidence that reveals something useful about the hypothesis variables in the decision context (Jensen 2001). In the context of this decision problem, whether or not mine mitigation results in a reduction in methylmercury concentration trends can be expressed as a hypothesis variable or a set of related hypothesis variables. Total mercury concentration, reactive mercury concentration in sediment, sulfate concentration, the distribution of methylmercury concentrations throughout the watershed, etc., can then be modeled as information variables that reveal something about the relevant hypotheses.

The variables included in an influence diagram model should fit one or more of several criteria. They are either: 1) manageable, which means that the alternative chosen influences its post-decision state (e.g., total mercury loads from a mine site); 2) predictable from available data, models, or expertise; or 3) observable at the scale of interest from the perspective of the water quality management problem. In addition, chance variables are only included if they are: 1) of interest to the decision-makers and/or stakeholders or; 2) helpful for assessing probability distributions for variables that are of interest. These last two criteria could be summarized by the requirement that a path exist between any chance variable and the value node. Another way of saying this is that chance variables should be relevant to the value of the decision outcome, if they are to be included in the influence diagram. [20]

A Bayesian network that is completely represented graphically (all nodes and arcs are present and correctly related), but that is missing some data, outcomes for decision variables, or conditional probabilistic data for any of the variables is said to be *partially specified*. If no data is missing, the network is said to be *fully specified*. Partially specified network models are meaningful representations that carry considerable information about the system being modeled. In fact, many predictive and inferential queries can be fully answered from a partially specified model, depending on the query, the model structure, and the required data (Shachter 1988).

## 3.2 LITERATURE ON RELEVANT APPLICATIONS OF BAYESIAN NETWORK MODELS

There are two examples in the literature of a belief network approach being taken to model regional water quality management situations: a series of papers regarding a comprehensive study of nitrogen load reduction strategies for the Neuse River in North Carolina (Borsuk et al. 2001; Borsuk et al. 2003; Reckhow 1999; Stow and Borsuk 2003) and a application in the case of a phosphorus load reduction for the East Canyon Creek in Utah (Ames 2002). The Neuse River work (Borsuk and others) develops a Bayesian network model relating nitrogen loadings to algal densities, eutrophication effects, and fish kills for several river segments. The purpose of the model is to make predictions of future consequences of nitrogen load reductions on these endpoints of interest to stakeholders. Stakeholder and decision-maker preferences were not explicitly considered in the model.

[20] An exception would be a variable or set of variables with no path to the value node, but that, for whatever reason, are of interest to one or more decision participants.

## 3.3 SUMMARY

This chapter introduces Bayesian networks as a mathematical tool for modeling uncertain causal relationships between variables of interest. It discusses several important concepts needed for understanding Bayesian networks, including: 1) types of variables; 2) the graphical notation for representing probabilistic relevance; 3) the importance of causal assertions for environmental modeling with Bayesian networks; 4) d-separation, information "flow", modularity, and the effects of evidence; 5) how new information can be incorporated through belief updating; and 6) the uses of Bayesian networks for making predictions and inferences and performing various analyses. Other aspects of Bayesian networks are discussed in the context of decision analysis (Chapter 4) and as the Bayesian network model of the Sulphur Creek mercury TMDL is explicated in Chapters 5 and 6.

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# CHAPTER 4: A DECISION ANALYTICAL PERSPECTIVE ON TMDL DEVELOPMENT

This chapter consists of a reviewed paper published as a conference proceedings paper for the Water Environment Federation's National TMDL Science and Policy 2003 Specialty Conference. The chapter describes the decision analytical framework built upon in Chapters 5 through 8, but it takes a much more general view of preferences in TMDL decision-making than the methodology actually used in these later chapters. Some edits of the original paper were made for clarity and consistency with other chapters in this dissertation.

# A DECISION ANALYSIS APPROACH TO TMDL IMPLEMENTATION DECISIONS: MERCURY TMDLS IN THE SAN FRANCISCO BAY AREA

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## ABSTRACT

This paper describes a decision analysis approach to TMDL implementation decisions for mercury using a mine-impacted tributary in the San Francisco Bay as an example. Decision analysis is a demonstrably sound approach for making best decisions under uncertainty (see, e.g., Howard 1968, 1988; Keeney and Raiffa 1976; Clemen 1996; Merkhofer 1999). The Bayesian probabilistic nature of decision analysis makes it ideal for integrating diverse information, including the results from scientific and engineering models, cost and benefit models, empirical data, and expert judgment. One significant advantage of a decision analysis approach is its explicit separation of a decision problem into alternatives, information, and preferences. This, in theory, allows decision-makers and stakeholders to separate “what we know” from “what we want”. It is hypothesized that a more explicit separation of information and values/preferences will focus the debate. While traditional decision analysis assumes a single rational decision-maker (where “single” may also denote a group that agrees on information and preferences), it can be extended to multiple decision-maker situations in a variety of ways. Evaluating various extensions of decision analysis in a

TMDL implementation stakeholder context is one of the primary goals of this on-going study. It is hypothesized that, in general, decision analysis provides a helpful decision framework for a TMDL implementation planning/stakeholder process in many circumstances.

KEYWORDS

Decision analysis, TMDLs, mercury, water quality predictions, influence diagrams, Bayesian networks, probabilistic networks, information-gathering decisions, load allocation decisions, mitigation decisions, sensitivity analysis, value of information

## 4.1 INTRODUCTION

### BACKGROUND

There are a number of examples of the use of decision analysis for environmental decision-making in the literature, often in the area of site selection or choosing between remediation, restoration, or technology alternatives (e.g., Keeney 1980; Merkhofer and Keeney 1987; Maguire and Boiney 1994; Reckhow 1994a; Merkhofer et al. 1997; Perdek 1997; Kruber and Schoene 1998; Freeze and Gorelick 1999; Merkhofer 1999; Bonano et al. 2000; Anderson and Hobbs 2001). Environmental decision situations are often rife with uncertainty and controversy, requiring the integration of diverse kinds of information and compromises between diverse interests. TMDL load allocation decisions are typical in this regard (NRC 2001; Boese 2002). Common TMDL decision issues include dealing with appreciable scientific uncertainty and information gaps in understanding the relationships between loadings, mitigation, and effects, determining whether to make allocation decisions based on what is currently known or whether to collect new data and perform new analyses before making those decisions, and prioritizing pre- and post-implementation monitoring activities. Decision analysis provides a normative (as opposed to descriptive) framework for providing decision clarity for these kinds of decision problems. The theory behind decision analysis does not attempt to predict decision strategies that people *will* choose, but rather, it attempts to predict decision strategies people *should* choose, given a set of beliefs, alternatives, and preferences (the decision basis). In a group decision situation, if consensus is achieved on the decision basis, decision analysis can be used to determine optimal decisions. If consensus is not achievable, decision analysis may be used to highlight areas of agreement and disagreement, allowing insights into potential compromises and/or defining positions for negotiation.

Decision analysis makes use of the Bayesian (subjective) definition of probability, which treats uncertainty as a probability and allows the decision-maker to combine various kinds of information into a unified probabilistic framework. For decisions that involve perturbations to natural systems, Bayesian (probabilistic) networks that are built up from the best available scientific models, data, and expert judgments can be used to predict the consequences of those decisions (Borsuk et al. 2001, 2002; Stow et al. 2003; Reckhow et al. 1999). In practice, empirical stochastic models, uncertainty analysis of semi-empirical models, and expert judgment are the only feasible means to creating the needed probabilistic relationships. While rigorous uncertainty analyses of large mechanistic models can be used for this purpose, the computational burden is excessive (Reckhow 1999).

Bayesian (probabilistic) networks are designed to model the variables that are of interest to decision-makers. Other variables that are useful for modeling the variables of interest may be initially included, then eliminated using probabilistic marginalization (Jensen 2001). In effect, the influences of hidden variables are included in the conditional probability distributions of the variables in the model. The cumulative effects of the many variables that may individually have a small effect on a variable of interest are modeled as random “noise”, as well. This approach allows the modeler to focus on predictive accuracy for the time and spatial scales desired for the variables of interest to the decision-makers, removing details that are determined to be extraneous to the decision problem. Again, the effects of these "details" are ideally present in the conditional probability distributions of the modeled variables. As pointed out by Reckhow (1999), this approach often leads to superior predictive accuracy for the modeled variables compared to larger, more detailed deterministic scientific models of water quality impacts. The loss of mechanistic descriptive power is compensated by the ability to perform sensitivity analyses, explore scenarios probabilistically, and estimate credibility of compliance predictions. Recent work has demonstrated that water quality management effects can be effectively modeled using Bayesian (probabilistic) networks (e.g., Reckhow 1999; Borsuk et al. 2001; Borsuk et al. 2002; Stow et al. 2003). Since compliance is predicted probabilistically, a margin of safety (MOS) can be explicitly considered in terms of credibility of compliance predictions.

From a decision analysis perspective, the Bayesian network model of interest is the influence diagram, which combines decisions ("what you can do") with a model of key uncertainties ("what you know"), subject to a valuation model ("what you care about") (Howard and Matheson 1984; Shachter 1986, 1988). If consensus is achieved on preferences, influence diagrams allow determinations of optimal decisions, sensitivity of the optimal decision to key uncertainties and assumptions, and value of information on uncertainties, which may be used to plan future information-gathering activities. Value of information refers to the fact that improvements in the state of information before a decision is made can lead to a change in the predicted optimal policy. It is the potential for changing the optimal policy that generates economic value (see Howard 1968; Lawrence 1999).

Even without consensus on preferences, sensitivity analysis can be performed to explore relationships between key uncertainties and variables of interest (e.g., water quality endpoints), allowing the decision-makers to explore "what-if" scenarios of interest. When preferences are ignored (i.e., the value model is removed), the underlying Bayesian network may be referred to as a "belief network". In the context of water quality management decisions, belief networks can be thought of as modeling the response of the natural system to management strategies. For example, one could use a belief network to probabilistically explore the relationship between mercury load reductions and fish tissue mercury levels under a variety of scenarios, in essence demonstrating how *beliefs* about future fish tissue mercury levels change with load reductions. This research project makes extensive use of influence diagrams and belief networks as tools for performing TMDL decision analysis. However, the emphasis is on the use of these tools for supporting decisions, not as water quality models *per se*.

This paper demonstrates an influence diagram model of mitigation/load allocation decisions for a simple mercury TMDL example. Such a model can be used throughout the TMDL decision process, including initial information-gathering decisions, load allocation/mitigation decisions, and post-implementation monitoring decisions. The essential insight is that information-gathering/monitoring decisions, whether made before or after allocation decisions, draw their value from making better load allocation/mitigation decisions. For this reason, information-gathering decision models *build on* load allocation/mitigation decision models. Our load allocation/mitigation decision model integrates a Bayesian (probabilistic) network model of environmental system response to mitigation decisions with a valuation model, allowing insights into the credibility of compliance with multiple numerical standards, insights into sensitivity of conclusions to small changes in model parameters, and, if a value model can be defined, the determination of optimal strategies.

It is emphasized that decision analysis applied to group decision situations should be thought of as a *process* by which groups may discover useful insights that highlight where consensus may be achieved and where obstacles requiring clarification, negotiation, mediation, or litigation may lie. There are many competing versions of decision analysis with variations on how alternatives are generated, uncertainty is represented, preferences are elicited, etc. In this paper we describe a decision analytic approach that is based on small group elicitation of goals, objectives, and alternatives, a probabilistic model of natural system response, and several potential methods for eliciting and representing preferences. Other related approaches may be just as appropriate, depending on circumstances. One of the focuses of this paper is dealing with the problem of competing preferences between stakeholders, both from the perspectives of making decisions and representing preferences.

At the highest level, decision analysis divides the decision problem into *alternatives*, *information*, and *preferences*. In the context of public environmental decision-making, these could be cast as: 1) decision framing/strategy generation; 2) information modeling/synthesis/forecasting; and 3) multiattribute utility analysis, negotiation among interest groups, or other methods of eliciting and representing preferences. Each of these aspects of decision analysis will be described further through examples, with the goal of showing how decision analysis can create clarity in a complex decision problem. But first, we discuss the importance of considering uncertainty in the TMDL decision-making process.

## UNCERTAINTY IN TMDL DECISIONS

Models play and will continue to play a central role in the TMDL development and implementation process (Reckhow 1999; NRC 2001; Lung 2001; USEPA 2002). Whether the models are empirical (statistical) or mechanistic, they represent the best scientific understanding of how contaminant loadings relate to water body impairment of designated beneficial uses (NRC 2001). Once a waterbody is listed as impaired, predictive models are used to assess the relative contributions of various pollution sources, to predict the total load reduction required to meet ambient water quality standards, and to predict the relationships between specific control measures (e.g., point source load reductions) and water quality targets (e.g., ambient water concentration of a particular pollutant) in the load allocation process.

Decision-making related to TMDL development and implementation requires one to answer questions related to determining the reasons for non-attainment of beneficial use and evaluating strategies for mitigating those determined causes.

Neither of these questions can be answered with certainty. Uncertainty, whether the source is incomplete knowledge about the natural system, analytical error, or the stochastic variability inherent in natural systems, is a reality that any water quality management decision framework must recognize, assess, and, when possible, reduce (NRC 2001). The decision analytic framework proposed in this paper specifically addresses model uncertainty in the context of decision-making, using Bayesian network models to integrate predictive uncertainty about the response of the natural system to proposed mitigation strategies with stakeholder valuations of the strategies being considered.

Uncertainty in model predictions can be large and, when explicitly considered, can confound interpretation of results in terms of the decisions that need to be made (Reckhow 1994b). Uncertainty has been, however, often treated superficially in water quality management decisions, which can be a major source of contention between stakeholders and regulatory agencies (Ortolano 1997; NRC 2001). Historically, this occurred because the ability to analyze uncertainty was limited by computing power and, in some cases, by a lack of understanding of how to feasibly model and propagate uncertainty in large mechanistic water quality models. Besides the technical aspects, even when uncertainty analysis is performed well, the political reality is that discussions of the estimated uncertainty often get bogged down with arguments that have more to do with preferences than information. In fact, the use of decision analysis is an attempt to incorporate uncertainty directly into TMDL modeling and decision-making in a manner that separates information and preferences. In effect, this attempts to separate the *estimation* of uncertainty from the *interpretation* of uncertainty. Disagreements about particular beliefs and preferences can be expected to remain, but decision analysis may be able to focus the argument on those sources of disagreement, reducing confusion about the impact of uncertainty on decisions. Downplaying uncertainty to avoid these confrontations may make for an easier stakeholder process in the short term, but that strategy runs of the risk of resulting in poorly informed decisions. The National Research Council (*ibid.*) suggests the use of adaptive management to deal with the significant uncertainty involved in TMDL decisions, an approach that is being employed in many TMDLs. As discussed by Reckhow et al. (2002), an adaptive management approach may be modeled with Bayesian networks, but further discussion of adaptive management is beyond the scope of this paper.

### PREFERENCES

If decision outcomes can be valued in terms of a single attribute (e.g., an exchangeable resource like dollars), and consensus can be reached regarding those values and attitudes toward risk, decision analysis can be applied straightforwardly to determine an optimal decision policy, sensitivity analysis can be used to determine the value of information, etc. (e.g., Howard 1968; 1988; Marshall and Oliver 1995; Clemen 1996; Merkhofer 1999). The optimal decision policy for an uncertain decision situation is the policy that maximizes expected utility, a measure of value. By making maximum expected utility the decision criterion, the utility of a particular outcome is weighted by its probability of occurrence, so that the strategy that yields the highest expected utility can be thought of as promising the "highest probability of achieving the best outcome".

When a group agrees to cooperate and work towards consensus on information beliefs and preferences, the *single decision-maker* decision analysis approach may be used. Single decision-maker problems involving utility over uncertain monetary outcomes are solved in terms of expected utilities, incorporating risk attitudes. Non-monetary outcomes can be accommodated in decision analysis using the "preference probability" interpretation of utility, in which the utility of an outcome is interpreted as the probability of obtaining the best outcome instead of the worst outcome. The approach we explore in this paper is the use of multiattribute utility analysis to directly define a mapping from either monetary or non-monetary outcomes to utilities (Howard 1984b; Marshall and Oliver 1995; Clemen 1996; Lawrence 1999).

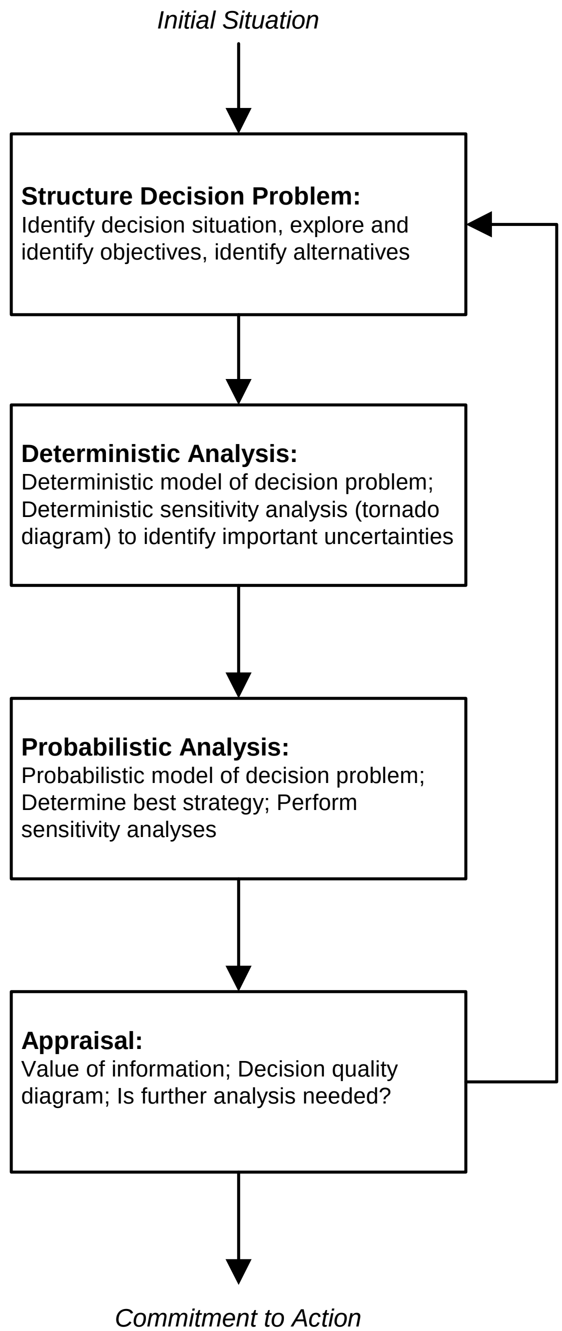
However, the assumptions applying in single decision-maker situations obviously would not describe many TMDL decision situations, which instead can be expected to have multiple goals with multiple associated attributes with perhaps no obvious consensus on valuing the various possible outcomes. Note that there are two important issues at stake here: 1) TMDL goals have multiple attributes that may not be expressible in terms of a single measure like dollars; and 2) based on experience, we can expect disagreements between work group/stakeholder group members about valuing outcomes even within an agreed-upon multiattribute framework. Each of these issues can be dealt with, if the TMDL decision-making group is willing to cooperate. This does not require that consensus in preferences is achieved, but it does require that group members agree to faithfully participate in the decision analysis process.

Work groups and stakeholder groups may use decision analysis in a number of ways, including a “competing models” approach in which the work group/stakeholder group partitions into sub-groups that agree to act cooperatively in determining mutual preferences and preferred alternatives for the purpose of arriving at negotiating positions for each sub-group (Chechile 1991). In other words, the sub-groups agree to effectively behave as a “single decision-maker” to determine recommended strategies according to the sub-group’s viewpoint. While major differences may be found between the various recommended approaches, numerous points of agreement are expected. At this point, decision analysis may be used further with mediated compromises on preferences and information that allows a group “best compromise strategy” to be formulated, but it may be necessary to resort to a purely negotiated or political compromise at this point. The advantage of applying decision analysis in this latter case is that the sources of disagreement can be more easily identified and that potential compromises may become more apparent. However, if a sub-group is non-cooperative and misrepresents their beliefs and preferences in the analysis, decision analysis may not be a useful tool for the TMDL decision-making process. Note that other analytical approaches are similarly hobbled by deliberate attempts to misrepresent positions (e.g., cost-benefit analysis). In such cases, political solutions may be inevitable. In cases in which group members are willing to cooperatively state their beliefs and preferences, decision analysis is a robust process that should be considered.

### DECISION ANALYSIS PROCESS

Figure 4-1 shows a flow diagram representing the decision analysis cycle (Howard 1984a). In a real application of decision analysis, individual steps may be emphasized or de-emphasized, depending on the particular situation. Also, a particular step may be accomplished using very different tools and some tools may be used in more than one step. So, from a “tools perspective”, two different decision analysis applications may appear to be very different, so much so that it may be difficult to see the relationships between the two approaches. However, taking a decision analysis cycle perspective, one can see how the seemingly different approaches accomplish the basic steps in decision analysis. For the purposes of this paper, we will focus on 1) decision framing/structuring; 2) probabilistic modeling of the natural system response; 3) sensitivity analyses; and 4) dealing with preferences and potentially determining optimal strategies and value of information. In particular, we will explore the application of decision analysis to load allocation/mitigation decisions and information-gathering decisions.

Figure 4-1. Decision Analysis cycle.



The initial step in the decision analysis cycle is preliminary framing and structuring of the decision situation in such a way that decision analysis may be used to evaluate the various alternatives. In particular, framing involves identifying and discussing decision performance measures, e.g., decision objectives and their associated measurable/ predictable attributes. Performance measures (attributes) can be thought of as gauging the consequences that the decision-maker cares about, so that the range of possible outcomes may be represented in a meaningful way (Keeney 1992).

The influence diagram (as a Bayesian network) is a powerful tool that allows the decision analyst to perform the deterministic analysis phase, the probabilistic analysis phase, and, if a value model can be determined, to estimate the value of information on key uncertainties and assumptions. In brief, the deterministic analysis phase translates the results of the framing analysis into a mathematical model for the purpose of determining which uncertainties are important enough to warrant probabilistic modeling in the subsequent probabilistic analysis phase. The probabilistic analysis phase assigns probabilities to the identified key uncertain variables. Input variables that have little effect on the value model output are assigned nominal (base) values and, thus, are treated deterministically. The required probability distributions are either modeled empirically from data or assessed from experts and/or decision-makers. In some cases, it may be advantageous to probabilistically combine empirical models with expert opinion. In the probabilistic analysis phase, optimal decisions may be determined if a value model can be constructed. The influence diagram may be further manipulated to perform probabilistic sensitivity analysis to determine how sensitive the optimal policy is to current beliefs about key uncertainties. The decision analyst may find that the optimal policy may change given small changes in probability distributions for a key uncertainty, in which case further analysis may be recommended. Performing and reporting the results of sensitivity analysis may be critical in achieving the degree of "decision transparency" that promotes buy-in from stakeholders.

Value of information analysis may also be performed as this stage to determine if additional information may have the potential to change the optimal policy. From a decision analysis perspective, new information only has value when the optimal policy may change in response to the new information (Howard 1968; Lawrence 1999). Since value of information analysis requires consensus in preferences, it may not resolve disagreements about information-gathering or technical review activities between sub-groups. However, it can provide the basis for positions on information-gathering and technical review activities within sub-groups and can shed light on the sources of agreement and disagreement regarding these activities.

### INFLUENCE DIAGRAMS (BAYESIAN NETWORKS) FOR ENVIRONMENTAL DECISION ANALYSIS: GRAPHICAL TOOLS FOR DECISION PROBLEM FRAMING

Influence diagrams are often used as framing tools for graphically representing the decision problem in terms of the relationships between decisions, uncertainties, and performance measures (Howard and Matheson 1984; Shachter 1988; Howard 1990; Merkhofer 1990; Marshall and Oliver 1995). The influence diagram can be constructed as a group exercise in decision framing, focusing attention on the relationships between the important variables in the decision situation, including decision strategies, uncertain variables describing the state and response of the natural system, and variables related to valuing outcomes. In addition to graphically representing important aspects of the decision problem, the influence diagram can be used to determine information/ forecasting requirements, probability assessment order, and, if decision trees are to be used, decision tree structure. Deterministic sensitivity analysis may later determine that one or more uncertainties can be treated deterministically and hence the influence diagram may evolve during the decision analysis problem. The role of the influence diagram in determining information and modeling/forecasting needs is very important: this approach helps decision-makers and technical experts/scientists communicate about what information is important *in terms of the decisions to be made.*

### INFLUENCE DIAGRAMS AS BAYESIAN NETWORKS FOR SOLVING DECISION PROBLEMS

In addition to decision framing, influence diagrams can also be used directly as Bayesian network models by adding to the graph the requisite probability structures needed for modeling consequences and value. In this use, an influence diagram is a class of Bayesian networks that may include nodes representing uncertain system variables, deterministic system variables, decision variables, and a value variable. Optimal decisions are those that maximize expected utility through relationships between the value variable and the other variables. Thus, influence diagrams can be used in lieu of or in parallel with decision trees to solve for optimal decisions, to evaluate sensitivity of the optimal decision to information and model assumptions, to estimate the value of information and control, and to make inferences from the available data important to the decision situation (Howard and Matheson 1984; Shachter 1986; Oliver and Smith 1990; Pearl et al. 1990). In the approach described in this paper, decision trees (Chechile 1991; Marshall and Oliver 1995) are avoided altogether and the Bayesian network is used as the primary analytical tool.

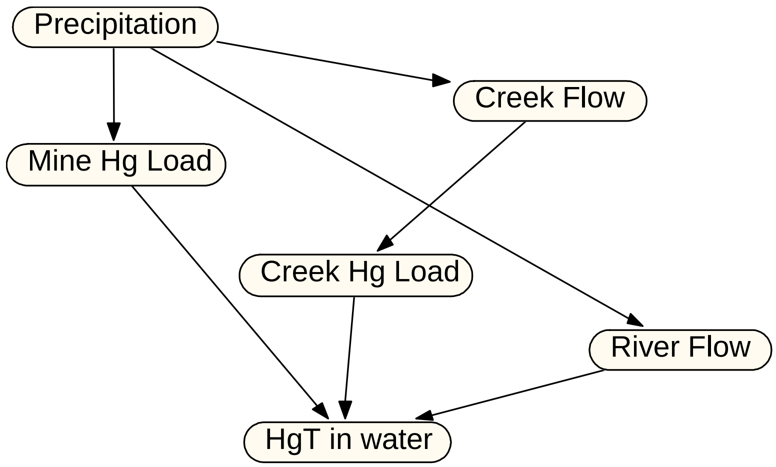
To emphasize the point, the Bayesian network version of the influence diagram may be used to make *predictions* about the response of the natural system to changes in those variables over which the decision-maker has some control. Bayesian networks without decision or value nodes ("belief networks") can be also used to model reasoning under uncertainty and may be used as predictive tools in decision situations, e.g., water quality management decision situations (Reckhow 1999; Borsuk et al. 2001). One of the advantages of using a Bayesian network approach is that the model evolves as new information is collected, yielding an updated model that reflects the current state of knowledge about the system of interest, synthesizing prior information and new evidence using theoretically sound probabilistic calculus (Jensen 2001; Shachter 1986, 1988; Reckhow 1999; Pearl et al. 1990; Varis 1995).

Figure 4-2 shows an example of a Bayesian (belief) network representing causal relationships between precipitation, creek flow, river flow, mine mercury load, creek mercury load, and total mercury in water ($Hg_T$). The belief network consists of a graph and probabilistic data associated with the nodes in the graph. The graph consists of nodes (ovals) connected by arrows. Ovals represent chance (uncertain) nodes and associated with each chance node is a random variable. The random variables in the Bayesian network represent the attributes of interest to decision-makers. Arrows represent potential conditional probabilistic dependence between the various random variables and can be drawn in a causal direction. Graphically, the arrow points from the “parent node” to the “child node”, which intuitively indicates that the child node somehow “depends” on the parent node. More precisely, an arrow from a parent node to an uncertain variable (child) means that the probability distribution in the uncertain variable (child) is conditioned on the state of the parent node. The absence of an arrow between two variables indicates that the variables are conditionally independent. If there is a directed path between two variables (i.e., there exists a set of arcs between them which can be traversed in the direction of the arcs) which do not have a direct parent/child relationship, those variables may or may not be relevant to one another, depending on the state of information. For example, Figure 4-2 asserts that precipitation may be relevant to total mercury in water ($Hg_T$) if at least one of the values for “Mine Hg Load”, “Creek Hg Load”, and “River Flow” has not been observed. But, it also asserts that, given observations for “Mine Hg Load”, “Creek Hg Load”, and “River Flow”, precipitation and total mercury in water are conditionally independent of each other. These assertions of conditional independence are very important in terms of understanding information needs and performing decision analysis.

The variables included in a network may be included for a variety of reasons, including the decision-makers’ direct interest in the state of a variable (e.g., $Hg_T$) or because the variable helps to interpret or predict those variables of direct interest (e.g., precipitation). It is important to understand that variables needed from a technical perspective for modeling a particular complex system do not need to be shown in the version of the Bayesian network used for decision analysis, communicating with decision-makers or stakeholders, etc. Variables needed only for modeling reasons can be probabilistically absorbed into the network, which yields the same results as before the nodes were removed. The local representation is changed, but the global probabilistic relationships are not affected (Shachter 1988; Pearl et al. 1990). As there may indeed be variables of interest to scientists about the natural system being modeled that are not important to decision-makers, this is an important point to understand.

The conditional probabilistic relationships between conditionally dependent variables can be quantified in a modular fashion using an approach suitable to the kind and amount of information available, where this modularity follows from the conditional independence relationships in the model (Reckhow 1999, 2002). This allows various kinds of statistical and subjective probabilistic information (from data, models, and expert judgment) to be integrated into a single probabilistic network model that can be used for predictions and inferences of use in decision-making situations. Prediction refers to following an arrow in the forward direction, i.e., predicting the probability distribution of a child node based on the values or distributions of its parent nodes. Inference refers to following an arrow in the reverse direction, i.e., inferring the probability distribution of the parent nodes based on evidence about the value of the child node(s) (Jensen 2001). The ability of a Bayesian network to make predictions is useful,

Figure 4-2. An example of a Bayesian network.




for example, when trying to model the effects of particular mitigation strategies on water quality attributes of interest. Learning what new evidence about a predicted variable means in terms of hypotheses about cause and effect between parent and child nodes is an example where the ability of Bayesian networks to perform inference may be useful.

A point that needs to be emphasized here is that while such an influence diagram model (or any other model) is an imperfect representation of the real system, it should faithfully represent how the decision-maker *believes* the real system will behave, given the available data and current scientific understanding. The decision-maker can do no better than this when making a decision. In particular, if the optimal strategy is sensitive to slight changes in the underlying probability distributions, then a value of information analysis may determine that re-framing the load allocation/mitigation decision problem as an information-gathering decision problem may be the best course of action. If there are regulatory constraints that prevent this re-framing, using the existing model to suggest optimal strategies is the best course of action, from the decision analytical perspective.

## 4.2 METHODOLOGY AND DISCUSSION

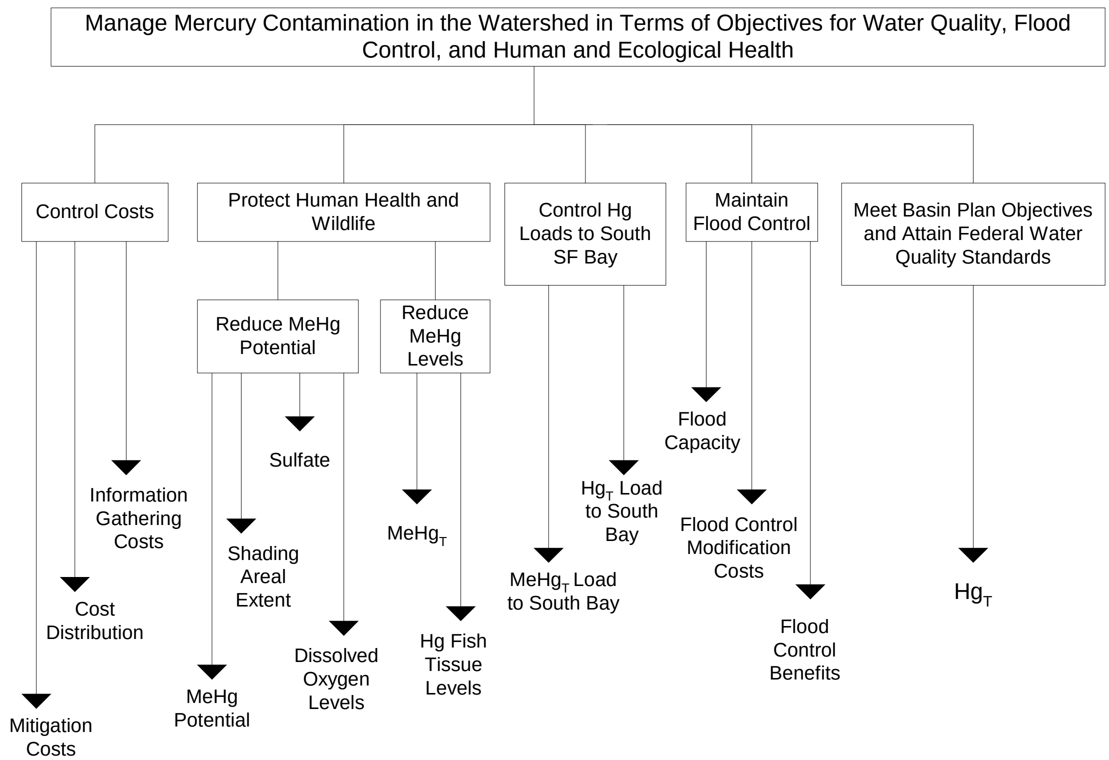
### FRAMING THE DECISION: OBJECTIVES HIERARCHY

Decision framing tools are used to represent the decision situation in a way that enables the evaluation and comparison of alternatives according to criteria that are meaningful to the decision-maker. The objectives hierarchy is a common framing tool that identifies and organizes decision outcome performance measures (attributes), which are used as evaluation criteria (Keeney 1992) and can be used as variables in an influence diagram representation of the decision problem. Keeney (*ibid.*) organizes the objectives hierarchy with: 1) an overarching decision goal at the top of the hierarchy; 2) a set of issue-specific objectives consistent with and subject to this top goal; and 3) a set of attributes consistent with and subject to the specific objectives. There may be more than one level of objectives between the top decision goal and the decision attributes, depending on the framing desired by the decision-makers. Attributes are ideally the performance measures that the decision-makers care about, and they should be chosen to be well-defined, measurable (at least in theory) and predictable. When the objectives hierarchy is complete, the attribute set formed should be comprehensive (capture all of the aspects of value at stake), minimal (as small in number as possible), independent of one another, and operationally feasible (Keeney and Raiffa 1976; Reckhow 1994a). These requirements ensure that there are no "holes" or "double-counting" in the analysis and that a suitable value model can be constructed (Merkhofer 1999).

Figure 4-3 shows a hypothetical objectives hierarchy for a mercury TMDL for a tributary to the south San Francisco Bay. In practice, the objectives hierarchy would be developed by the TMDL work group and/or stakeholder group, with the help of the decision analyst. The top goal in this example objectives hierarchy is to manage mercury contamination in the watershed, with objectives pertaining to protecting human health and wildlife (sub-objectives of reducing mercury methylation potential and methylmercury levels), meeting Basin Plan water quality objectives for total mercury, maintaining adequate flood control, meeting the ten and twenty year total mercury load reductions under the San Francisco Bay mercury TMDL, and controlling compliance costs. Each objective is translated into one or more attributes, and this is shown graphically by arrows pointing from a given objective to its attributes (performance measures). Attributes serve multiple roles in decision analysis. They form the basis of the value model, since they are the performance measures that matter to decision-makers, and they define information needs for decision modeling. In this latter role, TMDL decision situation attributes help define which natural system variables need to be modeled for relating management strategies to value, as will be demonstrated below.

For example, the “fish tissue mercury levels” attribute might be defined as the average fish tissue mercury burden of a particular fish species (with perhaps specified weight range, sex, etc.) within the watershed over some time scale. An attribute that might be less obvious in the context of mercury mitigation, but that may be very important to some stakeholders is flood capacity. The use of flood capacity as an attribute allows decision-makers to keep track of the impact of mitigation strategies on flood capacity, while simultaneously evaluating those strategies in terms of other attributes. While establishing TMDL performance measures is an explicit activity in the TMDL process, it is important to identify a list attributes that capture *all* stakeholder values that may be significantly affected. To emphasize the point, it is important to frame the problem not just in terms of “technical TMDL endpoints”, but also in terms of attributes that characterize objectives that matter to stakeholders in terms of idiosyncratic preferences. In fact, capturing this latter class of attributes may make the difference between understanding *why* stakeholder values lead to disagreements about acceptable strategies later in the decision process and finding a situation in which there are arguments that are seemingly about “technical information”, but that really reflect unstated preferences.

Figure 4-3. Hypothetical objectives hierarchy for managing mercury in a small mine-impacted tributary to the South Bay.




It is common, but often unheeded, advice in the decision analysis literature to appropriately focus attention at this step since careless framing can lead to "solving the wrong problem", leading to inappropriate or incomplete consideration of alternatives, a short-sighted understanding of the decision situation, and a misappropriation of resources (Howard 1968; 1988; Reckhow 1994a; Clemen 1996; Merkhofer 1999). Nevertheless, decision-makers often treat this stage cursorily and plunge quickly into more familiar territory: technical problem framing, information-gathering, modeling, and analysis. Decision-makers often have a good understanding of many aspects of the decision problem "going in" to a particular decision situation, which can sometimes lead to the misapprehension that detailed decision framing exercises are unneeded. However, extensive decision framing can lead to better planning and resource allocation and to evaluating the "right alternatives" in terms of the "right attributes" for making good TMDL decisions. To a significant degree, TMDL guidance documents already promote this activity from the technical perspective.

### IDENTIFYING ALTERNATIVES AND GENERATING STRATEGIES

Keeney (1992) describes a number of methods for using the attributes and objectives from the objectives hierarchy to explore and generate decision alternatives. Clemen (1996) provides a basic and useful summary of various techniques, including some of the methods discussed in Keeney (*ibid*). The methods build on the identified goals, objectives, and attributes, stressing the importance of flexibility and creativity. One tool in particular may be useful for generating TMDL strategies: the strategy table. Figure 4-4 shows a simple example of a strategy table with two strategies. Strategy tables are fairly intuitive and the tool can be used in a group setting without much introductory material required. The basic idea is to capture the possibilities, then to select a manageable number of strategies as alternatives for further decision analysis. A strategy consists of a set of single elements from each column in which the combination of those elements makes sense as an approach. There will, of course, be combinations that are incoherent and these combinations would not represent a viable strategy. In a real TMDL allocation decision situation, the strategy table would be expected to have more elements (columns), making such an approach useful for brainstorming and organizing complexity. In Figure 4-4, two strategies are shown for illustration: 1) a methylmercury potential mitigation strategy that includes "medium reductions" for mine site and creek mercury loads and an aggressive reduction of mercury methylation potential and 2) a mine site mercury load reduction strategy that includes a large reduction requirement for mine site mercury loading and minimal reductions for creek mercury loading and mercury methylation potential.

Once an objectives hierarchy has been created and alternatives have been generated, the decision analyst will work with the group to create an influence diagram from the chosen attributes, alternatives, and variables representing identified important

Figure 4-4. Strategy table example.

| Strategies ↓ | Mine Site Hg Load Allocation | Creek Hg Load Allocation | MeHg Potential Mitigation |
|---|---|---|---|
| *MeHg Potential Mitigation Focus* | Small Reduction | Small Reduction | Small Reduction |
| *Mine Site Load Reduction Focus* | *Medium Reduction* | *Medium Reduction* | Medium Reduction |
| | Large Reduction | Large Reduction | *Large Reduction* |

uncertainties. Attributes may become variables in an influence diagram or may become part of the value model, depending the nature of the attribute. It may be worthwhile to revisit the objectives hierarchy and strategy table after the influence diagram has been created to see if revisions are necessary.

## Multiattribute Utility Analysis

Multiattribute utility analysis (MUA) is designed to deal with the complexity of eliciting and representing the values at stake in complex decision problems like environmental decision situations (Keeney and Raiffa 1976; Gregory 1999; Merkhofer 1999; Prato 2003). In particular, multiattribute utility analysis (MUA) or other approaches (e.g, the analytic hierarchy process) may be used to elicit and represent preferences when multiple decision attributes/criteria are important (Chechile 1991; Marshall and Oliver 1995; Merkhofer 1999). In general, MUA is conceptually simple, but may become operationally complex with details that should burden the decision analyst and not the decision-makers/work group. One problem is that lay people may see this apparent complexity as being suspect, so great care should be taken to ensure that decision-makers/work group members sufficiently understand the concepts being used so that the preference representation approach is trusted (Morgan and Henrion 1990).

While there may be consensus that one alternative appears superior to the others in terms of one particular attribute, it may appear inferior in terms other attributes. Trade-offs between attributes is thus usually necessary and this idea is at the core of multiattribute decision-making (Keeney and Raiffa 1976; MacCrimmon and Wehrung 1977; Merkhofer et al. 1997). MUA can be used directly to rank alternatives in terms of weighted utilities (Prato 2003), ignoring probabilities of outcomes in the decision-making process. However, it can also be used in a decision analysis framework that includes a probabilistic treatment of uncertainty and that determines best policies based on expected utility.

Once the decision analyst elicits preferences between outcomes among the various decision attributes for each decision-maker sub-group, the consensus preferences for each sub-group can be aggregated into a multiple-attribute utility function and maximum expected utility can be determined. Note that MUA does not require monetization of preferences, one of the appeals of the technique. Other approaches like probabilistic cost-benefit analysis, cost-effectiveness analysis, minimization of chance of worst possible outcome, etc. could also be used, depending on the situation (Morgan and Henrion 1990).

To illustrate the MUA process, Table 4-1 shows an example multiattribute utility analysis (MUA) for a few outcomes for the two strategies from Figure 4-4, MeHg Potential mitigation focus (Strategy 1) and mine site Hg load reduction focus (Strategy 2), as evaluated by a hypothetical decision-maker sub-group. Other sub-groups could be expected to have different results. This analysis assumes that the decision problem is being modeled with discrete probabilities and that there are a finite number of possible outcomes. MUA can then be used to elicit a utility function from the decision-makers over those outcomes, as suggested by this example. Here the sub-group chose a weighting scheme of 0.3 for cost, 0.6 for credibility of compliance with total mercury load to the South Bay target, and 1.0 for credibility of compliance with fish tissue mercury level target. Composite utilities are shown in the rightmost column. Other approaches to defining a multiattribute utility function or analogous scoring functions could be used, depending on the wishes of the subgroup.

Credibility of compliance refers to the conditional probability (not "confidence" in the statistical sense) that a particular attribute has a value that meets a particular target (threshold) value, as computed within the network. The threshold could itself be uncertain, but need not be. The credibility of compliance in essence becomes a node in the Bayesian network conditioned on the attribute (target) of interest. The concept is similar to the "confidence of compliance" described in the literature, but is referred to here as a "credibility" since it is not statistical confidence to which we are referring. The concept may prove to be useful for evaluating mitigation/allocation strategies since strategies that yield higher probabilities of success would naturally be more appealing.

While the sub-groups may well arrive at different conclusions, their respective positions should be well-defined in terms of beliefs about probabilities of outcomes and their preferences. Consensus building exercises that attempt to arrive at compromises may be performed or negotiation between the various sub-groups may follow. Again, the advantage of using decision analysis is that the positions of each sub-group should be clear and the various sources of differences in positions should be apparent. The price that must be paid to get to this point is that the work group members must agree to accurately state their beliefs and preferences. If trust is lacking, then appropriate measures may be required (e.g., allowing sub-groups to develop their positions privately without sharing analyses) or non-analytical approaches may be required. Exploring the

Table 4-1. Multiattribute utility analysis for several outcomes for strategies 1 and 2 for a particular sub-group.

| **Possible Outcomes** | **Utility on Cost[1]** | **Utility on COC Load[2]** | **Utility on COC fish3** | **Composite Utility Using Weighting Scheme** |
|---|---|---|---|---|
| Strategy 1, Cost = 15, COC Load = 30%, COC fish = %20 | 10 | 2 | 1 | 5.2 |
| Strategy 1, Cost = 30, COC Load = 35%, COC fish = 50% | 6 | 3 | 9 | 12.6 |
| Strategy 2, Cost = 30, COC Load = 40%, COC fish = 30% | 6 | 4 | 4 | 8.2 |
| Strategy 2, Cost = 50, COC Load = 60%, COC fish = 45% | 2 | 8 | 6 | 11.4 |
| *.... other outcomes* | ... | ... | ... | ... |
| Notes:<br>1) Mitigation cost<br>2) Credibility of compliance with total mercury load to the South Bay target<br>3) Credibility of compliance with fish tissue mercury level target | | | | |

possibilities and determining “what works and why” is an active area of research in the field of collaborative group decision-making .

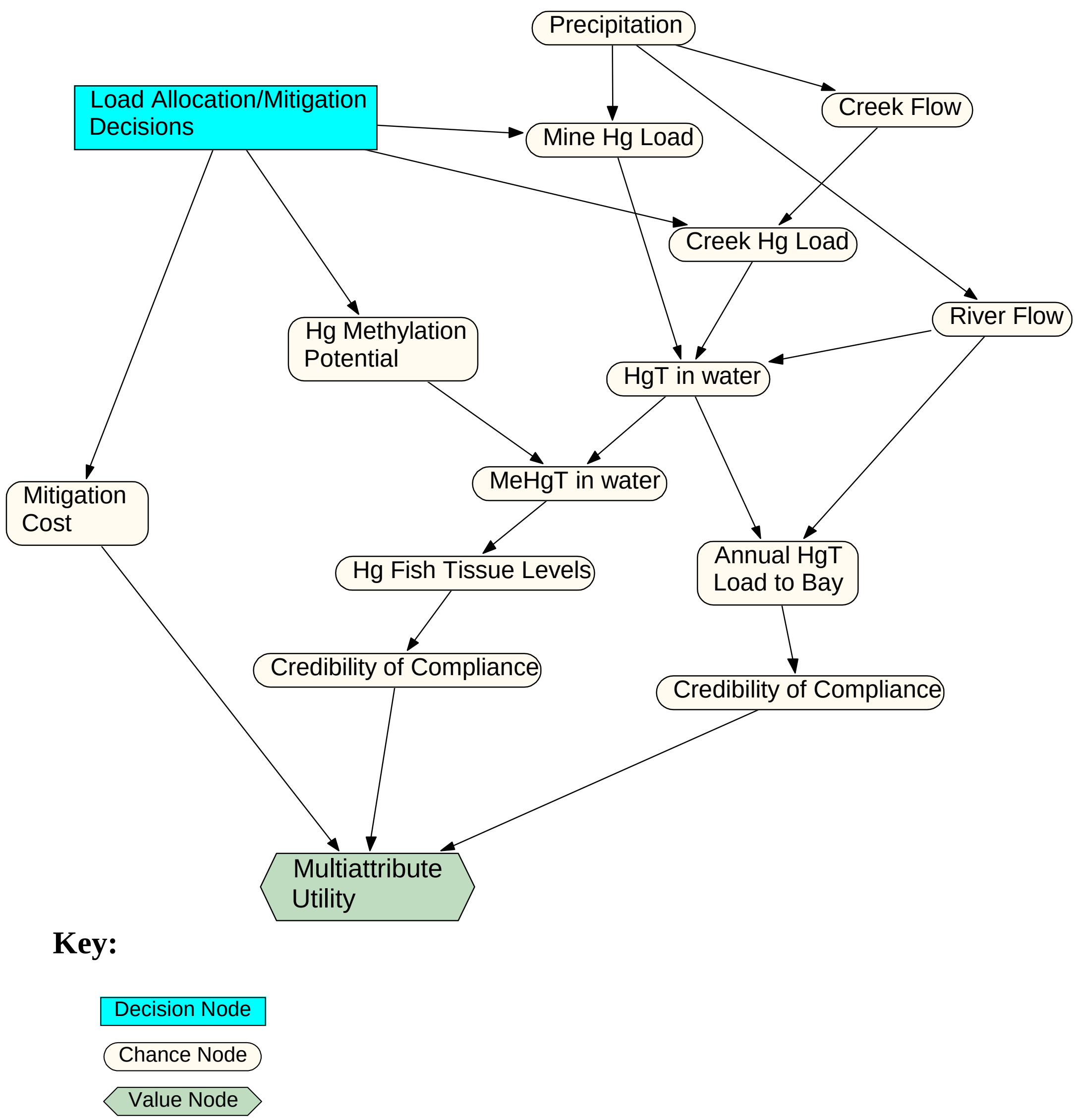
Such a multiattribute utility function could be used in an influence diagram model of TMDL decisions to determine optimal decisions, perform sensitivity analysis for expected utility, and estimate the value of information in terms of utility. If preferences can be expressed in monetary terms, a monetary value of information can be estimated for the uncertainties. One could argue whether or not this is appropriate, but the choice reflects the wishes of the sub-group cooperating in the analysis. Whether the scale is dollars or utility, value of information provides a useful signal for prioritizing information-gathering activities and technical review needs.

### INFLUENCE DIAGRAMS FOR FORECASTING ALLOCATION DECISION CONSEQUENCES

Designing and implementing a Bayesian network model occurs in three stages: 1) development of the graphical model linking the identified variables in terms of conditional independence relationships; 2) assessment of the required conditional or marginal probability distributions for each variable; 3) entering evidence/observed data (if applicable) on observable nodes in the compiled model to see how beliefs in unobserved nodes are affected (Jensen 2001). In the example that follows, the Netica™ Application for Belief Networks and Influence Diagrams (Norwys Software Corp. 1996) was used to implement the model. Other Bayesian network development environments include the MatLab Bayes Net Toolbox (Murphy 2002), the GeNIe© software package (University of Pittsburgh), Microsoft® Bayes Networks (MSBN), and Analytica® (Lumina Decision Systems, Inc.). Russell Almond at the University of Washington maintains a website listing and reviewing Bayesian network software: http://www.stat.washington.edu/bayes/almond/belief.html#MSBN. Morgan and Henrion (1990) discuss considerations and issues in choosing a computing environment for probabilistic analysis.

Figure 4-5 shows an influence diagram that describes a decision situation building on the belief network from Figure 4-2. This influence diagram includes a decision variable (Load Allocation/Mitigation Decisions), new chance variables for mercury methylation potential, total mercury in water ($MeHg_T$), fish tissue mercury levels, annual total mercury load to the Bay, mitigation cost, credibility of compliance (discussed below) for methyl mercury levels in fish, and, credibility of compliance for total mercury load to the Bay. It also includes a multiattribute utility node (value node) defined in terms of mitigation cost, credibility of compliance with a mercury fish tissue target, and credibility of compliance with the annual total load to the Bay target. By eliciting decision-maker (sub-group) preferences over outcomes in terms of these three attributes with multiattribute utility analysis, optimal load allocation/mitigation decisions can be determined for the sub-group using this model.

Figure 4-5. Influence diagram for mercury load allocation/mitigation decisions for a small watershed impacted by a mercury mine site and mine wastes.



The influence diagram in Figure 4-5 states that, given the total mercury concentration in water ($Hg_T$) and river flow, the annual total mercury load to the South Bay is independent of the mine and creek loads. Precipitation is modeled using a marginal (unconditional) distribution based on the available historical data and creek flow is modeled conditioned on precipitation. The mine mercury load is modeled as being conditional upon precipitation and the mine site mercury load allocation. The creek mercury load is modeled as being conditional upon creek flow and the creek mercury load allocation. To further illustrate the concept of conditional independence, note that *given observations* for $Hg_T$ and river flow (e.g., annual average values over the waterbody), the annual total mercury load to the South Bay is conditionally independent of the creek Hg load and mine site Hg load. This does *not* mean that creek Hg load and mine site Hg load do not impact the total annual Hg load to the Bay, but rather that the influence is through the HgT variable. From a causal perspective, the observed HgT value would "reflect" any influence from the mine site and creek Hg loadings, which is why the loadings become irrelevant upon observation of $Hg_T$. When HgT is not observed, the mine site Hg load and creek Hg load variables are relevant to the annual total Hg load to the Bay through their collective influence on the HgT variable.

Assumptions about spatial and temporal averaging are built into the Bayesian network, as appropriate to the particular decision problem. This is driven by the scope of the environmental problem, and includes consideration of natural processes, regulatory requirements, stakeholder objectives, etc. For this simple example, precipitation and creek flow probability distributions represent the available data over annual cycles and total mercury in water (HgT) refers to annual average concentration over the waterbody. These assumptions were made to keep the number of variables manageable for illustration.

The model in Figure 4-5 represents that fact that decision-makers have influence over the natural system, even though the decision outcomes are uncertain. Control is represented in the graph by arrows from the decision node to the Mine Hg

Load, Creek Hg Node, and Hg Methylation Potential nodes. In an influence diagram, if the parent node is a decision variable, the probability distribution for the uncertain variable child is conditioned on the decision made. This control can be thought of in causal terms as the ability of the decision-maker to require mitigation actions that reduce mercury loadings or alter environmental factors such that mercury methylation potential should be reduced (e.g., river or creek shading, reservoir aeration).

To understand how that influence over loading and methylation potential propagates through the other variables in the network, ultimately influencing value (multiattribute utility), we must understand how information "flows through" the network. For example, the Creek Hg Load node is the parent of HgT node. When the parent of a chance node is another chance node, the child's probability distribution is conditioned on the state of the parent chance node, which may either have an observed value or may itself be represented by a conditional probability distribution. In this example, the load allocation/mitigation decision alters the Creek Hg Load conditional probability distribution, which in turn alters the HgT conditional probability distribution. In this manner, the uncertain impacts from the chosen allocation/mitigation strategy propagate through the network, influencing the conditional probability distributions for the attributes of interest to decision-makers. A chance node with no parents is described by an unconditional (or marginal) probability distribution, typically created from historical data (e.g., precipitation).

Bayesian networks can accommodate a mixture of continuous and discrete probability distributions for uncertain variables. In special cases decision variables can be continuous (e.g., Gaussian influence diagrams), but in general decision variables are discrete. In the implementation for the influence diagram shown in Figure 4-5, precipitation, creek flow, mine and creek loads, total mercury concentration in water, annual mercury load to the South Bay, and mitigation costs are continuous[21]. Fish tissue mercury levels and MeHgT in water are modeled as discrete variables, given the high uncertainty in their predicted post-mitigation states.

### Optimal Decisions and Sensitivity Analysis Using Influence Diagrams Without a Value Model

To illustrate how influence diagrams can be used to perform decision analysis *without a value model*, Figure 4-6 simulates predictions for the hypothetical strategy focusing on reducing mercury methylation potential ("MeHg Potential Mitigation Focus") from the strategy table shown in Figure 4-4. For this strategy, "medium reductions" are chosen for mine site and creek Hg load reductions and a "high reduction" is chosen for MeHg potential reduction. This simplified hypothetical model predicts mine Hg load, creek Hg load, HgT, MeHgT, Hg fish tissue levels, the annual total mercury load to the South Bay, and credibility of compliance measures for fish tissue levels and the load to the Bay. For this strategy, the predicted credibility of compliance with mercury fish tissue targets is around 60% and the predicted credibility of compliance with the annual Hg load to the South Bay is around 42%. The average predicted cost for this strategy is 28 with a standard error of 19, where the units are arbitrary (e.g., \$10,000).

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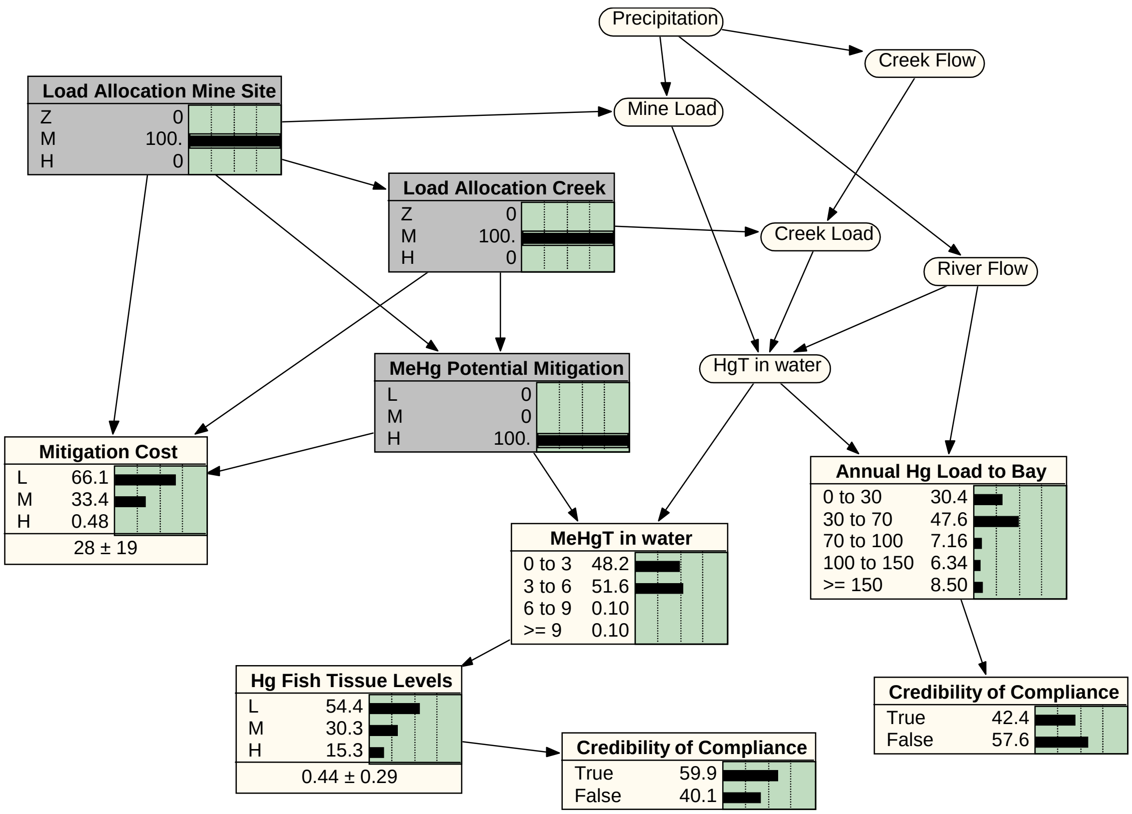
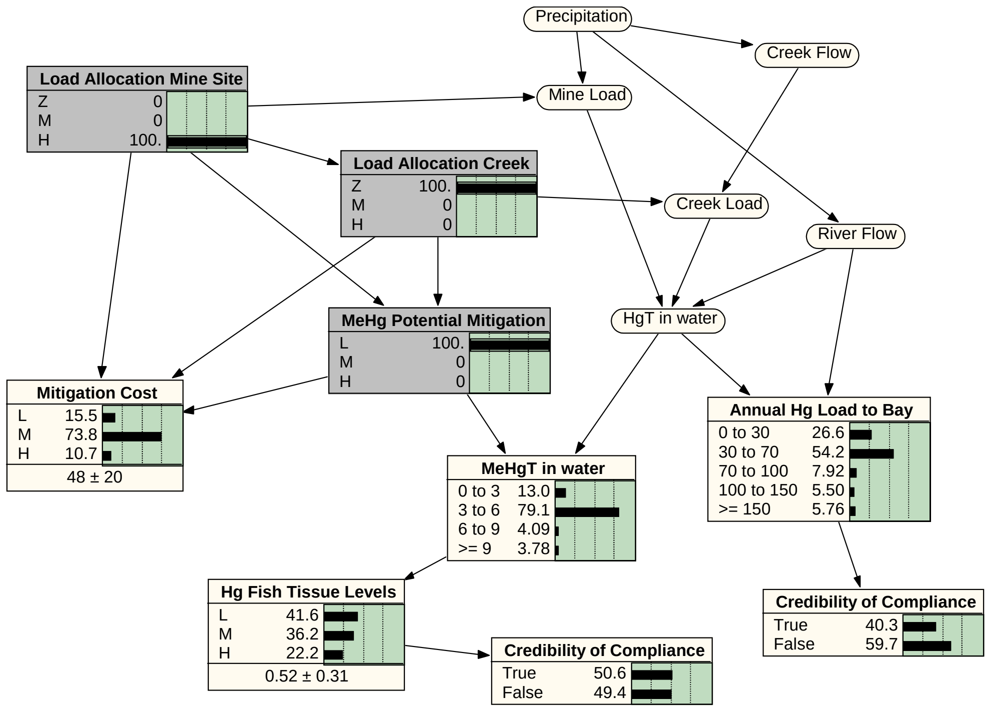
[21] Actually, all of the variables are modeled as discrete in the Netica software tool. Continuous variables are approximated using discretization algorithms from the entered continuous distribution functions.

Figure 4-6. Example predictions for "MeHg Potential Mitigation Focus" strategy.




For a comparison, Figure 4-7 simulates predictions for the other hypothetical strategy from the strategy table, "Mine Site Load Reduction Focus", in which a "high reduction" is chosen for the mine site Hg load and "low reductions" are chosen for the creek Hg load and MeHg potential. For this strategy, the predicted credibility of compliance with mercury fish tissue targets is around 50% and the predicted credibility of compliance with the annual Hg load to the South Bay is around 40%. The average predicted cost for this strategy is 48 with a standard error of 20 in the

Figure 4-7. Example predictions for “Mine Site Load Reduction Focus” strategy.




same arbitrary units. In this simple example, the “MeHg Potential Mitigation Focus” strategy is clearly superior in terms of predicted credibility of compliance for both endpoints (fish tissue levels and annual load to the Bay) and mitigation cost. The first question that arises at this point is how robust is this conclusion? Another question that arises is, what would happen if the results were “mixed”, in the sense that one strategy was superior in terms of one attribute and the another was superior in terms of another attribute? In most real world cases, “mixed results” would be anticipated. The first question may be addressed with sensitivity analysis and the second with multiattribute utility analysis, which will be explored next.

## Sensitivity Analysis in Decision Analysis Using Bayesian Networks

Sensitivity analysis within the framework of influence diagrams and decision analysis has several meanings and purposes. In general, the idea is to analyze how sensitive conclusions are to the various pieces that make up the model. In the context of influence diagrams, sensitivity analysis refers to analyzing how sensitive conclusions (probabilities of interest or expected utility) are to small changes in the conditional probabilities that influence those conclusions (Jensen 2001). Sensitivity analysis may be used, for example, to "tweak" the probability distributions within the network to meet constraints imposed by expert judgment or observations. In this paper, we will focus on some aspects of sensitivity analysis dealing with the robustness of conclusions in the context of influence diagrams describing decision situations. For more details, see Nielsen and Jensen (2003), Laskey (1995), Jensen (2002), and Castillo and others (1997).

Table 4-2 illustrates an analysis of the sensitivity of credibility of compliance for the total mercury load to the Bay to small changes in the conditional distributions for mine Hg load for the "Mine Site Load Reduction Focus" strategy. Note that while the numbers are based on actual output from the model in Figure 4-7 implemented in Netica, the underlying distributions are fictitious. The sensitivity analysis output shows that the credibility of compliance for total mercury to the Bay ranges from around 9% to 44% for changes to mine Hg load, where the current value is around 40%. "Quadratic scoring" and "Entropy reduction" refer to scoring rules that summarize how sensitive credibility of compliance is to mine site load (Jensen 2001). These scorings can be used to rank sensitivity of a particular attribute to the variables in the model, allowing the work group to focus attention on those variables that contribute the most uncertainty to conclusions. This information could be used to support, for example, information-gathering activities and prioritization of technical review.

Table 4-2. Sensitivity of "credibility of compliance for total mercury load to bay" to changes to mine Hg load for the mine site load reduction focus strategy.

| Example Output from Netica | | | | |
|---|---|---|---|---|
| Probability ranges | Min Value | Current Value | Max Value | RMS[1] Change |
| In Compliance | 0.09365 | 0.4028 | 0.4394 | 0.09382 |
| Out of Compliance | 0.5606 | 0.5972 | 0.9064 | 0.09382 |
| Quadratic scoring = 0.008803 | | | | |
| Entropy reduction = 0.005048 (0.519 %) | | | | |

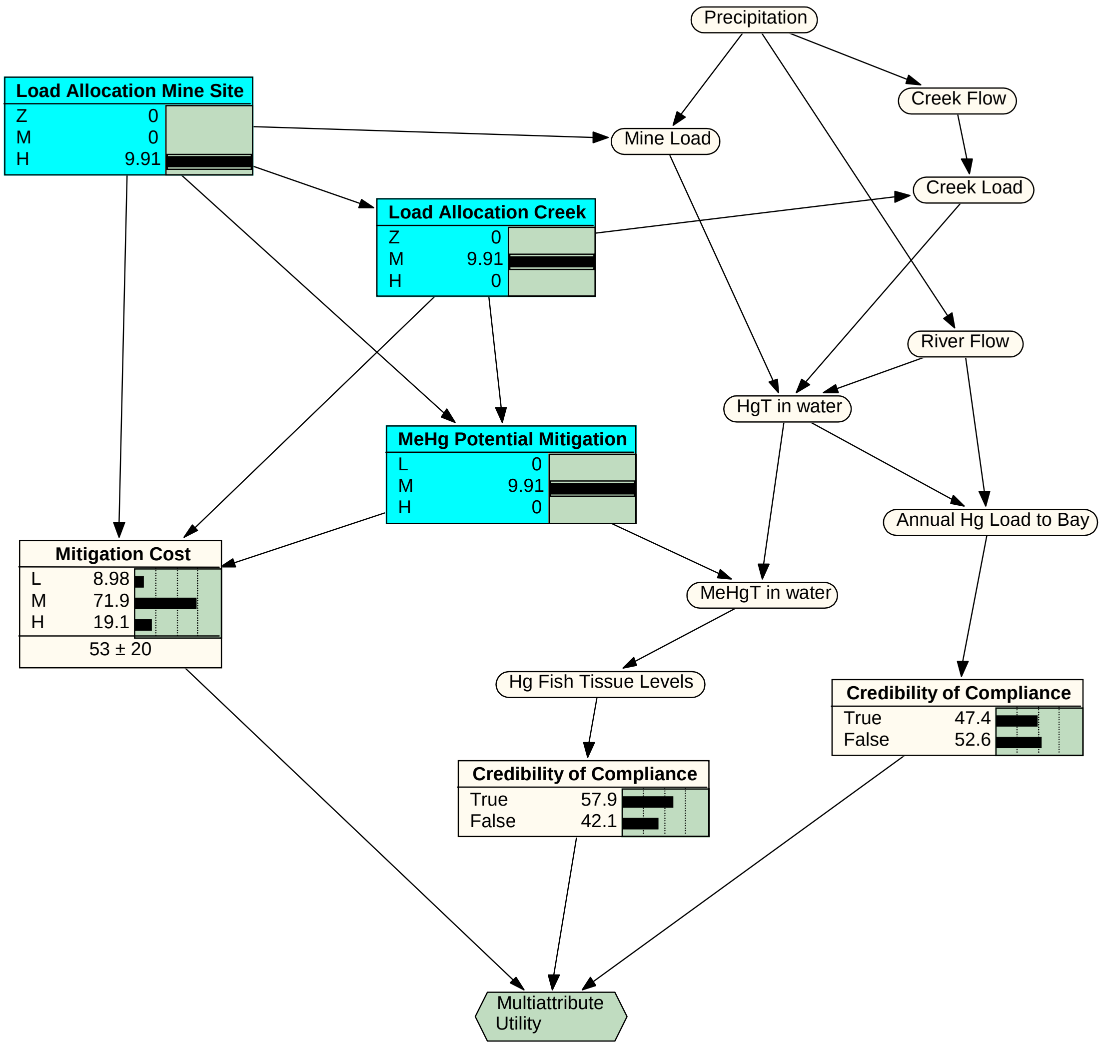
[1] Root Mean Square

The above represents "one-way" sensitivity analysis, in which sensitivity to individual attributes can be explored. "Two-way" analysis can also be performed, in which the sensitivity of an attribute of interest is computed by varying two variables simultaneously. "Three-way", etc., sensitivity analysis can be performed, but the computational burden grows exponentially and quickly becomes burdensome. Other methods of sensitivity analysis can be performed, including the conversion of the influence diagram into a decision tree by discretizing (if necessary) the probability distributions in the network, then performing probabilistic sensitivity analysis using the decision tree. There are many possibilities (see, e.g., Morgan and Henrion 1990 and Clemen 1996) and a lot can be learned about the decision problem using relatively simple methods.

### Optimal Decisions and Sensitivity Analysis Using Influence Diagrams With a Multiattribute Utility Value Model

Figure 4-8 shows an influence diagram model with a multiattribute utility function used to determine optimal decisions, using utility values similar to those in Table 4-1

Figure 4-8. Example optimal load allocation/mitigation strategy using an influence diagram with a multiattribute utility model.



for some hypothetical sub-group. For this simple example, a strategy with a "high reduction" for the mine site Hg load, a "medium reduction" for creek Hg load, and a "medium reduction" for mercury methylation potential is optimal in terms of maximizing expected utility. All of the other strategies yield lower expected utilities. Sensitivity analysis similar to that presented in the previous section could be used to determine the sensitivity of this conclusion to the various uncertainties (e.g., mine site Hg load and creek Hg load). Value of information could then be determined from this sensitivity analysis, enabling a ranking of the uncertainties in terms of importance from the point of view of the preferences of the sub-group.

## 4.3 CONCLUSIONS

This paper illustrates a decision analysis approach to TMDL load allocation decisions using a mercury TMDL for a small mercury-mine impacted watershed as an example. Decision analysis is a rigorous and robust common sense approach that, in many circumstances, is an attractive alternative to other decision analytical tools like cost/benefit analysis and what-if analysis. Decision analysis makes use of approaches for eliciting and representing preferences over both monetary and non-monetary outcomes, which is an appealing characteristic in environmental decision-making. While decision analysis does require active involvement of decision-makers relative to many other decision-making approaches, one could argue that this fact is responsible for much of the power of the decision analysis process. When decision analysis is properly performed, decision-makers (or sub-groups) should *believe* the insights, given that the expertise and knowledge represented in the model should reflect trusted information and that the preferences expressed should be their own. While the application of decision analysis in group decision-making situations can be problematic, since individual group members may have significantly different beliefs and preferences that cannot be simultaneously modeled, decision analysis can be used to generate sub-group negotiating positions and can shed light on the sources of disagreement (Merkhofer 1999).

The various decision analysis tools, including objectives hierarchies, strategy tables, influence diagrams, and decision trees, can be very useful aids for communicating, eliciting knowledge and preferences, organizing a complex decision situation, and generating insights that can highlight sources of disagreement and areas of agreement. When properly applied, decision analysis can help decision-makers make better decisions in terms of the consideration of uncertainty and value.

The approach highlighted in this paper makes extensive use of Bayesian networks for forecasting the response of the natural system to TMDL load allocations. As shown by Borsuk and others (2001, 2002), Reckhow (1999), and Stow and others (2003), Bayesian network models of water quality and ecological response are competitive with complex mechanistic models in terms of goodness-of-fit statistics and other indications of forecasting ability. They are superior in terms of model updating, since the Bayesian nature of the network allows new monitoring information to be incorporated directly into the existing network, generating an updated model that integrates the old and new information using robust probability calculus (Jensen 2001; Pearl 1988; Varis 1995). By using a Bayesian network as the basis of the decision analysis (i.e., for more than forecasting water quality and ecological response), the potential for consensus on allocation decisions can be explored, sources of differences can be analyzed for potential compromise, and, at the very least, negotiating positions for sub-groups of stakeholders can be rigorously defined in terms of information and preferences. In addition, sensitivity analysis can be performed using the Bayesian network to inform information-gathering priorities and peer-review activities.

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# CHAPTER 5: MERCURY TMDL CONCEPTUAL MODEL AS AN INFLUENCE DIAGRAM

The conceptual model of the biogeochemical behavior of mercury in response to potential mitigation projects is presented in two parts. The first part summarizes key aspects of what is currently known about the sources, fate, and transport of mercury in the Sulphur Creek watershed based on site-specific and other relevant research. The second part motivates and structures the current understanding of mercury behavior and controllability as an influence diagram, including the indication of which variables are targeted for control by decision-makers.

## 5.1 MERCURY SOURCES, FATE, AND TRANSPORT IN SULPHUR CREEK

### MERCURY SPECIATION IN WATER AND SEDIMENT IN TYPICAL SURFACE WATERS

Mercury species measured in typical surface waters include Hg(II) associated with particulate organic matter and the organic fraction of suspended sediment and dissolved species, e.g., Hg(II) complexed with dissolved organic carbon (DOC), chloride, or sulfide. It is hypothesized that mercury binds to organic materials primarily through sulfhydryl (thiol) functional groups (R-SH-). Some evidence suggests that when the sulfide concentration is significant (as in anoxic pore waters), dissolved mercury sulfide species dominate over mercury-DOC complexes . In surface waters with low sulfide concentration and significant DOC concentration, mercury-DOC complexes are probably the dominant dissolved species (Benoit et al. 1999; Benoit et al. 2003). It should be noted that the "dissolved fraction" is operationally defined as the fraction that passes through a 0.45 μm filter, which may include colloidal mercury sulfide species. In fact, the "dissolved mercury" fraction may be predominantly colloidal sulfide species in mercury mine-impacted watersheds. Colloidal mercury sulfide species have much lower methylation potential and bacterial bioavailability relative to dissolved mercury species . Methylation potential is defined as the fraction of the total mercury that gets methylated under experimental conditions meant to approximate the oxic/anoxic interface in sediments. The bacterial bioavailability of a mercury species refers to its ability to taken up by methylating bacteria and is a function of chemical properties that affect transport across membranes (Benoit et al. 2003; Kim et al. 2004; Lowry et al. 2004; Slowey 2005).

## Mercury Speciation in Water and Sediment in Sulphur Creek: The Available Evidence

Sulphur Creek is an atypical watershed in terms of mercury occurrence, with very high mercury inputs from both anthropogenic and natural sources. Sources of mercury include legacy mine-related waste rock and tailings, mine drainage, disturbed and undisturbed mineralized (associated with ore materials) and non-mineralized (background) soils throughout the watershed, stream sediments and suspended sediments, iron sulfide and iron oxyhydroxide precipitates from geothermal springs, and atmospheric deposition . Geothermal springs in the Sulphur Creek watershed are actively depositing mercury sulfides, other mercury phases, and iron sulfides. While the geothermal springs contribute relatively small volumes of water to the annual Sulphur Creek water budget (on average, > 10% of total flow in the dry season and < 2% of the flow in the wet season), the effluent total mercury concentrations (3,500 to 60,000 ng/L) and methylmercury concentrations (1 to 20 ng/L) are very high. The springs are also significant sources of sulfide, sulfate, dissolved organic carbon, and salinity, all of which can promote mercury methylation downstream of the springs.

Most of the mercury mass in the Sulphur Creek watershed is believed to consist of relatively insoluble sulfidic mercury species like cinnabar and metacinnabar originating from hot spring-type mercury ore deposits overprinting silica-carbonate mercury ore deposits (Rytuba 2003). Cinnabar and metacinnabar have low bioavailability to the bacterial species that methylate inorganic mercury *in-situ* (Benoit et al. 2003; Bloom 2001). Sediments and soils in the Sulphur Creek watershed downstream of mine sites and geothermal springs have been found to have total mercury concentrations ranging from < 0.2 mg/kg dry weight (ppm) to >> 300 ppm , where most of this mercury is thought to be mercury sulfides and mercury associated with elemental sulfur (Bloom 2001; Rytuba 2005b).

Studies suggest that the mercury species transported from mercury mine sites by run-off are particulate and colloidal cinnabar, metacinnabar, and other colloidal mineral associations, and not sorbed mercury species (Rytuba 2003). In larger flows, these mercury-containing particles/colloids may be associated with the particulate load or may be part of the operationally-defined "dissolved" load (< 0.45 μm). Colloidal mercury, defined here as mercury associated with particles < 45 μm, have been observed to have 2 to >10 times higher total mercury concentrations than larger particles. However, in the Sulphur Bank mine complex near Clear Lake, the intermediate size fraction (75 - 125 μm) has the highest total mercury concentrations (Kim et al. 2004; Rytuba 2003).

Kim et al. (2004) observed that colloids tend to consist of higher fractions of Hg-sulfides relative to larger suspended particles, explaining the higher mercury concentrations of colloids. This suggests that the suspended particles in run-off with the highest associated mercury concentrations would tend to have low methylation potentials. In a study of mercury methylation potential for various mine-related, geothermal spring, and background materials in the Cache Creek watershed (including Sulphur Creek), Bloom (2001) found that the mine materials had methylation potentials approximately 20 times less than Hg(II) chloride. While the methylation potential experiments are illustrative of trends, the sample preparation and incubation techniques limit any quantitative field-scale predictions (Bloom 2001). Because of the high total mercury concentrations and large amounts of mine wastes in the watershed, they may be significant sources of methylmercury over long time periods even with very low mercury methylation efficiencies.

Iron precipitates (sulfides deposited near spring orifices, called "muck", and oxyhydroxides that form as Fe(II) oxidizes during transport) from geothermal springs that contribute to Sulphur Creek have relatively high concentrations of Hg(II), ranging from 10 ppm to > 200 ppm. Precipitates from the Jones Fountain of Life geothermal spring (total aqueous mercury concentration ranging from 22,000 to 34,000 ng/L) show relatively high methylation potentials (Bloom 2001).

Bloom (2001) also found that while the "organo-complexed" fraction[22] of a Sulphur Creek sediment sample downstream of mine sites was relatively high (>40%), this fraction actually appeared to be associated with elemental sulfur rather than humic matter or chloride. Most of the balance of the $Hg_T$ in this sediment sample was in the fraction comprised of mercury sulfides (mostly cinnabar and metacinnabar). By comparison, the Jones Fountain of Life sample had a similar percentage of $Hg_T$ in the organo-complexed fraction, but had 28% in the strongly complexed fraction[23] and 27% in the mercury sulfides fraction. Bloom's one-year sediment microcosm incubation studies showed that the cinnabar and metacinnabar spiked samples did not change significantly through the year and showed very low levels of mercury methylation (Bloom 2001). In contrast, mercury chloride spiked samples transformed very quickly to the organo-complexed fraction and showed relatively high methylation potential. By the end of the year, the sample mercury speciation for these samples was similar to that of the control receiving sediment. There are no other studies of longer-term speciation changes in mercury sulfide-containing sediments in the Cache Creek and Sulphur Creek watersheds.

### REACTIVE MERCURY IN SEDIMENT

Reactive mercury in sediment ($Hg_{sed}^*$) is an operationally-defined fraction of total mercury in sediment that is used as surrogate for the pool of inorganic mercury that is available for microbial methylation. It is defined here according to recent extraction methods developed by the U.S. Geological Survey, which are described elsewhere (Marvin-DiPasquale 2005). This fraction may include some dissolved Hg(II) species

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[22] Extracted by 1 N NaOH. Typical associations are Hg-(humic acid) and $Hg_2Cl_2$ (Bloom, 2001)

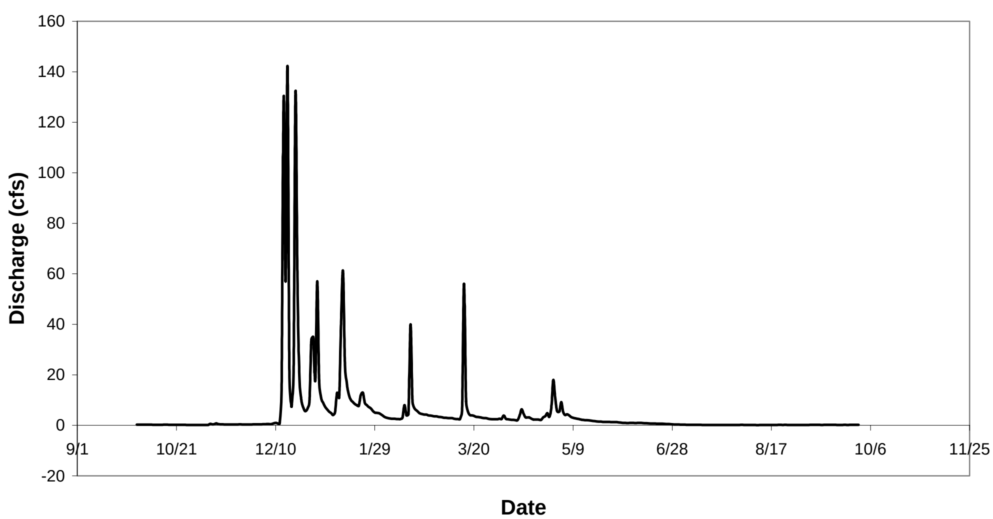
[23] Elemental mercury and mercury associated with solids soluble in 12 N nitric acid.

in porewater as well as some species weakly bound to particles, but there is some uncertainty about which species are extracted. The hypothesis is that this extracted fraction is likely available to microbes for methylation, and thus represents a surrogate measure of 'microbially available' Hg(II). Some researchers have speculated that uncharged dissolved species like $HgS^0_{aq}$ or $HgCl_2{}^0_{aq}$ may be the species taken up by microbes, but this is controversial (Benoit et al. 2003; Slowey 2005).

SEASONAL PRECIPITATION EVENT-DRIVEN MERCURY TRANSPORT IN SULPHUR CREEK

Estimated mercury loads in Sulphur Creek show very distinct seasonality with precipitation events dominating the annual loading pattern (Figure 5-1). Roughly 85% of the observed discharge and 89 – 96% of the estimated total mercury load occurred between December 1st and March 31st.

Figure 5-1. Hydrograph for the Sulphur Creek gage, 2003 water year (above normal year[24]), showing strong seasonality of discharge and event-driven discharge pattern. Data from U.S. Geological Survey (http://waterdata.usgs.gov/ca/nwis). The location of the gage is shown in Figure 2-3.




[24] "Above-normal" corresponds to a Sacramento Valley composite annual discharge greater than 7.8 maf and less than 9.2 maf. The composite annual discharge is the sum of the annual discharges for Sacramento River at Bend Bridge, Feather River inflow to Lake Oroville, Yuba River at Smartville, and American River inflow to Folsom Lake. The 2003 water year refers to flows between October 1, 2002 to September 30, 2003. For further information, see http://cdec.water.ca.gov/cgi-progs/iodir/WSIHIST.

### A TOTAL MERCURY LOADING MODEL FOR THE SULPHUR CREEK GAGE

Annual total mercury loading observed at the gage is modeled as (Equation 5-1):

$$HgTLoad_{Gauge} = HgTLoad_{Mines} + HgTLoad_{Springs} + HgTLoad_{\mathrm{Re}suspended} + HgTLoad_{Other}$$
.

$Hg_T Load_{Mines}$ refers to the annual total mercury loading contributed from run-off from mine waste materials during rain events, excluding deposition; $Hg_T Load_{Springs}$ refers to the annual $Hg_T$ loading from geothermal springs, including precipitates in run-off; $Hg_T Load_{Resuspended}$ refers to the annual mercury load associated with resuspended sediment, where the mercury may have originated from mine sources, geothermal springs, soil erosion, atmospheric deposition, ground water, and plant litter; and $Hg_T Load_{Other}$ refers to other annual background loadings from ground water inputs to creek flow, erosion of mineralized and non-mineralized soils, atmospherically deposited mercury in run-off, and mercury-enriched plant litter. The "background total mercury load" includes $Hg_T Load_{Springs}$, $Hg_T Load_{Other}$, and the fraction of $Hg_T Load_{Resuspended}$ not originating from mine-related sources.

### HIGH BACKGROUND MERCURY INPUTS IN SULPHUR CREEK

Recent evidence suggests that background total mercury, dissolved mercury, and methylmercury loadings related to geothermal sources may be much larger than previously thought in the Bear Creek and Sulphur Creek watersheds, potentially shifting some of the focus from mine waste remediation to geothermal source controls for mitigating methylmercury watershed patterns (Churchill and Clinkenbeard 2005; Rytuba 2005a). This "regional background data" was collected to help determine TMDL target loadings for Sulphur and Bear Creeks, rather than to test the hypothesis that geothermal sources were a significant contribution to the total mercury and methylmercury loadings observed within these watersheds. This being the case, most of the available water quality data collected to support the Sulphur Creek mercury TMDL focuses on mine-related sources, so there are few data to support the modeling of the expected effects of geothermal source controls (Rytuba 2005a).

### AVAILABLE RELEVANT SULPHUR CREEK DATA

While several relevant and useful studies have been conducted in the watersheds relevant to the Sulphur Creek mercury TMDL, the available data are sparse relative to the complexity of the modeling problem and the very large uncertainties involved (Bloom 2001; Domagalski et al. 2004; Domagalski et al. 2003; RWQCB-CV 2004a; RWQCB-CV 2004b; Slotton et al. 2004; Suchanek et al. 2004). The relevant data supporting the Central Valley Regional Water Quality Control Board's Sulphur Creek Mercury TMDL report were used to inform the conceptual model. These data include the mean daily flow data at the Sulphur Creek gage for the years 2000 – 2003 and the available water quality data presented in this section. Figure 5-2 shows the sample averages and standard deviations for all of the available total mercury ($Hg_T$) data collected throughout the Sulphur Creek watershed in 2000 – 2004. Figure 5-3 shows the sample averages and sample standard deviations for all of the available total methylmercury ($MeHg_T$) data collected on the same dates. Note that all of the sites have fewer than 10 data except Sulphur Creek at the USGS gage. Figure 5-4 shows all of the available sediment and geothermal spring "muck" $Hg_T$ concentrations distributed throughout the watershed. All of these data are described in the 2004 Sulphur Creek mercury TMDL report (RWQCB-CV 2004b). The supporting data are compiled from several studies (Goff et al. 2001; Slotton et al. 2004; Suchanek et al. 2004), including unpublished data collected by the RWQCB-CV. In general, the data coverage is very sparse for most of the watershed, with the vast majority of the water quality and flow data having been collected at the U.G. Geological gage in the lower watershed near the confluence with Bear Creek (Figure 5-4).

Figure 5-2. Average $Hg_T$ (in water) for sampled sites within sulphur creek watershed. Bubble size reflects the sample standard deviation for all samples by site. The number of samples for each site is indicated in the bubble. Site locations are shown in Figure 2-3.

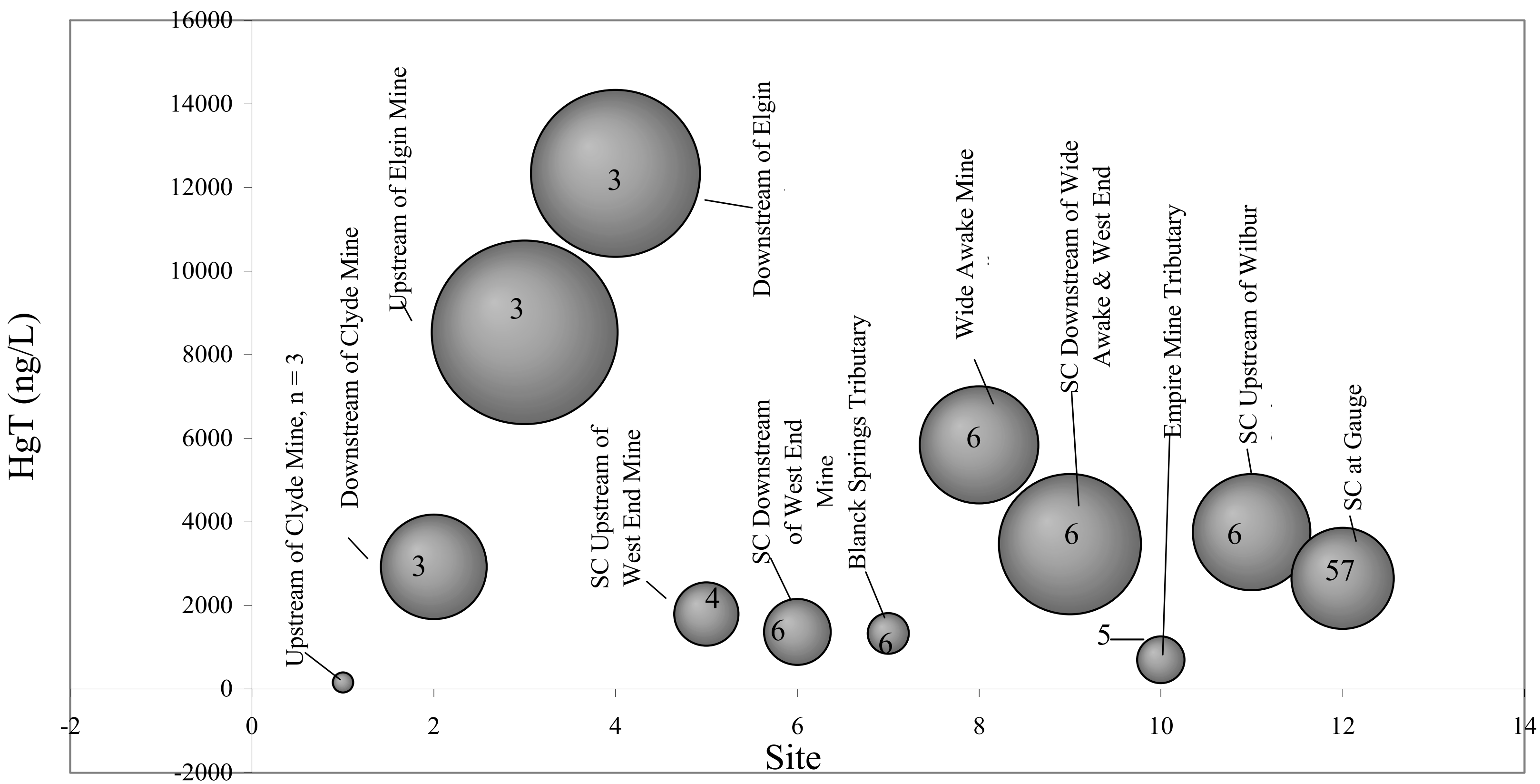


Figure 5-3. Average $MeHg_T$ (in water) for sampled sites within Sulphur Creek watershed. Bubble size reflects the sample standard deviation for all samples by site, except for hatched bubbles, as noted. The number of samples for sites with more than two samples is indicated in the bubble. Site locations are shown in Figure 2-3.

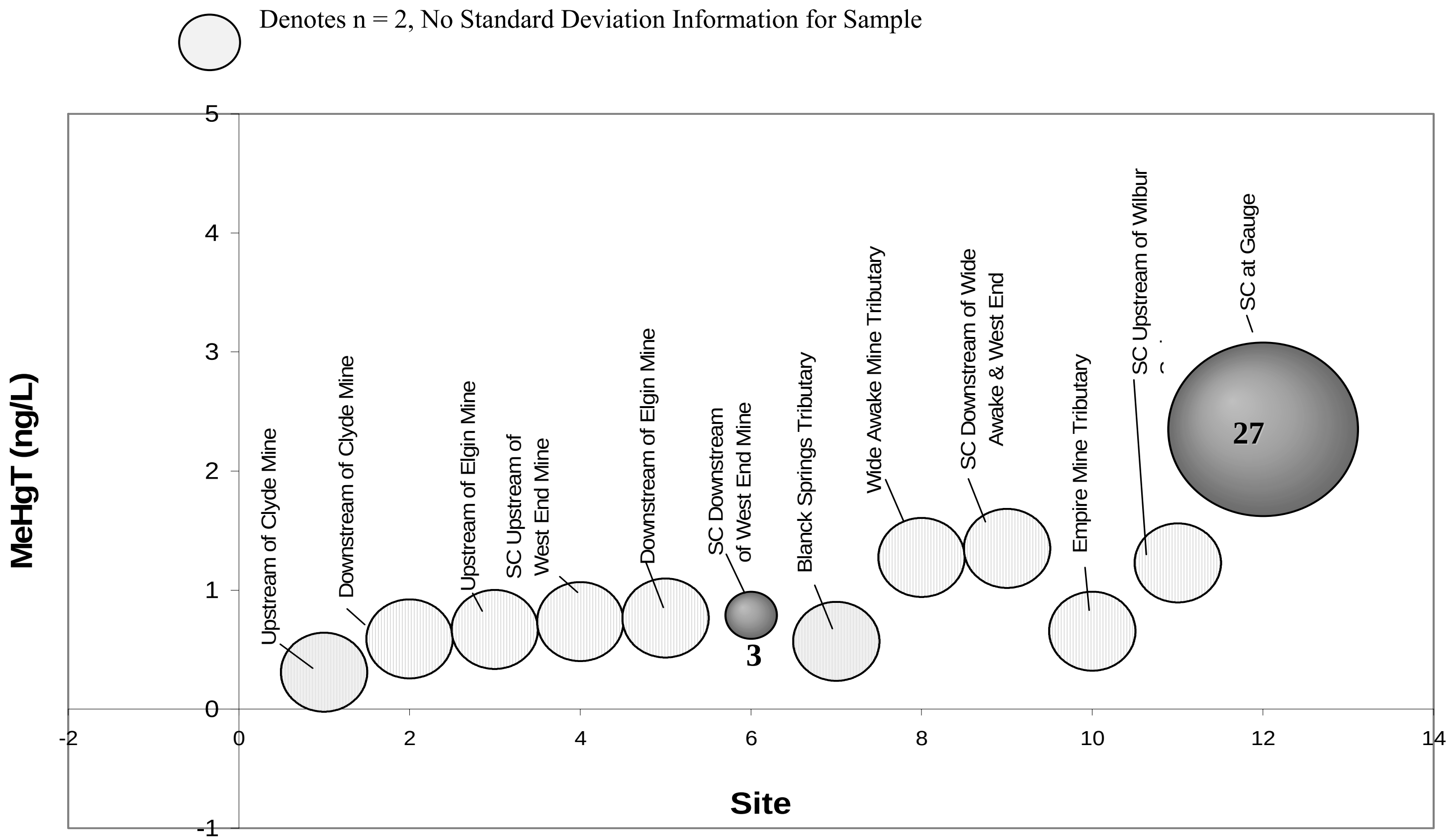
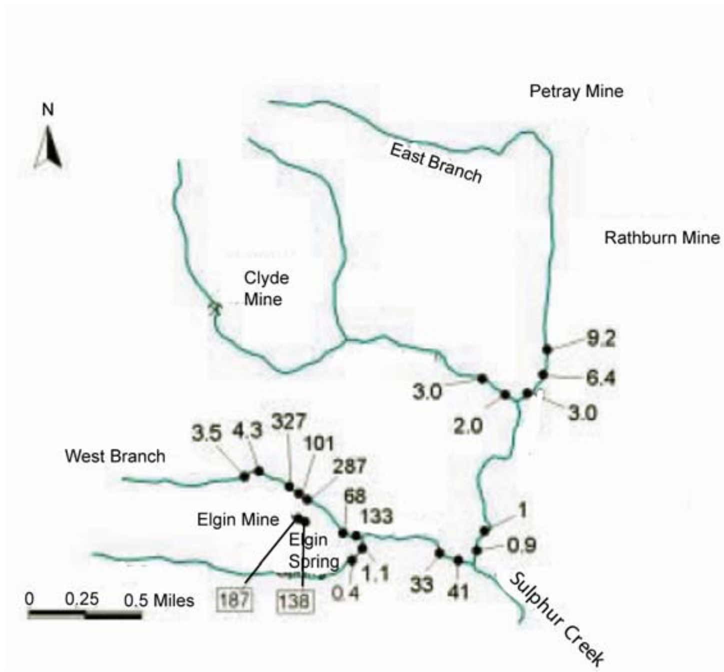


Figure 5-4. Total mercury concentrations (ng/mg, ppm) in fine-grained sediment in the upper (a) and lower (b) parts of the Sulphur Creek watershed (RWQCB-CV 2004b).

a)




b)

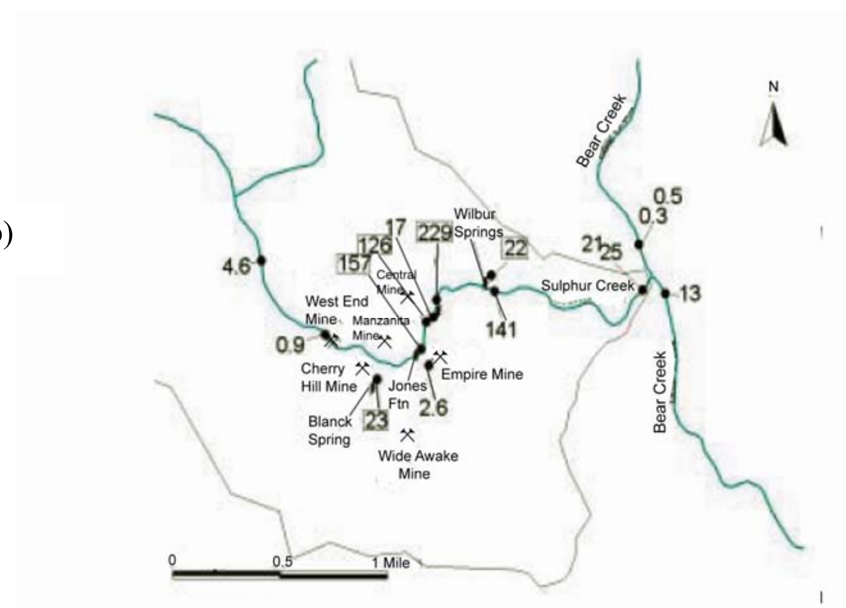


Figure 5-5 shows a plot of the all of available total mercury (ng/L) data against instantaneous flow (cfs) for Sulphur Creek at the USGS gage (n = 56), collected over the 1997 – 2004 time period. While most of these data were collected at long time intervals (weeks or months apart), 19 of the data were collected during a 30 hour time period at 1.5 to 3 hour time intervals in February of 2004. The flow/$Hg_T$ relationship is modeled as a lognormal distribution independent of flow for flows less than 55 cfs and as a ln-ln linear model for flows greater than 55 cfs. The circled values represent three flows at the rising limb of a hydrograph in response to a storm event. The $Hg_T$ value is thus sensitive to the time rate of change in flow, as well as to the current flow. This complexity is discussed further in the next section on the available time series data. Unfortunately, only mean daily flow data are available. At this time scale, the hysteresis in the flow/$Hg_T$ relationship is manifested as random scatter in the flow/$Hg_T$ model. Hysteresis in $Hg_T$ concentration and loads is described and demonstrated in the next section.

Figure 5-6 shows the relationship between instantaneous flow and $Hg_T$/TSS (the ratio of total mercury concentration in water in ng/L to the concentration of total suspended solids in mg/L). $Hg_T$/TSS is used as a surrogate for the concentration of total mercury in fine-grained suspended sediment. Dry season values are assumed to be lognormally distributed independently of flow. Wet season values are partitioned by flows > 55 cfs and flows < 55 cfs. Within these flow ranges, the values are assumed to lognormally distributed independent of flow (see Appendix B for normal probability plots of $Hg_T$/TSS in log space by season and flow regime, Figures B.1, B.2, and B.3). The first rains of the season show a “first flush” effect, with relatively large Hg/TSS values. This is thought to result from the mobilization of geothermal spring precipitates and colloidal $HgS_{(s)}$ that have deposited during the dry season. The wet season data include longer-term data shown as white circles (1997-2004) and data from a single storm event in February, 2004. While the relationship between flow and $Hg_T$/TSS is very noisy, the long-term and single-storm data overlap well.

Figure 5-5.  Instantaneous flow versus total mercury concentration for Sulphur Creek, all data.

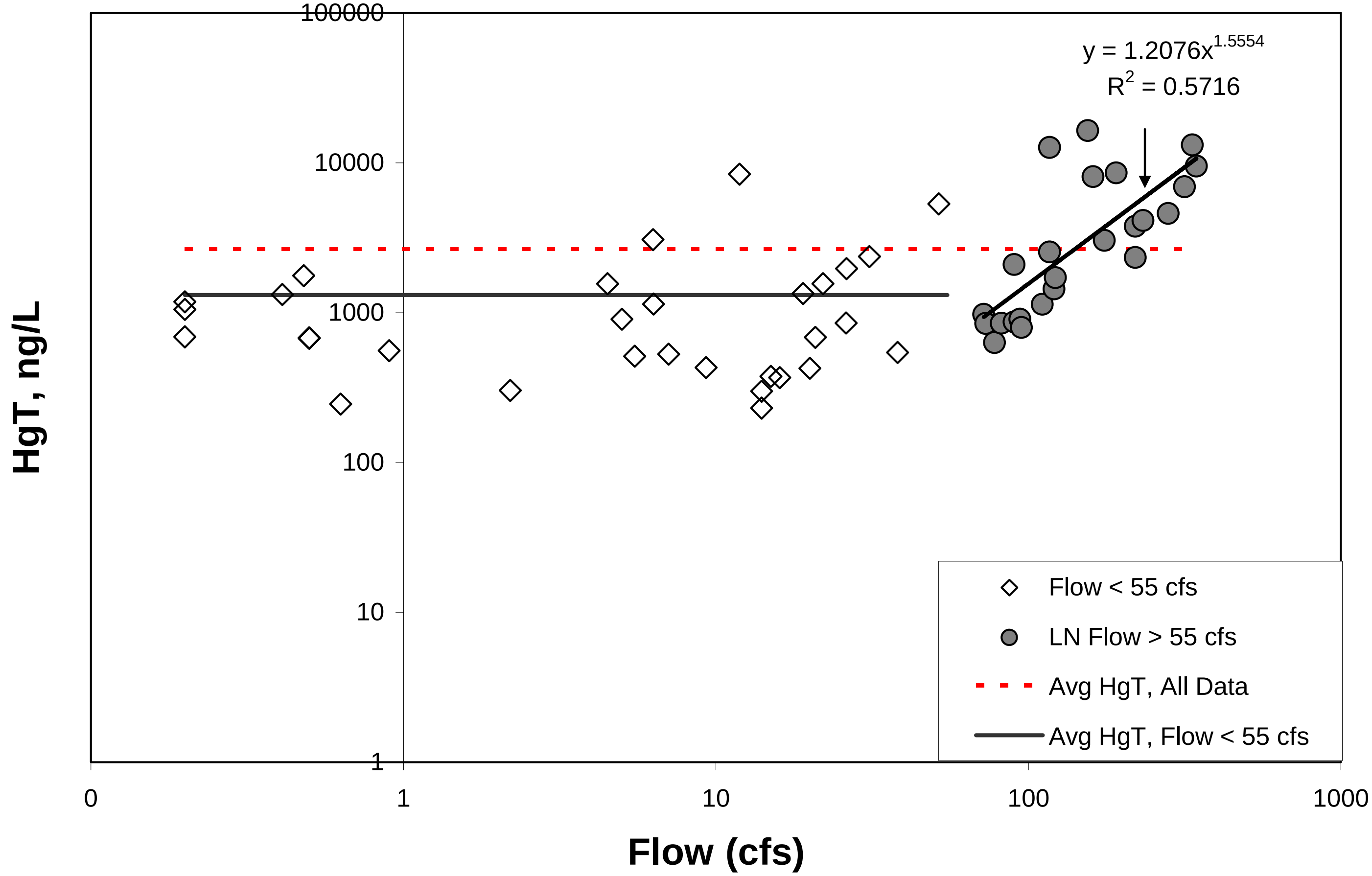
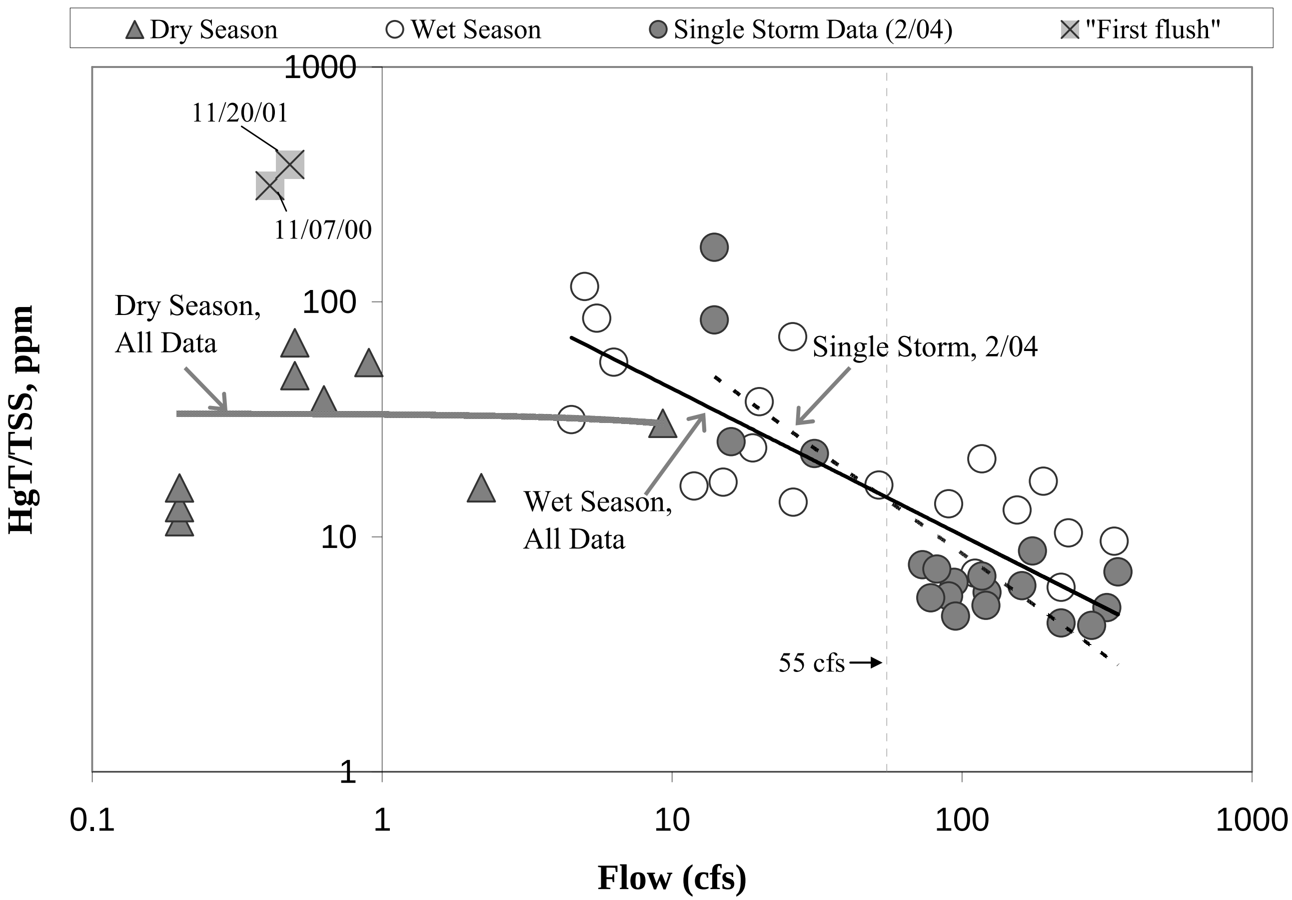


Figure 5-6. Relationship between $Hg_T$/TSS and flow by water season (mean daily flow) and for a single storm event (instantaneous flow) (2/2004).



### SULPHUR CREEK $Hg_T$, $Hg_T$/TSS LOADING TIME SERIES DATA

Figure 5-7 shows the time series for $Hg_T$, TSS, $Hg_T$/TSS, and flow for a 30-hour period (time step of 1.5 – 3.0 hours) on February 25/26, 2004, which included a storm event ("autosampler data"). The relationship between instantaneous flow and $Hg_T$ shown in Figure 5-7 collected for this single event is similar to the relationship between the instantaneous flow and $Hg_T$ data collected days, weeks, months apart (Figure 5-5 includes both the autosampler data and the hand collected data). However, several patterns emerge which emphasize the complexity of mercury/sediment transport. For example, the residual errors in a plot of ln(flow) versus ln($Hg_T$) in the time series data show significant autocorrelation. The Durbin-Watson statistic for this data set is 0.72, which is much less than the lower rejection level of 1.18 for 19 data points and one predictor variable, supporting the rejection of the hypothesis that the residuals are not autocorrelated (Chatterjee et al. 2000). Figure 5-8 shows a plot of the first-order residual error at time "t" ($Residual_t$) versus the residual error for the preceding time step ($Residual_{t-1}$). A plot of the second-order residuals ($Residual_t$ versus $Residual_{t-2}$) shows no significant correlation, suggesting that the autoregressive structure is approximately first-order for this time series.

Since most of the mercury comprising the total mercury concentration is associated with suspended sediment, the relationship between $Hg_T$ and flow can be understood in terms of the relationship between suspended sediment transport (or TSS transport), the grain size distribution, and flow or stream power. For example, Figure 5-9 shows that $Hg_T$ load versus discharge displays a hysteresis loop typical of suspended sediment load. Figure 5-10 shows the relationship between the time step change in $Hg_T$ ($Hg_{T,t} - Hg_{T,t+1}$) with the change in flow ($Flow_t - Flow_{t+1}$) during the storm event of 2/25-6/2004. In general, the "falling limb" of a storm event hydrograph carries less sediment than the "rising limb" (Dunne and Leopold 1978).

Figure 5-7. Time series data for $Hg_T$, TSS, $Hg_T$/TSS, and flow for 2/25-6/2005. Data are from the Sulphur Creek TMDL report (RWQCB-CV 2004b).



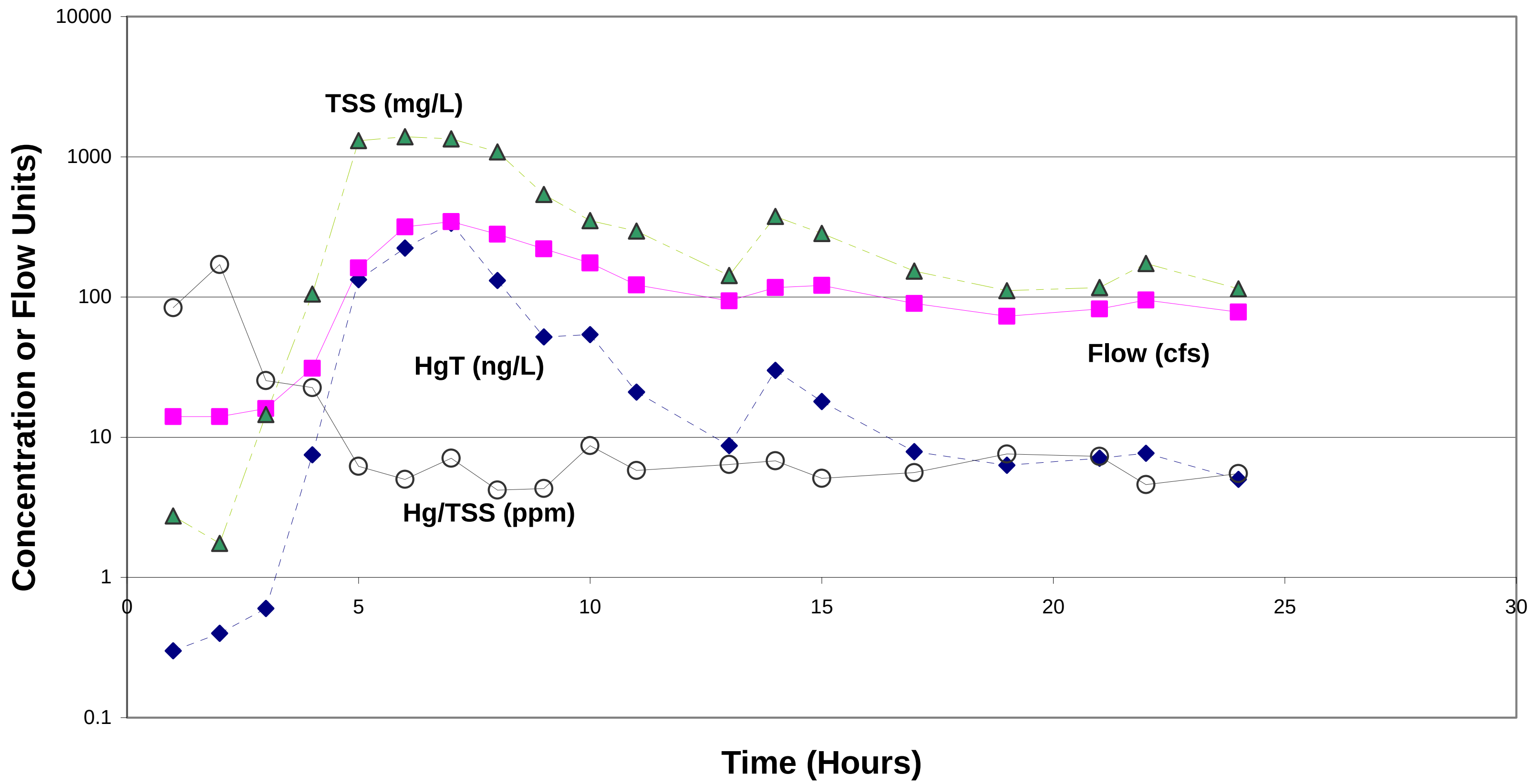


Figure 5-8. Test for first-order autoregressive structure in the Log(flow) vs Log($Hg_T$) autosampler data. The plot shows the residual (predicted $Hg_T$ – observed $Hg_T$) for a time step “t” (“$Residual_t$”) versus the residual for the previous time step (“$Residual_{t-1}$”). Data are from the Sulphur Creek TMDL report (RWQCB-CV 2004b).

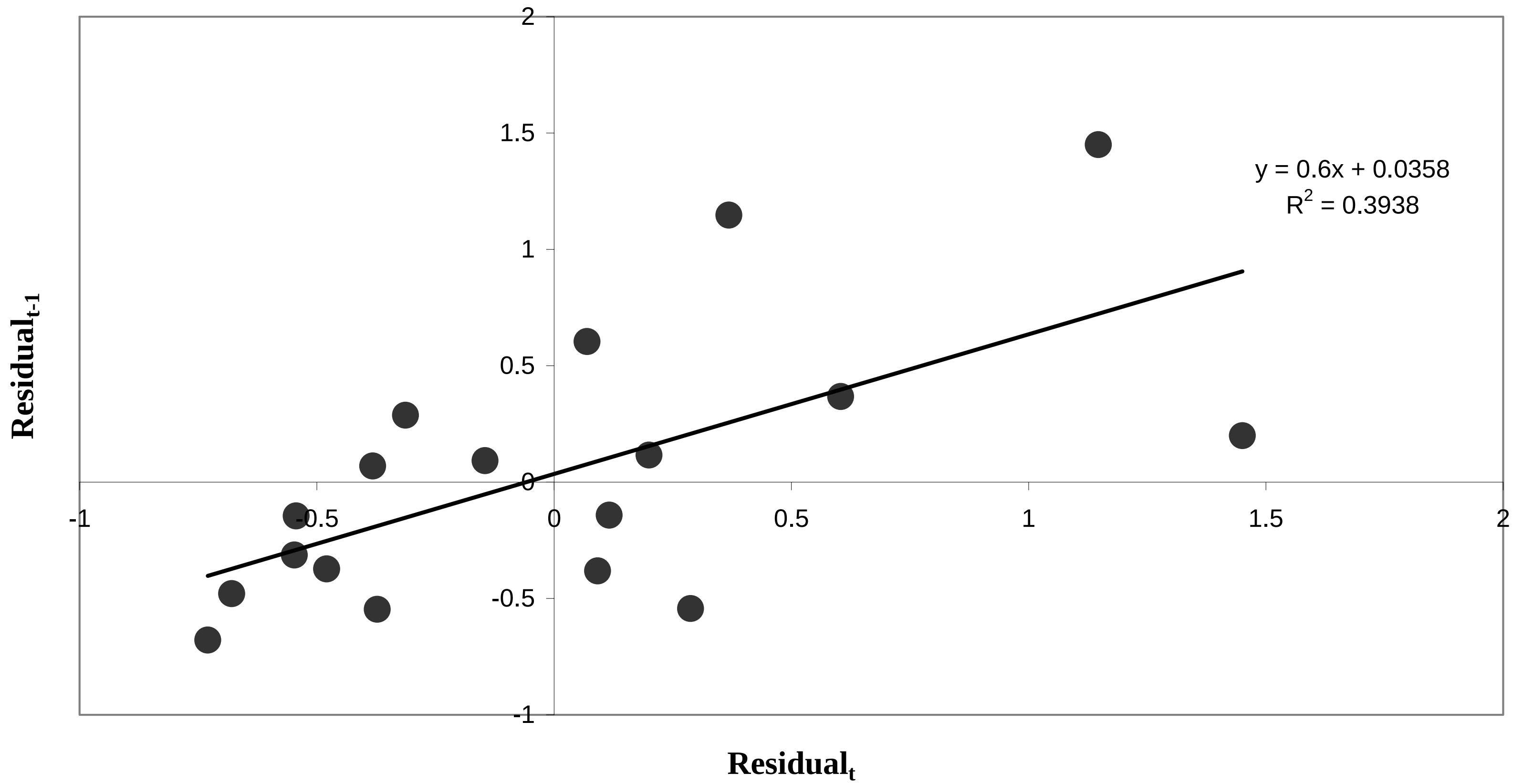
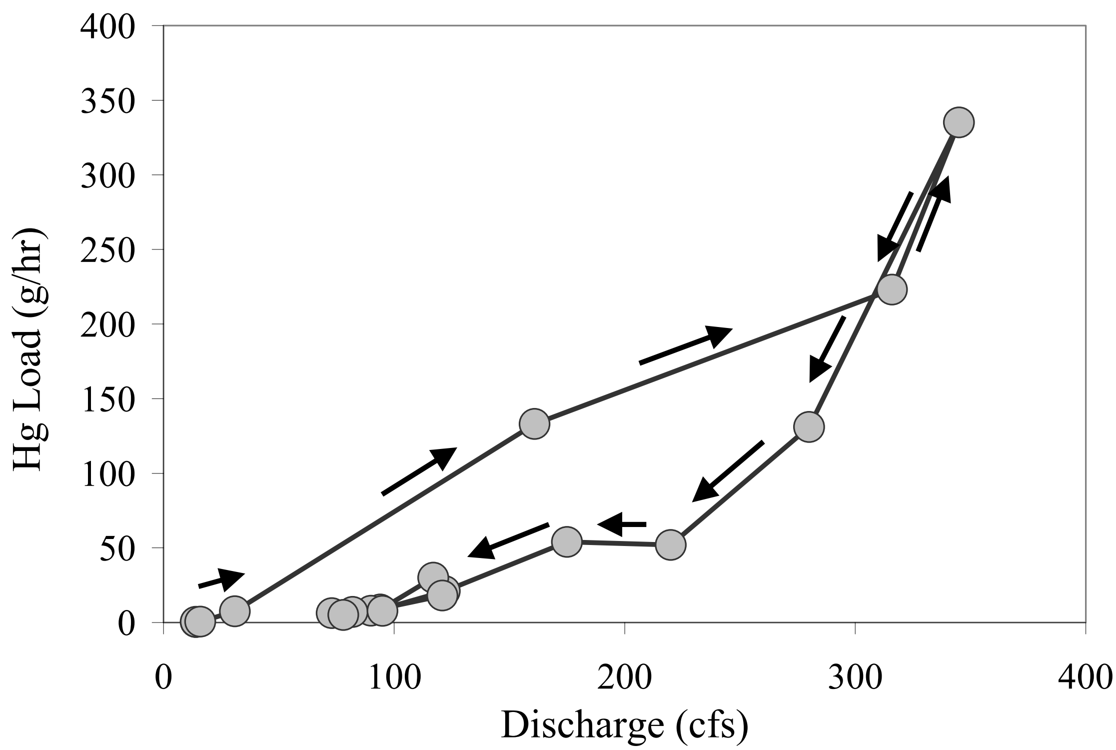


Figure 5-9. Hysteresis in $Hg_T$ load versus discharge, with arrows indicating time direction. Data are from the Sulphur Creek TMDL report (RWQCB-CV 2004b).




Sediment transport is a complicated phenomenon and is incompletely understood. In the case of the Sulphur Creek TMDL, data on the particle size distribution and direct measurements of stream velocity are missing. Given this state of affairs and the magnitude of the other uncertainties in this decision problem, the simple flow versus $Hg_T$ model shown in Figure 5-5 was used to simulate $Hg_T$ loading patterns. Table 5-1 compares the predicted $Hg_T$ and $Hg_T$ load results from this model with the calculated $Hg_T$ and $Hg_T$ load values from the time series observations. The predictions match the observed values fairly well, but the comparison is based on very few data. While this check is inconclusive, it represents all of the available data for decision support.

Figure 5-10. Change in total mercury concentration versus change in flow during a storm event (2/25/04 – 2/26/04). Numbers depict the time sequence, with "1" being the first observation, where the time step is 1.5 to 3 hours. Part "a" shows the first nine time steps and "b" shows the next eight time steps. Note that part "a" includes the major discharge peak and part "b" includes a much smaller discharge peak around hour 14, as shown in Figure 5-7. Data are from the Sulphur Creek TMDL report (RWQCB-CV 2004b).

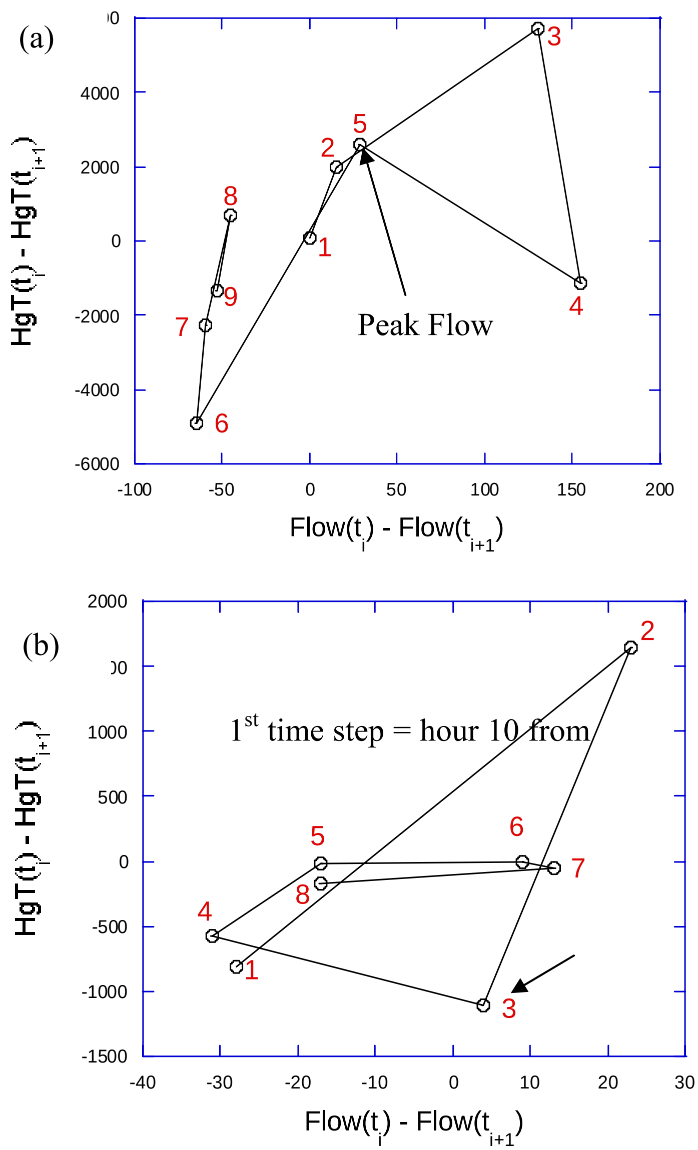


Table 5-1. Mean daily $Hg_T$ and daily $Hg_T$ loading prediction for 2/25/04 using mean daily flow versus estimation of mean daily $Hg_T$ and daily $Hg_T$ loading from observed time series values. Data are from the Sulphur Creek TMDL report (RWQCB-CV 2004b).

| Predicted $Hg_T$[1], ng/L (95% confidence interval) | Estimated $Hg_T$[2], ng/L | Predicted $Hg_T$ Loading[1], g/day (95% confidence interval) | Estimated $Hg_T$ Loading[2], g/day |
|---|---|---|---|
| 2600 (680 – 9,900) | 3000 | 920 (240 – 3,500) | 1600 |
| Notes: 1) Mean daily values predicted from mean daily flow using model. 2) Mean daily values estimated from summation over time step observations. | | | |

METHYLMERCURY DATA

Most of the limited methylmercury data within the Sulphur Creek watershed were collected at the USGS gage (Figures 5-3, 2-3). Looking more closely at these data, several things are apparent. First, the data set (including both wet and dry season samples) appears to be approximately lognormally distributed (Figure 5-11). Secondly, the $MeHg_T$ data show a distinct seasonality, with distinct very high values in the hot, low flow months of July and August. Figure 5-12 shows the seasonal trend of the $MeHg_T$ sample average. One possible explanation for this seasonality is that the microbial activity of mercury methylating bacteria is very high in July and August due to in part to low flow conditions and high temperatures (low dissolved oxygen).

Figure 5-11. a) Histogram of $MeHg_T$ data from the Sulphur Creek gage in log space (RWQCB-CV 2004b). Data frequencies are represented by bars (NOTE: bins are not evenly spaced). Model frequencies for a lognormal distribution using the sample average and standard deviation are shown by the dashed line. Twice as many data were collected in the wet season (n = 18) relative to the dry season (n = 9). b) The histogram over the data in arithmetic space is shown for comparison.

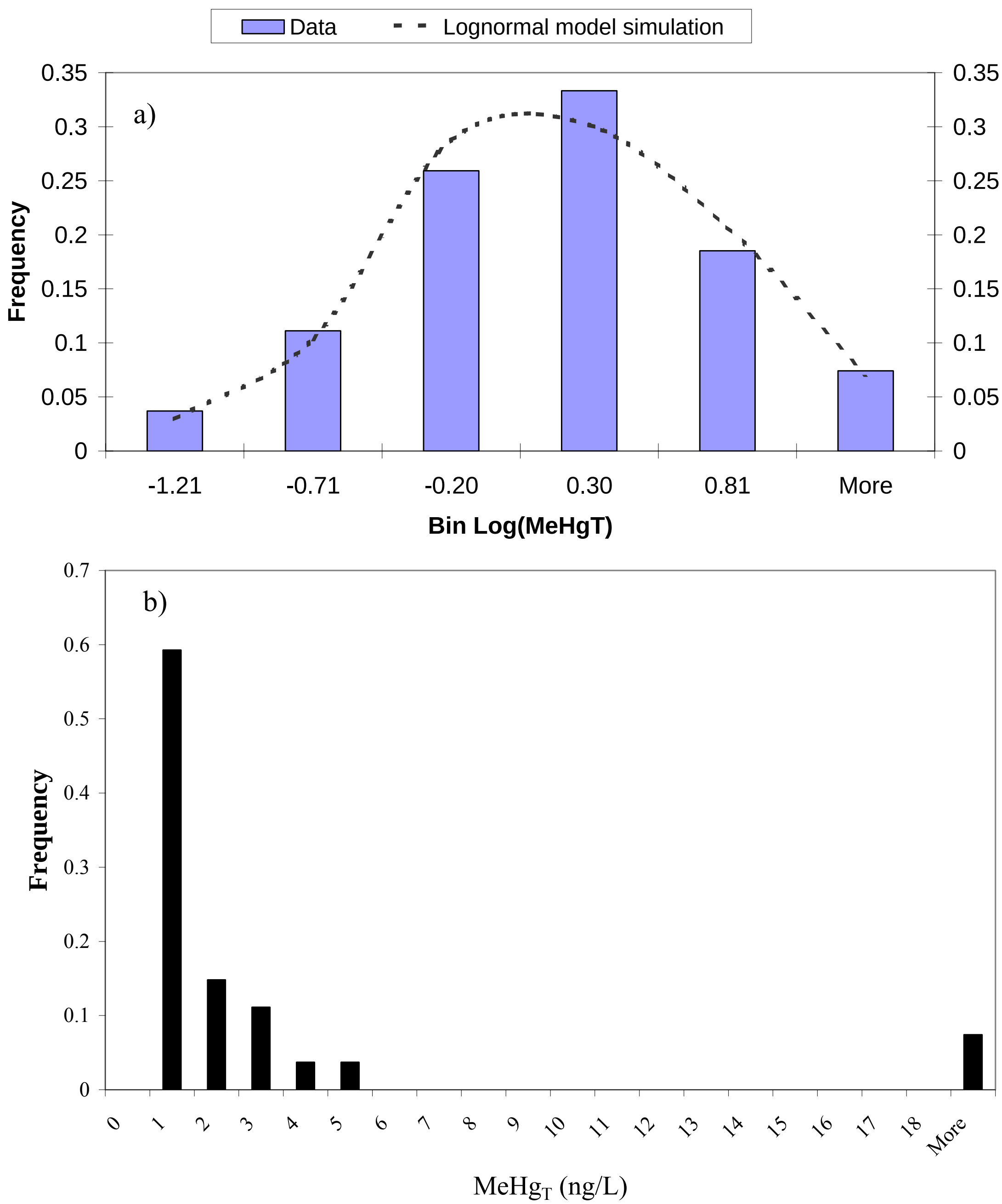
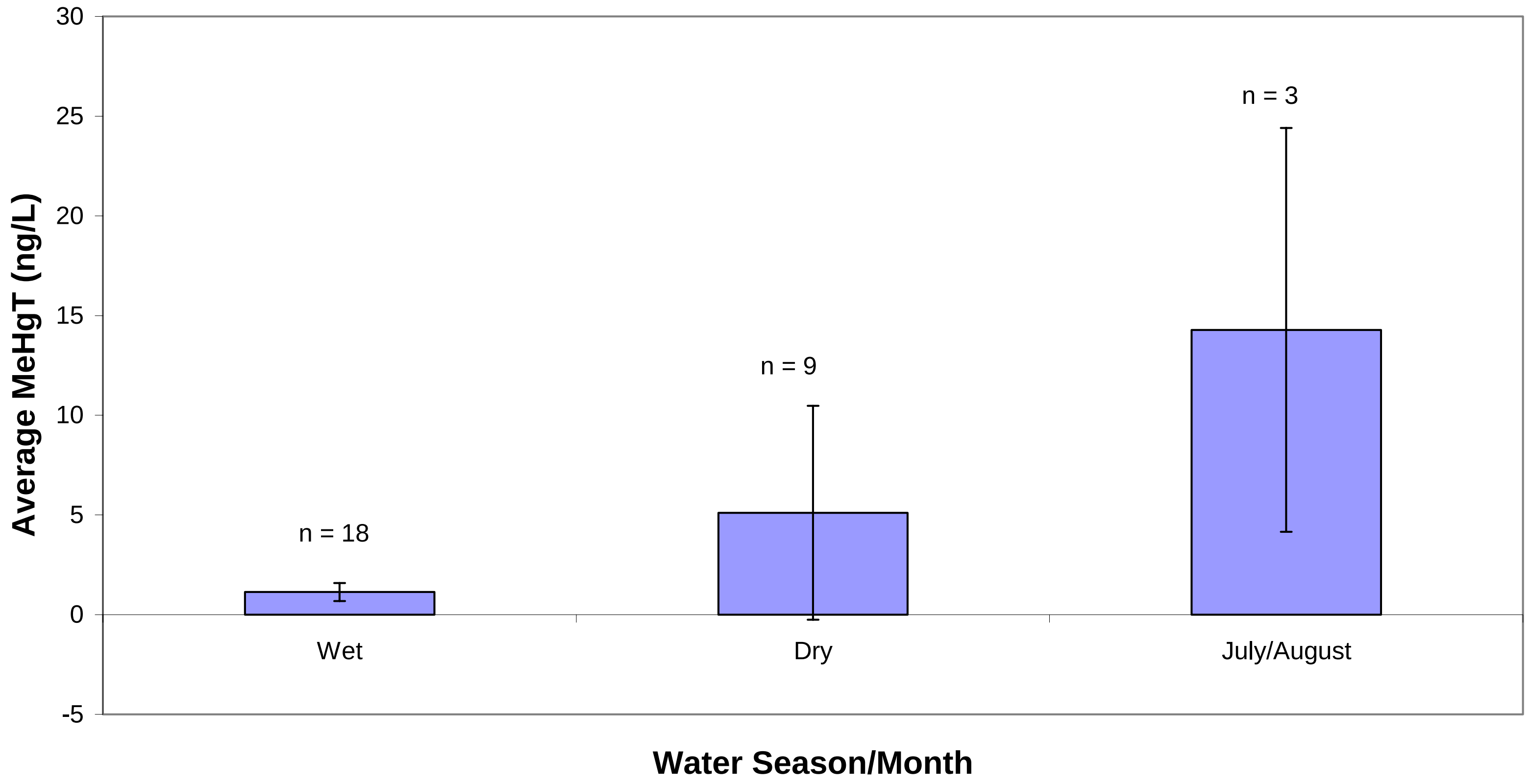
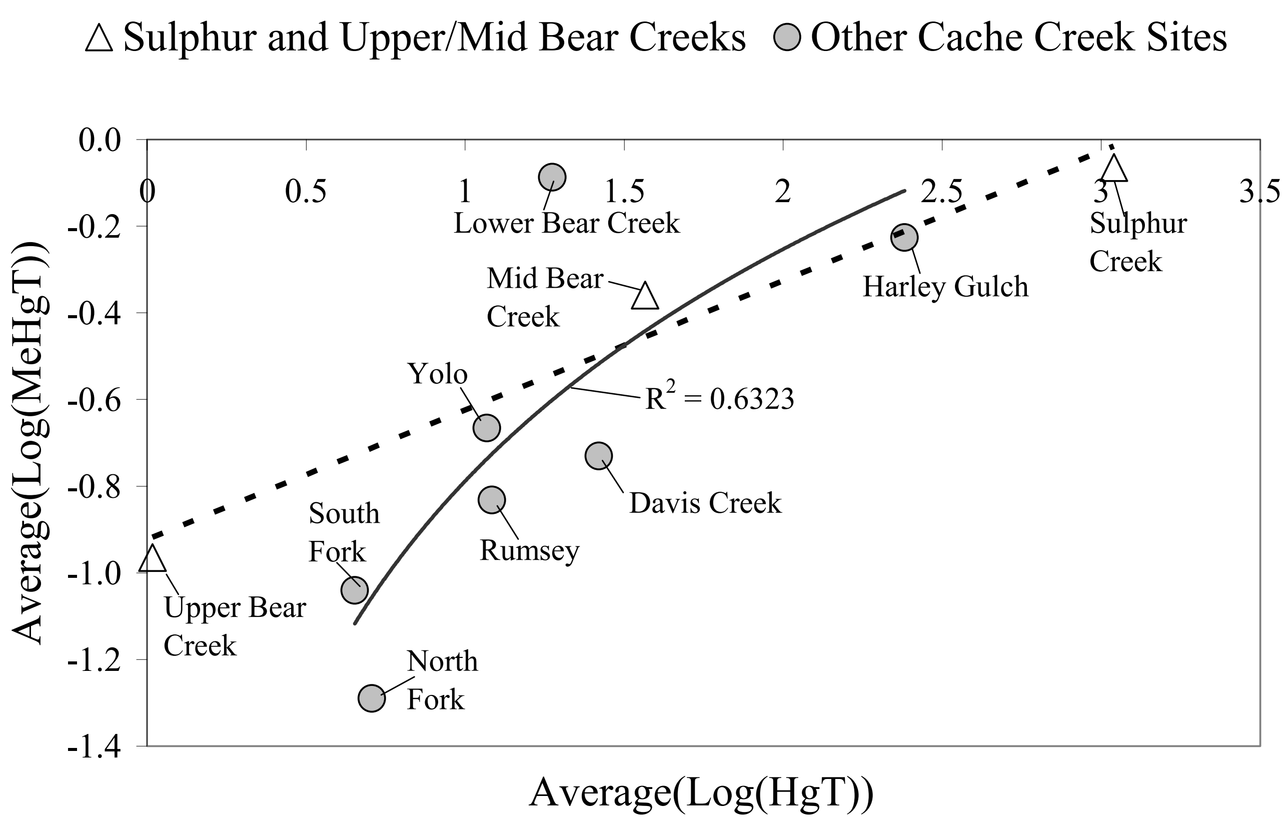


Figure 5-12. Seasonal Trend in Average $MeHg_T$. The dry season data includes the three data broken out in the July/August average. Data are from the Sulphur Creek TMDL report (RWQCB-CV 2004b).



While there is no discernible pattern between $Hg_T$ and $MeHg_T$ in Sulphur Creek, some trends do appear at the larger scale of the Cache Creek watershed. Figure 5-13 plots the average of $\log(Hg_T)$ against the average of $\log(MeHg_T)$ for each site with data in the Cache Creek watershed. The Sulphur Creek and Upper & Mid-Bear Creek data are grouped because of significant local geothermal influences not present at the other sites. While these groupings indicate that $Hg_T$ and $MeHg_T$ correlate at the scale of the Cache Creek watershed, missing data on other important predictive variables at this scale (sulfate concentration, dissolved organic carbon concentration, reactive mercury concentration in sediment concentration) prevent a causal interpretation of this relationship. The causal probabilistic model used to predict $MeHg_T$ is discussed in Chapter 6.

Figure 5-13. A plot of the average of the log-transformed $Hg_T$ data (Average Log($Hg_T$)) versus the average of the log-transformed $MeHg_T$ data (Average log($MeHg_T$)) for sites within cache creek watershed. Data are grouped for Sulphur Creek and Upper, Mid-Bear Creeks because of significant geothermal spring and ground water sources not present at the other sites. These sources provide significant loads of total mercury and methylmercury, sulfate, nutrients, and DOC (Rytuba 2005b).



## 5.2 A CONCEPTUAL MODEL OF THE SULPHUR CREEK MERCURY TMDL AS AN INFLUENCE DIAGRAM

Figure 5-14 shows a high level conceptual model of the behavior of mercury in the Sulphur Creek watershed, as observed at the gage, represented as an influence diagram. At the highest level, this model shows the relationship of potential controls (“Potential Control Decision”), the variables that could be influenced by control projects (“Annual $Hg_T$ Loading” and “$Hg_T$/TSS”), and the variables that are valued by decision-makers in this decision (“Annual $Hg_T$ Loading” and “Annual $MeHg_T$ Loading”), as indicated by the arcs from these variables to the “Strategy Value” node. This model includes the uncertain environmental relationships between total mercury loading (“Annual $Hg_T$ Loading”), total mercury concentration in total suspended solids (TSS) (“$Hg_T$/TSS”), methylmercury concentration in water (“$[MeHg_T]_w$”), and methylmercury loading (“Annual $MeHg_T$ loading”), conditioned on water year (“Wet/Dry Year”) and/or season, as indicated by the presence of an arc (“Water Season”: wet or dry). The environmental variables shown in Figure 5-14 reflect sets of probability distributions over loadings and concentrations observed at the gage for a particular water season in a wet or dry year. The posterior distribution over an environmental variable takes into consideration wet and dry years and the wet and dry season within a water year, so that its distribution reflects the full range of hydrologic conditions. These variables could be defined at other spatial and temporal scales, but the scale shown reflects the level of aggregation appropriate for this TMDL decision. It is important to note that the appropriate time and spatial scales for variable definitions should be determined by the decision-makers’ goals and objectives, not by technical considerations. The basis for this statement is the use of the Bayesian definition of probability. Of course, decision participants may choose to use scales supported by technical considerations, but this point is noted to emphasize the importance of the decision situation in the definition of variables.

Details about the construction of these probability distributions are described in detail in Chapter 6. The models and methods used include consideration of the partially-understood physical, chemical, and biological processes that drive the movement and fate of mercury species in the Sulphur Creek watershed and the available data. With too little causal detail, the probability distributions are very difficult to interpret and to construct. Sub-models are used to represent the additional detail needed to perform the later construction of the needed probability tables. Figure 5-15 shows the more detailed causal influence diagram used to construct these tables.

Figure 5-14. Conceptual model relating the highly uncertain relationship between annual total mercury ($Hg_T$) loading and annual total methylmercury ($MeHg_T$) loading at the Sulphur Creek gage as a causal influence diagram.

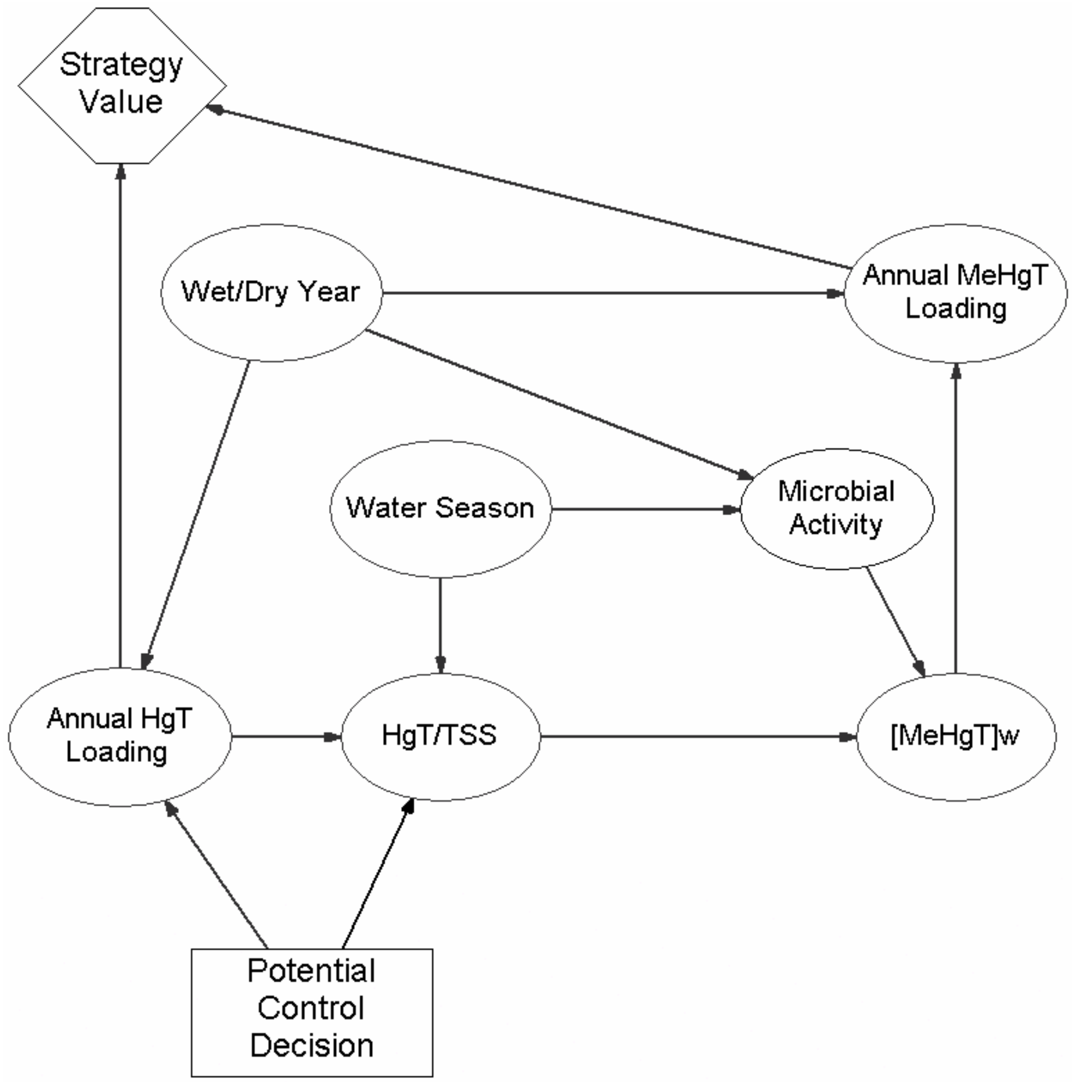
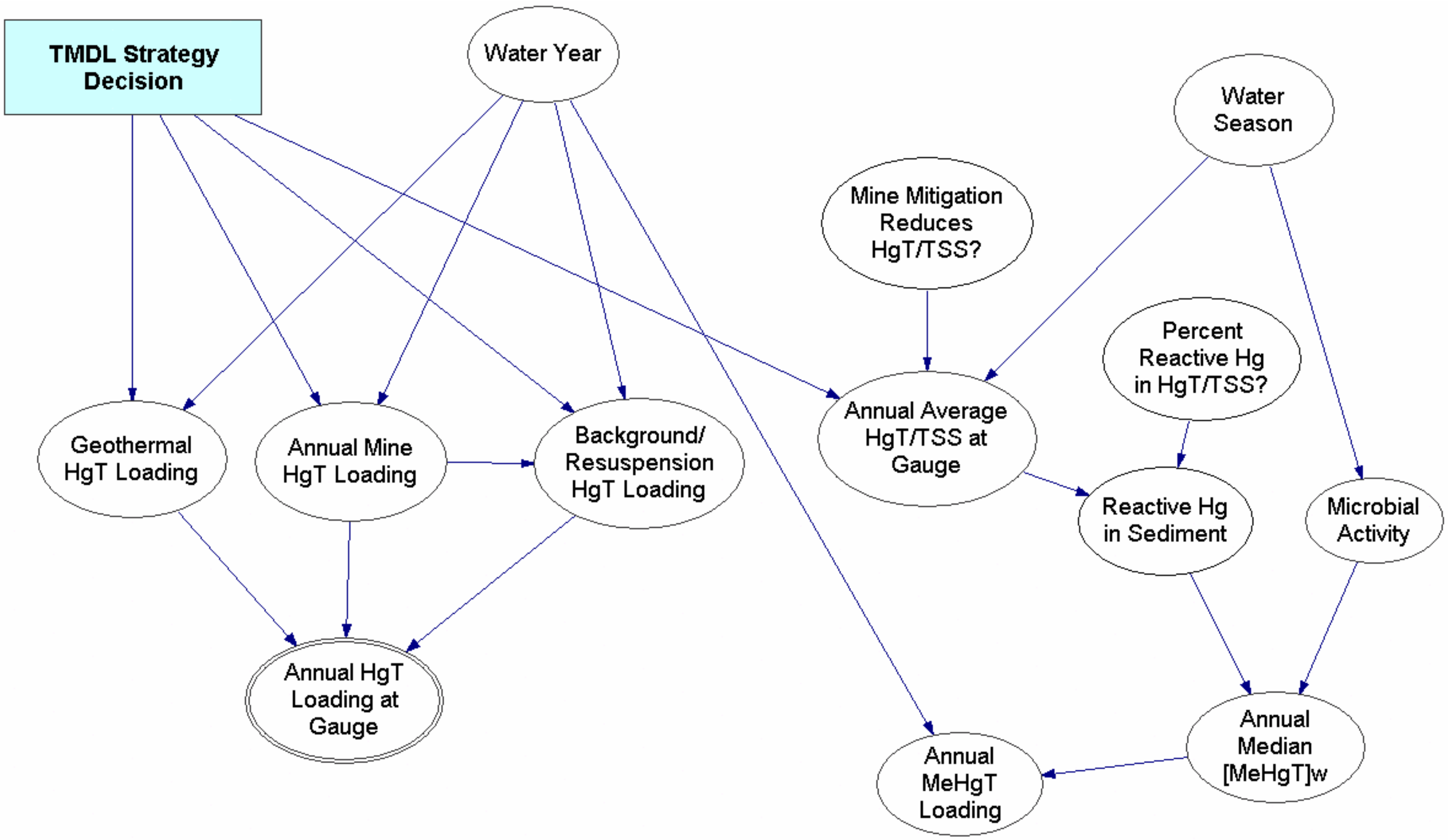


Figure 5-15. More detailed Sulphur Creek mercury TMDL conceptual model, expanding the sub-models shown in the influence diagram shown in Figure 5-14.



This additional detail is represented by expanding the decision-level influence diagram with new variables that explicitly represent additional spatial resolution in mercury concentrations and loadings and/or additional process-based relationships that aid in relating total mercury concentrations in sediment to methylmercury concentration in water. The additional detail is warranted because it adds causal understanding to these relationships, albeit partial understanding.

The variables in the model in Figure 5-15 include the predicted total mercury loading at the gage conditioned on the various total mercury sources within Sulphur Creek, which includes mine waste-related run-off ("Annual Mine $Hg_T$ Loading"), geothermal spring related run-off ("Annual Geothermal Spring $Hg_T$ Loading"), and loadings from other background sources and re-suspended contaminated sediment, including air deposition, ground water, and soil erosion sediment, etc. ("Background /Resuspension $Hg_T$ Loading"). Annual Mine $Hg_T$ Loading, Geothermal $Hg_T$ Loading, and Background/Resuspension $Hg_T$ Loading are conditioned on the available record of mean daily flows for the water year ("Water Year"). The flow conditions for a water year can be summarized by an index of the amount of precipitation received for a particular water year, e.g., "wet" (W), "dry " (D), "above-normal" (AN), "below-normal" (BN), and "critical" (C), as defined by the California Department of Water Resources. In this model, "wet" and "dry" year states were used to capture the range of natural variability and uncertainty in the influence of flow on total mercury loading.

The influence diagram may be used to predict the probability distributions over several variables of interest to decision-makers and scientists: 1) annual median $Hg_T$/TSS concentration in fine grained sediment above the gage ("$Hg_T$/TSS") in response to the various TMDL mitigation alternatives; 2) median reactive mercury in sediment ("$Hg_{sed}^*$") above the gage; 3) annual median methylmercury ("$MeHg_T$") at the gage; and 4) $MeHg_T$ loading at the gage. Other variables are included in the influence diagram to aid in the prediction of these variables of interest, including the hypothesis variable, "Mine Mitigation Reduces $Hg_T$/TSS?", which has states TRUE and FALSE. FALSE refers to the outcome in which mine mitigation results in no discernable change in annual median $Hg_T$/TSS because of the high background mercury sources. TRUE refers to the outcome in which mine mitigation reduces $Hg_T$/TSS during wet season flows to the regional background level of 1 - 10 ppm. "Percent Reactive $Hg_T$" refers to the fraction of $Hg_T$/TSS that contributes to the pool of reactive mercury in sediment.

The structure of the model reflects the fact that mercury methylation is believed to be controlled by the concentration of reactive mercury in sediment (Hgsed*) and the "level of microbial activity" of bacterial species that methylate reactive mercury in-situ. There is no direct information on the concentrations of reactive mercury in sediment in Sulphur Creek. However, some relevant information is available from mercury methylation potential studies in the Cache Creek watershed (Bloom 2001; Domagalski et al. 2003; Suchanek et al. 2004) and studies from other watersheds (Benoit et al. 2003; Marvin-DiPasquale 2005). In this model, Hgsed* is conditioned by Annual Average Hg/TSS at Gage and Percent Reactive Hg in $Hg_T$/TSS. While the uncertainty in Hgsed* is very large, this structure suggests that observed Hg/TSS provides relevant information about concentration and that the source of the mercury (mines/geothermal/soils) provides some limited information about speciation.

The use of hypothesis variables to describe the effectiveness of mine mitigation in reducing annual average $Hg_T$/TSS (Mine Reduction Reduces $Hg_T$/TSS?, "$Hg_T$/TSS reduction hypothesis") and the percentage of reactive mercury in sediment (Percent Reactive Hg in Sediment?, "percent reactive mercury hypothesis") is a reflection of the fact that both variables will remain unobserved before the decision is made. While research could do much to inform the $Hg_T$/TSS reduction hypothesis, that variable can not be completely resolved until mine mitigation has been performed and the remaining contaminated sediment has been partially flushed from the creek. The percent reactive mercury hypothesis variable could be observed before the decision is made, but this was determined to be too expensive by decision-makers. The use of hypothesis variables allows decision-makers to consider the decision to collect more information about these hypotheses in terms of TMDL decision value, the current state of information, and a consideration of which other variables could also be observed in the future. This allows much more robust information collection decisions to be made, formalizing many of the intuitive approaches currently used (Howard 1970).

The state of the "microbial activity" variable can also be thought of as a hypothesis variable, since it cannot be directly observed. Instead, it should be thought of as a useful construct that describes the aggregate effect of the many factors that we partially understand as influencing the efficiency of the microbial methylation of mercury (Marvin-DiPasquale 2005). For example, it could be modeled as being conditionally dependent on seasonal sulfate and sulfide concentrations, temperature, flow conditions (redox conditions), etc. Also, the state of microbial activity can be updated based on a test set of current or future observations of methylmercury data. It is in this sense that "microbial activity" can be thought of as a hypothesis variable in a Bayesian network.

This model represents the current understanding of the available experts and decision-makers of the relationships between potential mercury TMDL mitigation strategies and the environmental targets of interest, total mercury and methylmercury loads exported from the Sulphur Creek watershed. Contrary to typical water quality model development practice, the purpose of this model is not to replace *less realistic* models, but rather to provide an alternative model framework specifically for decision support. In addition to probabilistic causal representation of a complex environmental system, modeling for decision support should provide decision-makers with an understanding of the *meaning* of predictive uncertainty in the context of the decisions being made and in terms meaningful to decision-makers. This obviously goes beyond the purposes and methods of traditional water quality modeling and potentially enters into the many sub-fields that make use of results from the decision sciences, including "decision support", decision analysis, multi-criteria decision-making, the analytic hierarchy process, and others.

This chapter concludes with a precise definition of the states for each of the variables shown in Figure 5-15. Table 5-2 lists each variable and its type (chance, hypothesis, deterministic, or decision) and defines the states for each. The generation of the probability distributions over the states of the variables shown in Table 5-2 and the decision analytical use of the fully-specified influence diagram model will be shown in subsequent chapters.

Table 5-2.  Definitions of variables used in the influence diagram shown in Figure 5-15.

| Variable Name | Variable Type | States | Definition | Model/ Expertise/ Data Source |
|---|---|---|---|---|
| TMDL Strategy Decision | Decision | Mine Mitigation, Geothermal & Mine Mitigation, and Status Quo | Mine mitigation is the alternative in which $Hg_T$ loadings from mines are reduced according to the load allocation scheme explained in Chapter 2. Geothermal & mine mitigation includes the mine reductions from the Mine Mitigation alternative, but also includes $Hg_T$ load reductions from geothermal springs.  The Status Quo alternative refers to the conclusion from a use attainability analysis that the current beneficial uses are inappropriate given background loadings and includes a public information campaign.  See Chapter 2 for more details. | Not applicable |
| Water Year | Chance | Wet, Dry | CA Dept of Water Resources (DWR) Index for the Sacramento River .  A wet year (W) is defined by a combined discharge ≥ 9 maf.  A dry year (D) is defined by a combined discharge > 5.4 maf but ≤ 6.5 maf.  See the footnote to Figure 5-1 for more information. | Definition from CA DWR |
| Water Season | Chance | Wet, Dry | Dry = March 31 to September 30; Wet = Rest of year | Definition from RWQCB-CV (2005b) |
| Annual Mine $Hg_T$ Loading | Chance | Low, High | Low =  1 kg/year, High = 20 kg/year | Expert judgment informed by limited data |
| Background/Resuspension $Hg_T$ Loading | Chance | Low, High | Low = 1 kg/year, High = 20 kg/year | Expert judgment informed by limited data |
| Annual Geothermal Spring $Hg_T$ Loading | Chance | Low, High | Low = 0.1 kg/year, High = 4 kg/year | Expert judgment informed by limited data |
| Annual $Hg_T$ Loading at Gage | Deterministic | LLL, LLH, LHL, LHH, etc. | Functionally determined sum of parents | Simulation |

Table 5-2. (Continued)

| Variable Name | Variable Type | States | Definition | Model/ Expertise/ Data Source |
|---|---|---|---|---|
| Annual Average $Hg_T$/TSS at Gage | Chance | Low, Nominal, High | Low = 1 ppm, Nominal = 10 ppm, High = 100 ppm | Expert judgment informed by limited data |
| Mine Mitigation Reduces $Hg_T$/TSS? | Hypothesis | True, False | True = $Hg_T$/TSS reduced to regional background levels, False = No change | Expert judgment informed by other studies |
| Reactive Mercury in Sediment | Chance | Low, High | Low = 0.0001 ppm, High = 5 ppm | Expert judgment informed by limited data |
| Percent Reactive Mercury $Hg_T$/TSS? | Hypothesis | Low, High | Low = 0.01%, High = 5% | Expert judgment informed by other studies |
| Microbial Activity | Hypothesis | Low, High | High = 5 times more efficient methylation for a given $Hg_{xed}^*$ concentration relative to Low. | Expert judgment informed by other studies |
| Annual Median $[MeHg_T]_w$ | Chance | Low, Nominal, High | Low = 0.05 ng/L, Nominal = 1 ng/L, High = 5 ng/L | Simulation |
| Annual $MeHg_T$ Loading at Gage | Chance | Low, Nominal, High | Low = 0.25 g/year, Nominal = 5 g/year, High = 100 g/year | Simulation |

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# CHAPTER 6: SULPHUR CREEK MERCURY TMDL SOURCE AND LINKAGE ANALYSIS USING A BAYESIAN NETWORK APPROACH

This chapter briefly reviews current practice in TMDL source analysis and linkage analysis, as relevant to the mercury TMDL case study used in this work. It also presents a probabilistic mercury source analysis and linkage analysis for the Sulphur Creek mercury TMDL that organizes the results as probability tables. These probabilistic data are then integrated into a Bayesian network model (influence diagram) that serves as the basis for TMDL decision analysis and decision support, the subject of Chapter 8.

## 6.1 CURRENT PRACTICE IN MERCURY-MINE IMPACTED WATERSHED SOURCE AND LINKAGE ANALYSIS

### Deterministic Total Mercury Source Analysis

The TMDL reports for the Sulphur Creek and Cache Creek, Bear Creek, and Harley Gulch mercury TMDLs present typical deterministic approaches for estimating annual budgets for water, total mercury, methylmercury, and sediment. The available data for these TMDLs consist of mean daily flows measured at the gage stations shown in Figures 2-2 and 2-3 for 1995 – present (some missing data) and the available relevant water quality data for selected dates: instantaneous total mercury, methylmercury, and total suspended solids concentrations ($Hg_T$, $MeHg_T$, and TSS, respectively). TSS is used as a surrogate for suspended sediment concentration and $Hg_T$ /TSS is used as a surrogate for total mercury concentration in fine-grained sediment (RWQCB-CV 2004b). Table 6-1 summarizes the available relevant water quality data for Sulphur Creek and Lower Bear Creek, the stream segments focused on in this paper. As an illustration of the amount of available data, the number of $Hg_T$ data for all stream segments within the Cache Creek watershed range from 16 to 65, with a mean of 30.

The annual water budget was estimated by summing mean daily flows over a given water year for gaged stream segments. Water budgets for ungaged segments were estimated from a version of the rational runoff method or, in some cases, using the assumption that the percentage discharge from a sub-basin could be directly approximated by its areal percentage of the watershed (Dunne and Leopold 1978). The Regional Water Quality Control Board (RWQCB) staff's approach for estimating annual loads ($L_{Ann}$) involves multiplying the mean daily flow (mdf) by the water quality concentration predicted for that flow (C(mdf)) to calculate the mean daily load, then summing over the water year:

$$L_{Ann} = \sum_{wateryear} mdf * C(mdf)$$

For some stream segments (South Fork, Cache Creek at Rumsey, and Cache Creek at Yolo), stream flow appears to be linearly correlated with $Hg_T$ and TSS over the entire observed flow range. For these segments, C(mdf) was deterministically estimated from linear correlations of the untransformed variables. For the other stream segments, the arithmetic averages of $Hg_T$ and TSS were used to estimate C(mdf). For $MeHg_T$, arithmetic averages were used for all segments to estimate C(mdf). The use of arithmetic averages and linear models with no transformation of the variables for predicted concentrations implies that the variables/residuals are normally distributed, an assumption that is not supported by the data in several cases. As shown in Chapter 5, hysteresis in the C(flow) relationship at the scale of individual storm events may account for much of the scatter in the log-log linear regions of the $Hg_T$ (TSS) versus flow relationship.

It should be kept in mind that estimates of total mercury loadings within Sulphur Creek and the other stream segments in Cache Creek have significant associated uncertainties. While estimating the annual water budget from gaged flows is operationally straightforward[25], *predicted* total mercury concentrations are used in the annual $Hg_T$ load estimates. Since the associated prediction errors are quite large relative to the predicted means and the concentrations appear to be lognormally distributed in most cases, a probabilistic estimate of average annual loadings based on log transformed concentration values is more informative than the typical deterministic estimation approaches. It should be noted that additive errors in a lognormal flow vs. concentration model reflect the fact that the

Table 6-1. Sulphur Creek and Lower Bear Creek Data Summary, from Cache Creek Mercury TMDL Report (RWQCB-CV 2004a) and Sulphur Creek TMDL Report (RWQCB-CV 2004b).

| **Stream Segment** | **Water Quality Parameter** | **Number of observations** | **Range** | **Mean / Median** |
|---|---|---|---|---|
| **Sulphur Creek** | $Hg_T$ (ng/L) | 34 | 245 – 16,410 | 2,890 / 1,094 |
| | $MeHg_T$ (ng/L) | 27 | 0.1 – 21 | 2 / 1 |
| | TSS (mg/L) | 31 | 4 – 1,372 | 214 / 56 |
| | $Hg_T$ (ng/L), 2/25/04 Storm Event | 19 | 231 – 9,510 | 2,540 / 1,440 |
| | TSS (ng/L), 2/25/04 Storm Event | 19 | 1.8 – 1,390 | 416 / 173 |
| **Lower Bear Creek** | $Hg_T$ (ng/L) | 16 | 18.5 – 1,290 | 281 / 81.9 |
| | $MeHg_T$ (ng/L) | 1 | 0.82 | NA |
| | TSS (mg/L) | 15 | 1.7 - 670 | 118 / 29.3 |

scatter in the underlying untransformed data is proportional to flow. By log-transforming the flow and concentration variables, the residuals in log-space obey the assumptions behind the linear regression model for the selected flow ranges.

### DETERMINISTIC MERCURY LINKAGE ANALYSIS

While inorganic mercury associated with particulates is often the dominant mercury fraction in aquatic environments, methylmercury is the chemical species that

[25] While the estimation method is straightforward, the estimate has significant uncertainty.

bioaccumulates and biomagnifies in aquatic food webs, potentially resulting in fish tissue mercury levels that are toxic to humans and wildlife (Benoit et al. 2003). Although most fish advisories apply to watersheds dominated by atmospherically deposited mercury (Wiener et al. 2003), this research focuses on a watershed impacted by relatively large total mercury inputs from legacy mine wastes, active geothermal sources, and high regional background levels in soils. In the creeks in this watershed, like most aquatic environments, *in situ* microbially mediated methylmercury production from available reactive inorganic mercury at the oxic/anoxic sediment interface is believed to be the dominant source of methylmercury. While methylmercury formation is positively correlated with total mercury concentration in the Cache Creek watershed and many other watersheds, environmental factors other than total mercury loading (e.g., sulfate and sulfide sediment concentrations, dissolved organic carbon (DOC) levels, temperature, etc.) may strongly influence methylmercury concentrations and bioaccumulation in aquatic ecosystems (Benoit et al. 2003; Wiener et al. 2003). In general, the range of mercury methylation rates across aquatic ecosystems is greater than the range in total mercury loading rates (Benoit et al. 2003). In fact, it may be the case that high methylmercury concentrations may be more of a localized "hotspot problem" under conditions of high microbial activity and high reactive mercury than a watershed-wide mercury contamination problem (Calfed Bay-Delta Program 2005). However, this issue is still an active area of research (Marvin-DiPasquale 2005).

The observed aqueous MeHg concentration at any point in time integrates the many processes influencing MeHg production and loss (Benoit et al. 2003). Relevant factors include total mercury loadings, reactive mercury concentrations in sediment, low flow duration, and temperature, all of which vary spatially and temporally. Even with ample data on the most relevant environmental factors, there is significant uncertainty in predicting the value of $MeHg_T$ for a given set of conditions. In practice, the data on the most relevant environmental factors (reactive mercury concentration in sediment, acetate and lactate concentrations, sulfate and dissolved sulfide concentrations in sediment, pore water temperature, etc.) are very sparse or missing altogether for the watershed of interest.

The large uncertainties in linking total mercury concentrations and loadings to methylmercury concentrations and loadings are widely acknowledged. At present, trustworthy process-based models of the formation of methylmercury do not exist and the available empirical (statistical) models based on aqueous concentrations of total mercury ($Hg_T$) and total methylmercury ($MeHg_T$) lack clear causal predictive power. While semi-empirical methylmercury predictive models based on the concentration of reactive mercury in sediment ($Hg_{sed,\ rct}$) and microbial activity are the state of the art (Mark Marvin-DiPasquale, personal communication), there are no data available to describe $Hg_{sed,\ rct}$ and very little relevant data for describing microbial activity in Sulphur Creek, other than what can be inferred from the small number of available $MeHg_T$, sulfate, and DOC data.

Rather than relying on a potentially non-causal empirical relationship between $Hg_T$ and $MeHg_T$ in the linkage analysis, I propose an alternative way of thinking about the causal relationship between inorganic mercury and methylmercury, one that focuses on the what experts know about the causal relationships between potential controls and the environmental targets of interest, making the best use of the available data and expertise.

## 6.2 CURRENT PRACTICE IN DEALING WITH SOURCE AND LINKAGE ANALYSIS UNCERTAINTY

The consideration of uncertainty in TMDLs is constrained by the regulatory requirements for the use of a Margin of Safety (MOS) and thus most discussions of uncertainty in TMDL decisions take the MOS as a starting point. From this perspective, an uncertainty analysis of the relevant (deterministic) models can be performed (in theory) and, from this uncertainty analysis, the choice of an appropriate MOS in the TMDL target can be made. The use of conservative modeling assumptions, or even conservative mitigation goals, as "the MOS" is another strategy in use. From a decision analytical point of view, the *choice* of "how conservative" the MOS should be is *itself* a decision of fundamental importance. To leave this choice as a conventional "scientific/engineering judgment" is to risk making a poor decision. While a poor *outcome* may result from any decision under uncertainty, a good *decision* means that, given the available information, the alternatives considered, and the decision-makers' preferences over the outcomes, the course of action chosen is the rational one (see Chapter 4 for a discussion of utility maximization in decision analysis).

## 6.3 SOURCE ANALYSIS UNCERTAINTIES AS RANDOM VARIABLES IN A PROBABILISTIC (BAYESIAN) NETWORK

### ESTIMATING PROBABILITY DISTRIBUTIONS OVER MERCURY LOADINGS

Depending on the types and amounts of available data, two basic approaches were used to estimate the probability distributions over total mercury and methylmercury loadings in the Sulphur Creek watershed. For the gage sites, the empirical log-log linear model shown in Figure 5-5 was used to predict $Hg_T$ from flow using Monte Carlo simulation[26]. A random error term based on the residual error from Figure 5-5 was used in the simulation. Since $MeHg_T$ appears to be independent of flow (RWQCB-CV 2004b) and approximately lognormally distributed (Figure 6-1), simulated values from a lognormal model were used with flow data to estimate annual $MeHg_T$ loads. To estimate the highly uncertain total mercury loadings from the various mine sites, geothermal springs, erosion of undisturbed soil, and erosion of the contaminated streambed, experts were asked to look at the available data for this watershed and any other relevant data from elsewhere in the Cache Creek watershed (Rytuba 2005a). Probability distributions for the various sources reflecting their expert judgment were assessed and used to represent the current background state of

[26] Convergence of the mean was used to limit the number of trials. Typically, 1000 to 5000 trials were sufficient. The

information. Discrete approximations for the loading distributions were created from the simulated distributions using standard methods (Miller and Rice 1983; Poland 1996; Smith 1993).

### PROBABILITY DISTRIBUTION OVER THE ANNUAL TOTAL MERCURY ($HG_T$) AND METHYLMERCURY ($MEHG_T$) AT THE SULPHUR CREEK GAGE

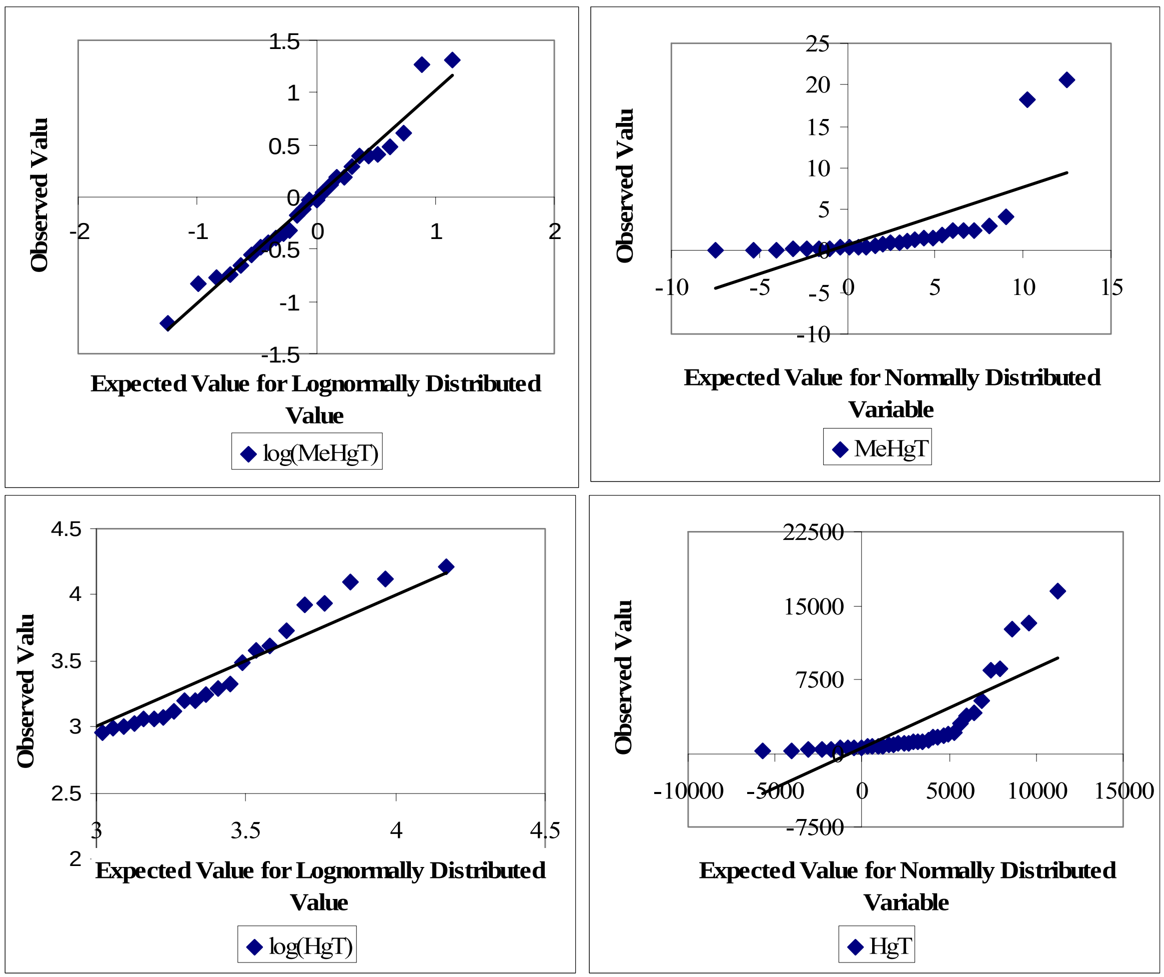
Mean daily loadings over the water year were predicted using mean daily flow data and the total ($Hg_T$) and methylmercury ($MeHg_T$) concentrations predicted for that flow. The summation over the water year for the mean daily loadings is the best estimate of the annual loading. Note that I assumed that $Hg_T$ and $MeHg_T$ are lognormally distributed (i.e., $\log(Hg_T)$ and $\log(MeHg_T)$ are normally distributed). Figure 6-1 shows that an assumption of lognormality leads to much better $Hg_T$ and $MeHg_T$ predictions from flow than the assumption of normality, based on the fit of observed versus expected values. This means that using arithmetic averages and linear models using untransformed concentration data will lead to biased predictions.

To simulate the uncertain concentration distribution over the flow-independent range (e.g., $MeHg_T$ for all flows and $Hg_T$ for flows < 55 cfs) for a given water year, concentrations were simply randomly generated from a lognormal distribution. To simulate uncertainty in the $Hg_T$ predictions for flow greater than 55 cfs, I used a log-log linear model that included an estimate of the prediction error based on cross-validation using five data sub-sets (Hastie et al. 2001):

$$\ln(C(mdf)) = f(\ln(mdf)) + \ln(Error),$$

where the terms are defined as before. Note that the fact that error is assumed to be additive in ln-space means that error is multiplicative in arithmetic space. In other words, larger flows have larger errors for $Hg_T$, which is supported by the data. Since the purpose of this simulation to estimate the uncertainty in the loading in *any* wet or

Figure 6-1. Observed Versus Expected Values For Normal And Lognormal Distributions For Total Mercury ($Hg_T$) and Methylmercury Concentrations ($MeHg_T$) for All Available Data, Representing Dry and Wet Seasons and All Flow Ranges.



dry water year and not to construct a time series prediction for a given set of flows in a *particular* water year, the autocorrelation in the error term is not a concern (Chatterjee et al. 2000). The scatter introduced by the hysteresis in the flow versus $Hg_T$ relationship (one of the sources of autocorrelation) is treated as random error in this model.

A histogram over a water year's or water season's simulated mean daily loadings approximates the desired loading probability distribution for that water year or water season. The resulting probability distributions represent what we know from the available flow and water quality data and what we do *not* know about the complicated relationship between flow and $Hg_T$ or $MeHg_T$. The total uncertainty considered includes our uncertainty in the data measurements themselves and in the noisy relationships between flow and $Hg_T$ and $MeHg_T$. Future flow variability is represented by a marginal distribution over water year with two states, "Wet Year" and "Dry Year". Based on the historical record (1906 – 2004) for the Sacramento Valley, wet years and dry years were represented as equally probable.

Figure 6-2 shows the simulated cumulative distribution over the annual $Hg_T$ loading for Sulphur Creek in the 2000 water year, which includes flow variability, measurement uncertainty, and $Hg_T$ prediction uncertainty. Figure 6-2 also shows the annual load estimate made using the deterministic methodology of the Central Valley Regional Water Quality Control Board staff, which uses the arithmetic average of the available $Hg_T$ data to predict the concentration for any flow. This estimate results in a value that occurs well beyond the $99^{th}$ percentile, indicating strong high bias. This bias results from the use of the arithmetic average of the $Hg_T$ data as the measure of central tendency, in part because wet season sampling was done more often than dry season sampling, and, as shown in Figure 5-5, there is a significant log-log linear correlation between flow and $Hg_T$ for flows larger than 55 cfs. Also, the use of an arithmetic average to predict $Hg_T$ significantly overestimates the value for flows less than 55 cfs, as can be seen from Figure 5-5. This results in significant load overestimates for most of the water year.

Figure 6-2. Simulated Cumulative Distribution of Annual Total Mercury ($Hg_T$) Loading for Sulphur Creek, 2000 Water Year.

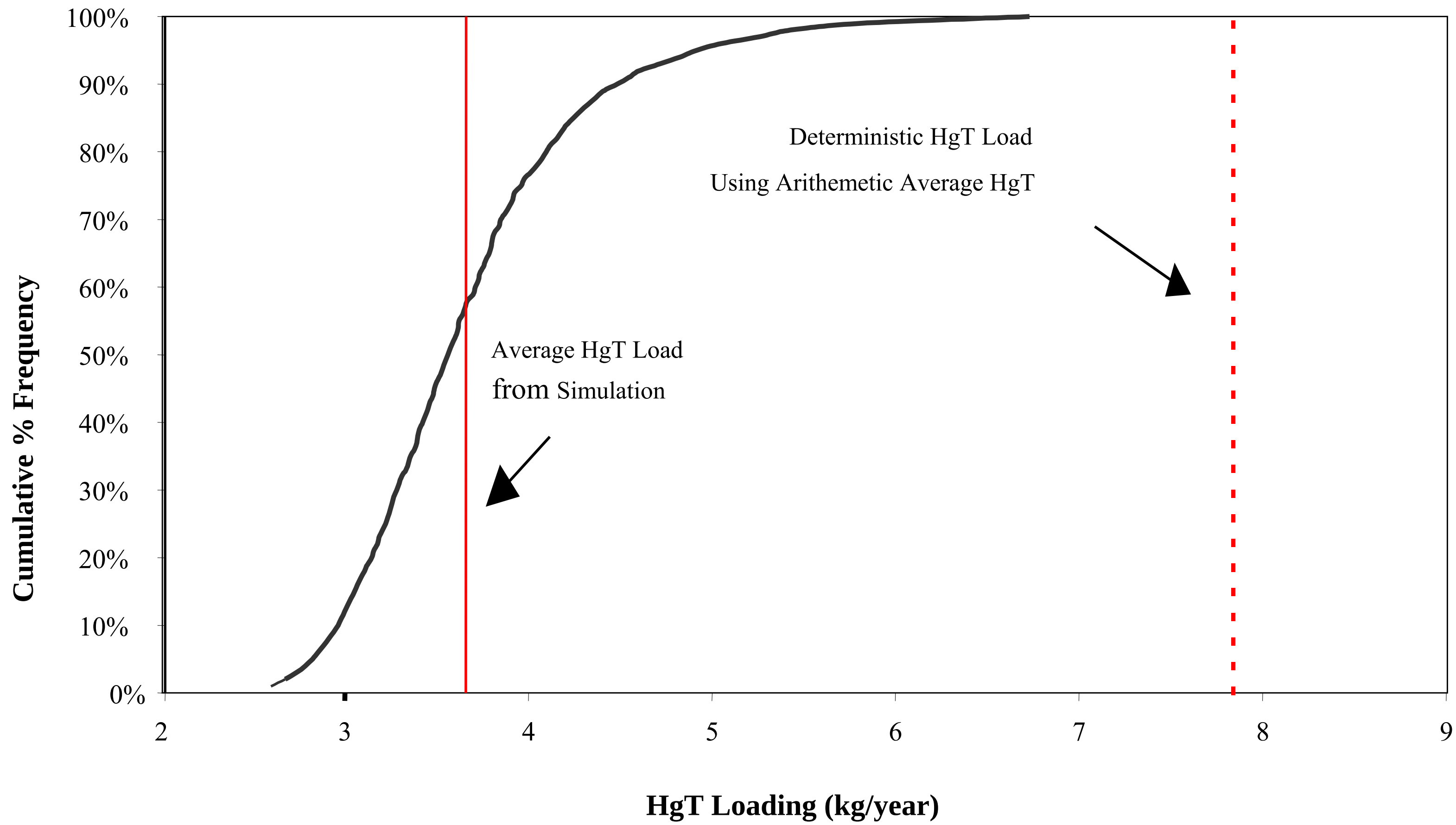


Figure 6-3 shows the correlation between the log of the best estimate annual $Hg_T$ loading and annual discharge at the Sulphur Creek gage for the period of record, 2000 – 2004. This information is summarized in Table 6-2, which also shows the numerical values for the averages and standard deviations for the annual $Hg_T$ loads for the years of record. A "dry year" was defined using the data from the 2001 water year, which had an average annual $Hg_T$ load of 2.4 kg/year. Using the definition of

Figure 6-3. Relationship between Log(annual $Hg_T$ Loading) and annual discharge at the Sulphur Creek gage.

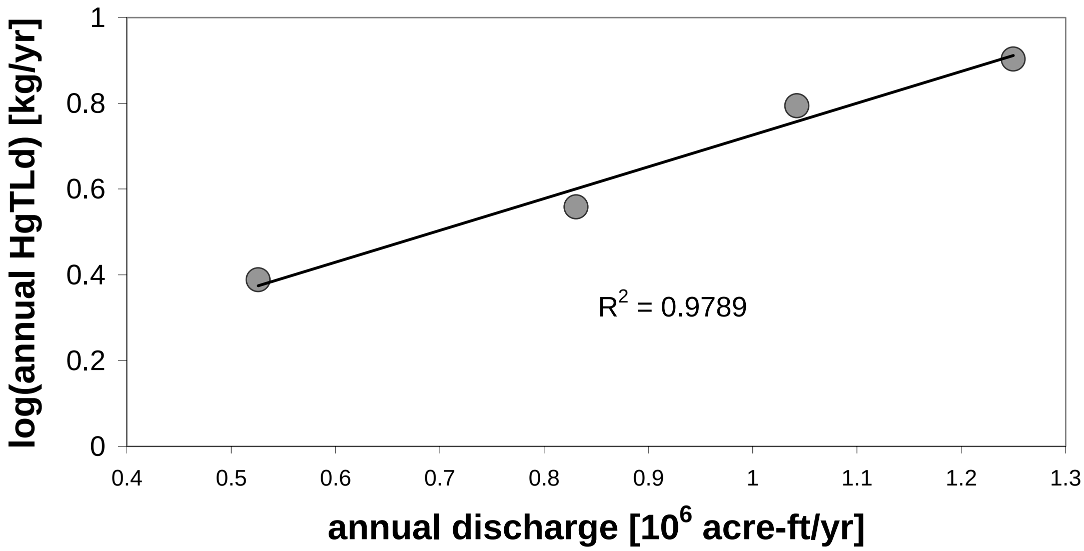


Table 6-2. Statistical summary from simulation of annual total mercury load at the Sulphur Creek gage.

| Water Year | Annual Discharge ($10^6$ Acre-ft/yr) | Average Annual $Hg_T$ Load (kg/yr) | Standard Deviation for $Hg_T$ Load (kg/yr) |
|---|---|---|---|
| 2000 | 0.83 | 3.6 | 0.7 |
| 2001 | 0.53 | 2.4 | 0.8 |
| 2002 | 1.0 | 6.2 | 3.8 |
| 2003 | 1.2 | 8.0 | 3.1 |

wet year as an annual discharge of 1.5 x $10^6$ acre-feet/year, the average value for the wet year annual $Hg_T$ loading at the gage was estimated from this relationship as 13 kg/year. The simulated distributions for the dry and wet years were approximated as two-point discrete probability distributions using a standard approach (Miller and Rice 1983; Poland 1996; Smith 1993) and are shown in Table 6-4.

#### PROBABILITY DISTRIBUTION OVER THE ANNUAL MINE $HG_T$ LOADING CONTRIBUTION

The probability distribution over the aggregate annual mine $Hg_T$ loading contribution was estimated as an uncertain percentage of the annual $Hg_T$ loading observed at the gage. Using published $Hg_T$ data collected upstream and downstream of individual mine sites in 2000 – 2004 and the flows estimated by RWQCB staff (RWQCB-CV 2004b), annual mine-related loadings were estimated to comprise around 70% of the observed annual $Hg_T$ load at the gage. However, this is an upper bound of the direct contribution of the mine sites to the $Hg_T$ loading at the gage, since it does not account for any sediment deposition during transport from the mine sites to the gage. Researchers estimate that run-off from the mine sites contributed approximately 20% of the $Hg_T$ loading observed at the gage during 2000 – 2002 (Churchill and

Clinkenbeard 2003; Suchanek et al. 2004). To simulate our uncertainty in the percentage contribution, I used a triangular distribution with values {0.10,0.20,0.90}. The triangular distribution is typically used when the minimum and maximum values are the most well-understood parts of the distribution and the estimate of the modal value is an "inspired guess". Despite being a simplistic description of a population, it is a very useful distribution for modeling processes where the relationship between variables is known, but data are scarce (Johnson et al. 2002; Williams 1992).

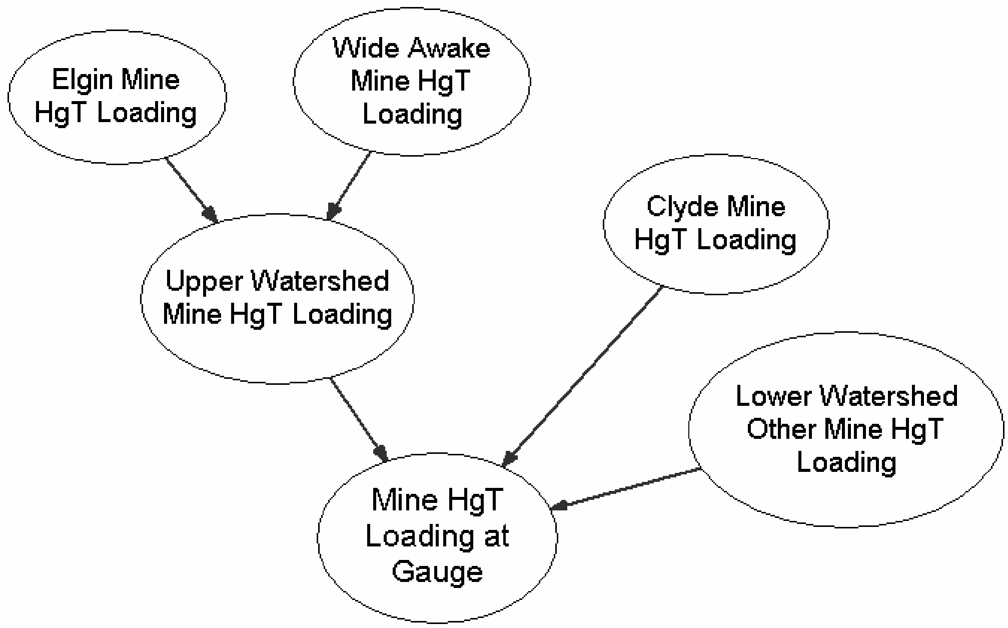
I used Monte Carlo analysis to estimate the distribution over annual mine $Hg_T$ loading contribution from run-off using wet season flow data for a given water year:

$$HgTLoad_{Mines} = (\%HgTLoad_{Gauge}\ \ from\ Mines) * (HgTLoad_{Gauge}) =$$
$$\sum\nolimits_{WetSeasonFlows} \mathrm{Tr}(0.10,0.20,0.90) * \{\mathrm{Load}(\mathrm{flow}_i)\mathrm{Gauge} \mid \mathrm{Wet\ Season,\ Water\ Year}\}$$

where Tr(•) represents a triangular distribution generation function, $\mathrm{Load(flow)}_{\mathrm{Gage}}$|Wet Season represents the $Hg_T$ loading at the gage predicted for a given wet season flow, and the summation is over the wet season flows for a given water year.

Note that the source loading model could be much more detailed, if the available data warranted it and if the decision were framed at the level of choosing between individual mine site remediation projects. For example, Figure 6-4 shows a more detailed probabilistic sub-model for the Annual Mine $Hg_T$ T Loading variable that includes the relationships between individual mine sites in the upper watershed (Elgin and Wide Awake mines), the aggregate mine contribution from the upper watershed, lower watershed mines (Clyde and others), and the total aggregate mine contribution observed at the gage. Such a model could be used to evaluate specific mine site remediation projects, partly based on the uncertainty in these relationships.

Figure 6-4. More Detailed Bayesian Network Sub-model for Mine $Hg_T$ Loading at Gage.




However, such detail was not needed for the TMDL decisions evaluated in this research, as framed.

PROBABILITY DISTRIBUTION OVER THE GEOTHERMAL $HG_T$ LOADING CONTRIBUTION

The uncertainty in the annual geothermal $Hg_T$ inputs to Sulphur Creek is much smaller than the uncertainty in the annual mine $Hg_T$ inputs (Churchill and Clinkenbeard 2003). The best estimate of the total annual geothermal input to Sulphur Creek is 1.7 kg/year (RWQCB-CV 2004b). The major uncertainty involves the unknown net deposition factor on an annual basis aggregated over the watershed. There are some relevant observations concerning this factor. For example, some segments of Sulphur Creek (e.g., between the Jones Fountain of Life and Wilbur Hot Springs) were determined to have net sediment deposition of precipitates venting from thermal springs during dry and wet season flows. The uncertainty in this net deposition factor was modeled as a triangular distribution with values {0.2, 0.8, 0.95}(Rytuba 2005b). The annual $Hg_T$ load contribution from geothermal springs to the gage load is modeled as:

$$Hg_T Load_{Springs} = \{(\%\ Geothermal\ Inputs\ Deposited\ in\ Creeks\ Annually) \\ * (Total\ Annual\ Geothermal\ Load)\} = Tr(0.2, 0.8, 0.95) * 1.5\ kg / year.$$

The annual variation in the spring $Hg_T$ loading is negligible.

### PROBABILITY DISTRIBUTION OVER THE BACKGROUND/RESUSPENSION $HG_T$ LOADING CONTRIBUTION

The Background/Resuspension $Hg_T$ Loading variable in Figure 5-15 is defined to include mercury loading contributions from resuspended contaminated sediment along Sulphur Creek upstream of the gage, erosion of regional soils, and atmospheric deposition within the watershed. The triangular distribution was approximated from a consideration of mass balance and uncertainty in the loadings terms:

$$HgTLoad_{Background/Resuspension} = HgTLoad_{Gauge} - HgTLoad_{Springs} - HgTLoad_{Mines}$$

While this method is gross, it reflects the very sparse data available to support the mercury TMDL setting decision.

### ANNUAL $HG_T$ LOADING AT THE GAGE AS A DETERMINISTIC VARIABLE

The Annual $Hg_T$ Loading at Gage variable was modeled as a deterministic function (mapping) of its parent variables, Annual Mine $Hg_T$ Loading (High/Low), Geothermal $Hg_T$ Loading (High/Low), and Background/Resuspension $Hg_T$ Loading (High/Low). Each of the eight possible combinations of the states of its parents was assigned its unique numerical result. Table 6-3 shows the mapping used to predict the annual $Hg_T$ loading at the Sulphur Creek gage. The posterior distribution over this predicted loading is shown in the next section.

Table 6-3. Deterministic mapping for predicting the annual $Hg_T$ loading at the Sulphur Creek gage from source loadings.

| **Parental Combinations** | | | **Resulting $Hg_T$ Load at Gage (kg/year)** |
|---|---|---|---|
| **$Hg_T$ Load Mines** | **$Hg_T$ Load Springs** | **$Hg_T$ Load Background/ Resuspension** | |
| Low | Low | Low | 2.2 |
| Low | Low | High | 21.2 |
| Low | High | Low | 3.5 |
| Low | High | High | 22.5 |
| High | Low | Low | 21.2 |
| High | Low | High | 40.2 |
| High | High | Low | 22.5 |
| High | High | High | 41.5 |

## 6.4 TOTAL MERCURY SOURCE ANALYSIS USING A BAYESIAN NETWORK

Figure 6-5 shows the Sulphur Creek $Hg_T$ source analysis as a Bayesian network. The conditional probability distributions derived in the previous section are associated with the variables shown and can be used to calculate the posterior probability distributions relevant to the source analysis. This network will be incorporated in the linkage analysis influence diagram in the next section. Table 6-4 shows the generated marginal probability table for Water Year and the conditional probability tables for Geothermal $Hg_T$ Loading, Annual Mine $Hg_T$ Loading and Background/Resuspension $Hg_T$ Loading.

Figure 6-5. Total mercury source analysis as a Bayesian network. a) When Annual $Hg_T$ Loading at Gage is unobserved (not shaded), Annual Mine $Hg_T$ Loading is *not* relevant to Background/Resuspension $Hg_T$ Loading given the TMDL Strategy Decision and Water Year. b) If Annual $Hg_T$ Loading at Gage is observed (shaded), Annual Mine $Hg_T$ Loading is relevant (additional arc) to Background/Resuspension $Hg_T$ Loading given the TMDL Strategy Decision and Water Year.

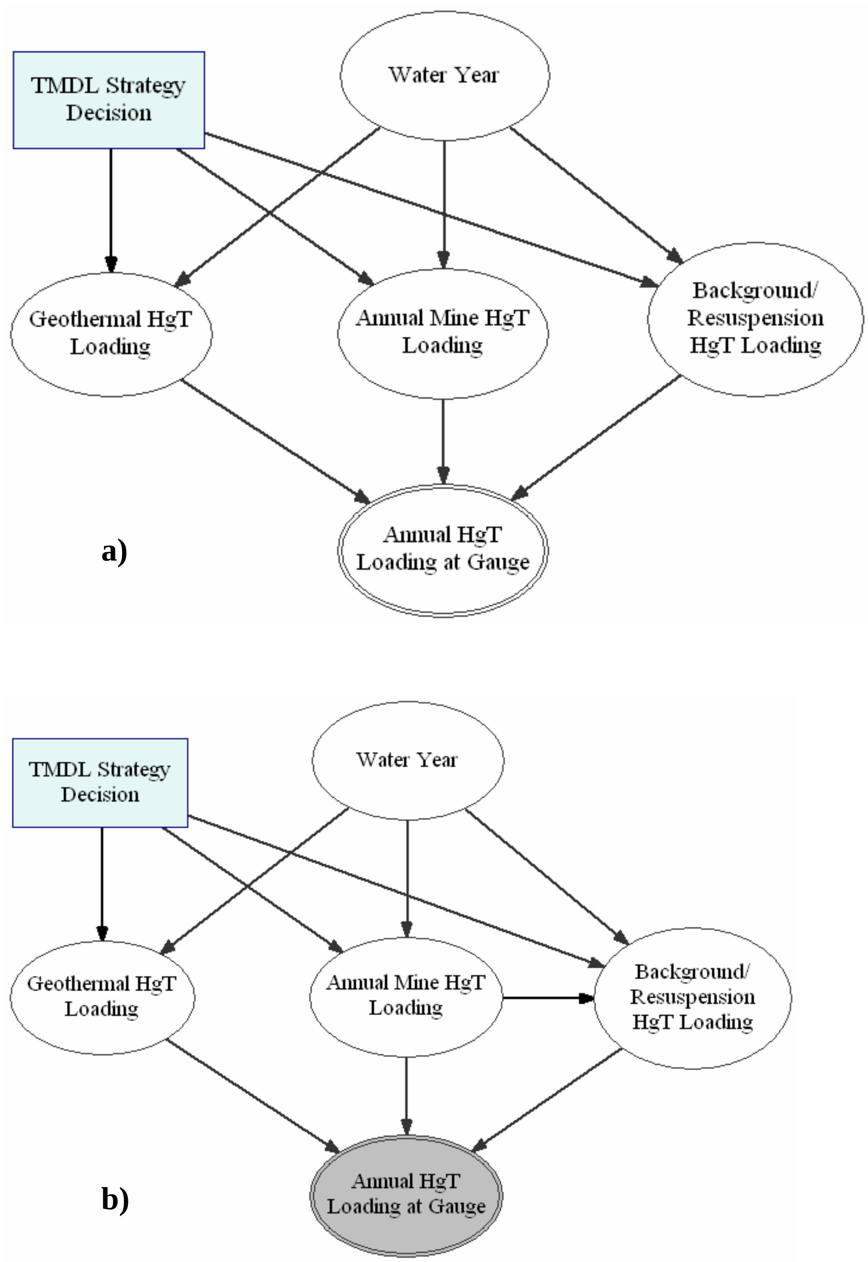


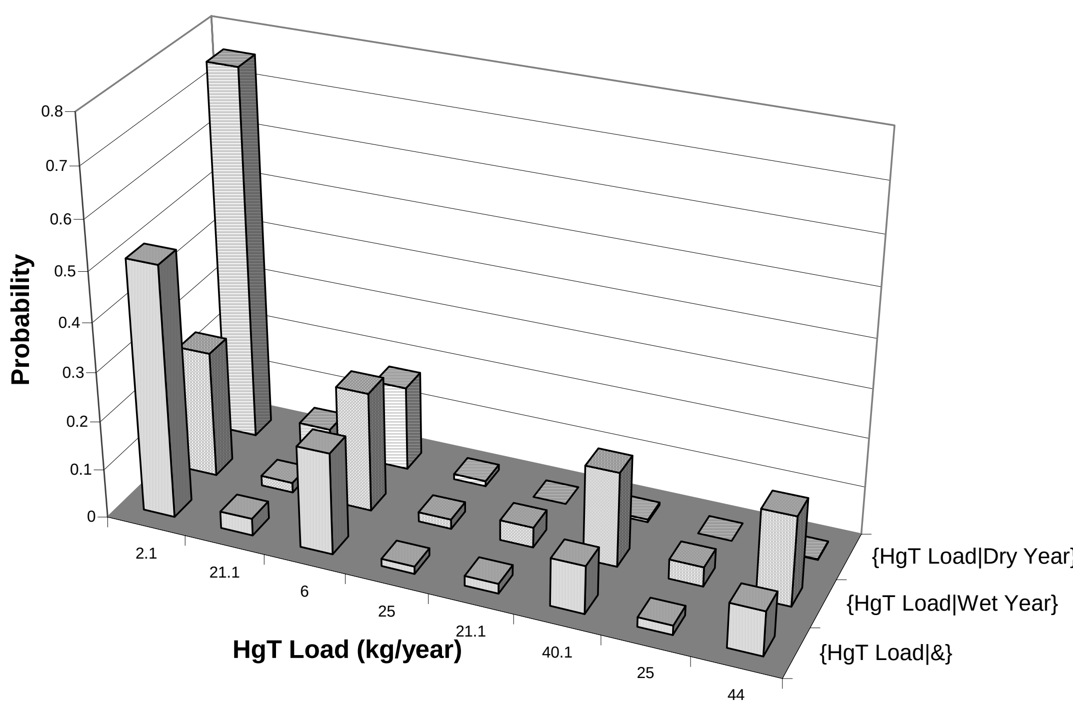
Table 6-4. Probability tables for source analysis variables.

| **{Water Year\|&}** | **Probability** | | | **Source** |
|---|---|---|---|---|
| Dry | 51 | | | Frequency from data[1] |
| Wet | 49 | | | Frequency from data[1] |
| **{Annual Mine $Hg_T$ Loading\|Dry Year}** | **Probability** | | | **Source** |
| | **Status Quo** | **Mine Strategy** | **Geothermal & Mine Strategy** | |
| Low | 0.993 | 0.999 | 0.993 | Simulation from published data[2], expert judgment |
| High | 0.007 | 0.001 | 0.007 | |
| **{Annual Mine $Hg_T$ Loading\|Wet Year}** | **Probability** | | | **Source** |
| | **Status Quo** | **Mine Strategy** | **Geothermal & Mine Strategy** | |
| Low | 0.54 | 0.964 | 0.54 | Simulation from published data[2,3], expert judgment |
| High | 0.46 | 0.036 | 0.46 | |
| **{Geothermal $Hg_T$ Loading\|Dry Year}** | **Probability** | | | **Source** |
| | **Status Quo** | **Mine Strategy** | **Geothermal & Mine Strategy** | |
| Low | 0.81 | 0.81 | 1 | Simulation from published data[2], expert judgment |
| High | 0.19 | 0.19 | 0 | |
| **{Geothermal $Hg_T$ Loading\|Wet Year}** | **Probability** | | | **Source** |
| | **Status Quo** | **Mine Strategy** | **Geothermal & Mine Strategy** | |
| Low | 0.51 | 0.51 | 0.962 | Simulation from published data[2,3], expert judgment |
| High | 0.49 | 0.49 | 0.038 | |
| **{Annual Background/ Resuspension $Hg_T$ Loading \| Dry Year }** | **Probability** | | | **Source** |
| | **Status Quo** | **Mine Strategy** | **Geothermal & Mine Strategy** | |
| Low | 0.89 | 0.999 | 0.99999 | Simulation from published data[2], expert judgment |
| High | 0.11 | 0.001 | 1e-005 | |
| **{Annual Background/ Resuspension $Hg_T$ Loading \| Wet Year }** | **Probability** | | | **Source** |
| | **Status Quo** | **Mine Strategy** | **Geothermal & Mine Strategy** | |
| Low | 0.21 | 0.8 | 0.9 | Simulation from published data[2,3], expert judgment |
| High | 0.79 | 0.2 | 0.1 | |

Notes:
1) Based on California Department of Water Resources, 1906 – 2004 water year indices for Sacramento Valley: {indices for dry, critical years} = dry and {index for wet years} = wet.
2) Data from RWQCB-CV, 2004b
3) Wet year average load estimate from representative wet year index.

Figure 6-6 shows the discrete posterior probability distributions (predicted from its parents) for the "Predicted Annual $Hg_T$ Loading at Gage" variable as a marginal distribution (summed over water year) and as distributions conditioned on dry and wet years. The average for the predicted annual $Hg_T$ loads at the gage is 8.5 kg/year for the marginal distribution, 13 kg/year for a wet year, and 4.1 kg/year for a dry year.

Figure 6-6. Discrete probability distributions over the Annual $Hg_T$ Loading predicted for the Sulphur Creek gage, given either value of Water Year (&), given a Wet Year (Wet), and given a Dry Year (Dry). Note that "&" designates the "background state of information" and, in this model, indicates that the type of water year has not been observed.



## 6.5 MERCURY TMDL LINKAGE ANALYSIS AS A CAUSAL INFLUENCE DIAGRAM

### MODELING UNCERTAIN CAUSE-AND-EFFECT USING EXPERT ELICITED PROBABILITY DISTRIBUTIONS

While the uncertainties in current total and methylmercury loading estimates for the source analysis are significant, largely due to a lack of data, the uncertainties in the linkage analysis are much larger, and include a lack a data as well as significant gaps in the understanding of the causal relationships between inorganic mercury loading and factors that promote the net formation of methylmercury (Benoit et al. 2003; Calfed Bay-Delta Program 2005; Marvin-DiPasquale et al. 2000; Slotton et al. 2004; Wiener et al. 2003). Current research suggests that methylmercury may be more of a "hotspot" problem than an inorganic mercury loading problem. Hotspots are thought to occur when relevant environmental conditions are optimized for promoting the net formation of methylmercury. In such conditions, while reactive mercury in sediment is a necessary factor for the formation of methylmercury, it may rarely be the limiting factor in many watersheds (Calfed Bay-Delta Program 2005). The environmental factors that promote the net methylation of mercury are discussed below.

One observation that supports the hotspot view is the strong relationship between methylmercury concentration and season. In the latter hot period of the dry season (July and August), when flows are low, temperatures are high, and oxygen levels are low in water, methylmercury concentrations can be more than 300 times higher than in the latter part of the wet season (RWQCB-CV 2004b). In the wet season, observed methylmercury comprises from 0.01% to 0.16% of total mercury. In the dry season, the range is from 0.03% to 2%. This seasonal hotspot aspect of the linkage between inorganic mercury loading and local methylmercury concentration has significant implications for addressing the problem of environmental methylmercury, but at this time, the appropriate measures to address the problem are still controversial, even at a site specific level (Calfed Bay-Delta Program 2005).

As discussed in more detail below, part of the difficulty in relating total mercury loading to methylmercury formation is due to a lack of data on the relationship between total mercury loading, the spatial distribution on the concentration of total mercury in sediments and erodable materials throughout the watershed, and the spatial and temporal distributions of reactive mercury in sediment near the primary zone of mercury methylation in Sulphur Creek, the creekbed oxic/anoxic sediment interface.

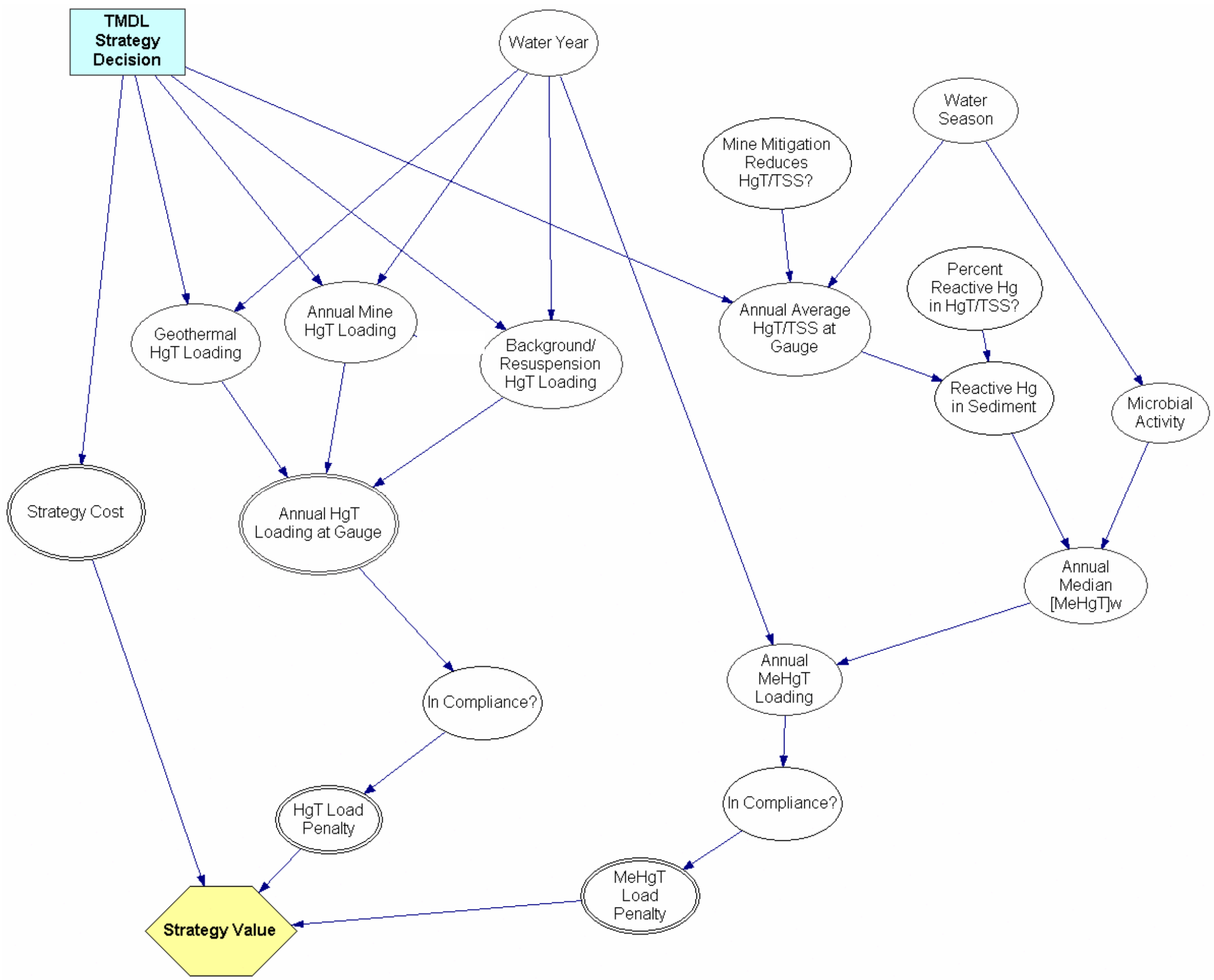
Data limitations and knowledge gaps make the predicted response of seasonal methylmercury concentrations to changes in total mercury loadings a very difficult and highly uncertain endeavor. When one also considers the issue of the unknown contribution of background geothermal mercury sources to the concentration of reactive mercury in sediment, the uncertainty in the predicted consequences of mine mitigation efforts becomes enormous (Churchill and Clinkenbeard 2005; Rytuba 2005b). In fact, a first order analysis could be made in which one assumes that the uncertainty in the resulting future post-mine mitigation methylmercury concentration trend is independent of the decision to mitigate. In other words, it is arguable that an appropriate decision model could be made in which future methylmercury concentrations are an uncertainty that are independent of the mitigation strategy chosen. Rather than take this approach, the proposed model includes hypotheses in which mine mitigation may or may not have an effect on the concentrations of reactive mercury in sediment and methylmercury in the watershed. This preserves the causal relationship between the potential controls and the desired environmental targets, while allowing for the very real possibility that methylmercury concentrations are outside of the feasible control of Sulphur Creek mercury TMDL decision-makers.

While other work (nutrient loading and eutrophication-related water quality problems) has focused on the using uncertainty analysis on calibrated semi-empirical models to generate the needed probability distributions for modeling water quality control decisions as a Bayesian network (Borsuk et al. 2003; Reckhow 1999; Stow et al. 2003), this work takes a very different approach. Many aspects of the linkage analysis for the nutrient loading-related problem addressed by Borsuk, Reckhow, and Stow were supported by a relatively large data set and accepted semi-empirical models. As discussed above, the Sulphur Creek mercury linkage analysis is comparatively fraught with missing information. Given this situation, the integrated use of the scant available data and scientific expertise in a probabilistic framework was determined to be the most useful way to proceed for the mercury TMDL linkage analysis. Because of the absence of accepted deterministic models, it was also judged that the best way to integrate the available relevant data (both site-specific and from other watersheds) was to have the domain experts subjectively consider the data before expressing their uncertainty in the needed conditional probabilistic relationships between the variables of interest. Methodologies for reducing bias, avoiding the introduction of bias, etc., in the elicitation of probability distributions have been reviewed extensively in the literature (Morgan and Henrion 1990; Spetzler and von Holstein 1975; Tversky and Kahneman 1974). Experts from Stanford University (Aaron Slowey) and the U.S. Geological Survey (James J. Rytuba and Mark Marvin-DiPasquale) were interviewed following a description of the approach and a review of the available information.

### LINKAGE ANALYSIS

Figure 6-7 shows a Bayesian network version of a mercury linkage analysis for the Sulphur Creek watershed. It predicts the probability distributions over several variables of interest to decision-makers and scientists: 1) annual median $Hg_T$/TSS concentration in fine grained sediment above the gage ("$Hg_T$/TSS") in response to the various TMDL mitigation alternatives; 2) median reactive mercury in sediment ("$Hg_{sed}^*$") above the gage; 3) annual median methylmercury ("$MeHg_T$") at the gage; and 4) $MeHg_T$ loading at the gage. Other variables are included in the linkage analysis to aid in the prediction of these variables of interest, including the hypothesis variable, "Mine Mitigation Reduces $Hg_T$/TSS?", which has states TRUE and FALSE. FALSE refers to the outcome in which mine mitigation results in no discernable change in annual median $Hg_T$/TSS because of the high background mercury sources. TRUE

Figure 6-7. TMDL linkage analysis as a Bayesian network relating total mercury loading to environmental targets of interest.



refers to the outcome in which mine mitigation reduces $Hg_T$/TSS during wet season flows to the regional background level of 1 - 10 ppm. “Percent Reactive $Hg_T$” refers to the fraction of $Hg_T$/TSS that contributes to the pool of reactive mercury in sediment. “Water Season” has states “Wet”, which refers to the rainy season defined as October 1 to March 31, and “Dry”, which refers to the balance of the water year. “Water year” has the same definition as in the source analysis.

The structure of the model reflects the fact that mercury methylation is believed to be controlled by the concentration of reactive mercury in sediment (Hgsed*), as defined in Chapter 5, and the “level of microbial activity” of bacterial species that methylate reactive mercury in-situ. There is no direct information on the concentrations of reactive mercury in sediment in Cache Creek. However, some relevant information is available from mercury methylation potential studies in the Cache Creek watershed (Bloom 2001; Domagalski et al. 2003; Suchanek et al. 2004) and studies from other watersheds (Benoit et al. 2003; Marvin-DiPasquale 2005). In this model, Hgsed* is conditioned by Annual Average Hg/TSS at Gage and Percent Reactive Hg in $Hg_T$/TSS. While the uncertainty in Hgsed* is very large, this structure suggests that observed Hg/TSS provides relevant information about concentration and that the source of the mercury (mines/geothermal/soils) provides some limited information about speciation.

The use of hypothesis variables to describe the effectiveness of mine mitigation in reducing annual average $Hg_T$/TSS (Mine Reduction Reduces $Hg_T$/TSS?, “$Hg_T$/TSS reduction hypothesis”) and the percentage of reactive mercury in sediment (Percent Reactive Hg in Sediment?, “percent reactive mercury hypothesis”) is a reflection of the fact that both variables will remain unobserved before the decision is made. While research could do much to inform the $Hg_T$/TSS reduction hypothesis, that variable can not be completely resolved until mine mitigation has been performed and the remaining contaminated sediment has been partially flushed from the creek. The percent reactive mercury hypothesis variable could be observed before the decision is made, but this was determined to be too expensive by decision-makers.

The use of hypothesis variables allows decision-makers to consider the decision to collect more information about these hypotheses in terms of TMDL decision value, the current state of information, and a consideration of which other variables could also be observed in the future. This allows much more robust information collection decisions to be made, formalizing many of the intuitive approaches currently used (Howard 1970).

The state of the "microbial activity" variable can also be thought of as a hypothesis variable, since it cannot be directly observed. Instead, it should be thought of as a useful construct that describes the aggregate effect of the many factors that we partially understand as influencing the efficiency of the microbial methylation of mercury (Marvin-DiPasquale 2005). For example, it could be modeled as being conditionally dependent on seasonal sulfate and sulfide concentrations, temperature, flow conditions, redox conditions, etc. Also, the state of microbial activity can be updated based on a test set of current or future observations of methylmercury data. It is in this sense that "microbial activity" can be thought of as a hypothesis variable in a Bayesian network.

### PROBABILITY DISTRIBUTION OVER ANNUAL AVERAGE $HG_T$/TSS AT GAGE

The concentration of total mercury in water ($Hg_T$, ng/L) divided by the concentration of total suspended solids (TSS, mg/L), $Hg_T$/TSS (ppm), provides an indicator of the average concentration of total mercury in suspended and re-suspended sediment upstream of the point of sample collection. In the following discussion, the annual average $Hg_T$/TSS value observed/predicted at the Sulphur Creek gage will be referred to as "$Hg_T$/TSS". Figure 6-8 shows the relationship between the sub-model for $Hg_T$/TSS and the sub-model for reactive mercury in sediment.

What is known about the complex relationship between $Hg_T$/TSS, flow, and water season is discussed in Chapter 5. That discussion suggests that the available water quality and flow data and the available information about mercury sources and speciation support the use of a seasonal model that uses flow ranges for the wet season. In addition, the potential influence of the mine mitigation and geothermal spring mitigation alternatives on $Hg_T$/TSS is modeled by conditioning $Hg_T$/TSS by the mitigation decision. The large uncertainty in the effects of mine mitigation on $Hg_T$/TSS is modeled by conditioning $Hg_T$/TSS on the hypothesis variable, "Mine Mitigation Reduces $Hg_T$/TSS", as discussed previously. In this hypothesis variable, FALSE designates the result that mine mitigation does not influence $Hg_T$/TSS and TRUE designates the result that annual average $Hg_T$/TSS is reduced towards regional background levels of 1 – 10 ppm. This approach allows decision-makers to consider the possibility that mine mitigation may have a negligible impact on $Hg_T$/TSS at the gage due to large background $Hg_T$ loadings and contaminated sediments (Churchill and Clinkenbeard 2005; Rytuba 2005a). Reductions in $Hg_T$/TSS due to geothermal spring mitigation were also modeled as resulting in the attainment of regional background levels. While there is uncertainty that this could be achieved, the uncertainty is small relative to the uncertainty in the effect of mine mitigation on $Hg_T$/TSS.

For dry season flows, the probability distribution over $Hg_T$/TSS for current conditions ("status quo alternative") is modeled as a lognormal distribution independent of flow (n = 8). For wet season flows, $Hg_T$/TSS is modeled as two different lognormal distributions for flows less than (n = 16) and greater than (n = 23) 60 cfs. Table 6-5 summarizes the parameters used for modeling $Hg_T$/TSS. The assumption of population lognormality was checked using the available data for all season/flow data partitions using normal probability plots (Rice 1995). The probabilities used to express the uncertainty in the relationship between mitigation and $Hg_T$/TSS conditioned on water season and the $Hg_T$/TSS reduction hypothesis are shown in Table 6-6.

Figure 6-8. Sub-model for Annual Average $Hg_T$/TSS at Gage and Reactive Mercury in Sediment

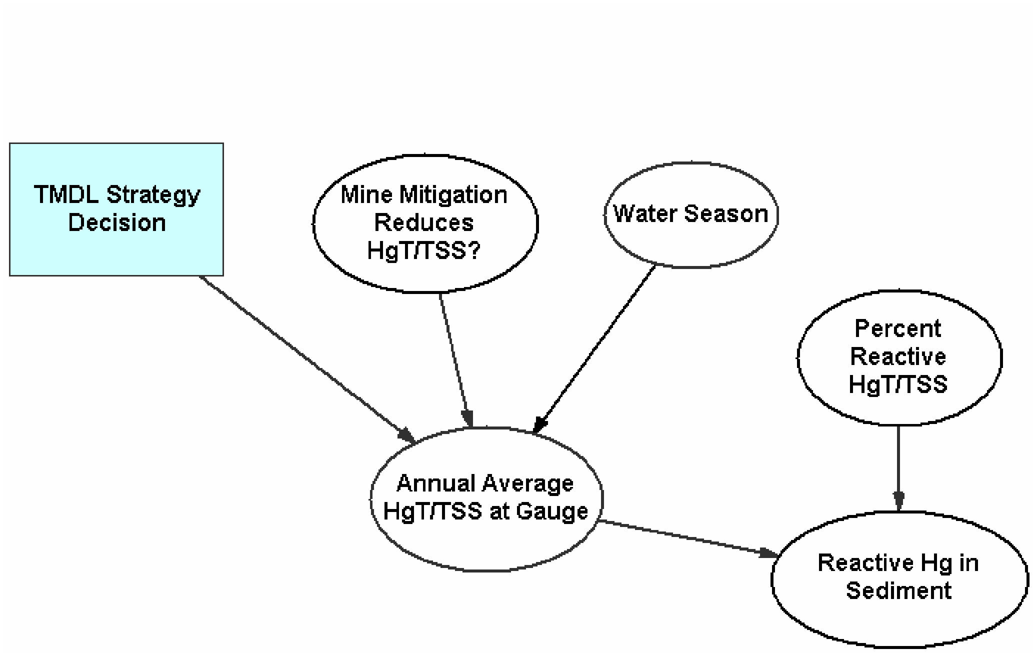


Table 6-5. Parameters for season/flow dependent $Hg_T$/TSS model.

| Water Season | Flow Range | Average[1] (± S.E.) | Standard Deviation[1] (± S.E.) |
|---|---|---|---|
| Dry | All | 1.4 ± 0.0009 | 0.25 ± 0.04 |
| Wet | Flow < 60 cfs | 1.5 ± 0.001 | 0.43 ± 0.0009 |
| Wet | Flow > 60 cfs | 0.87 ± 0.0004 | 0.18 ± 0.0003 |
| Note: Estimated by bootstrapping the available data for that season/flow partition (10,000 iterations). The average and standard deviation refer to the distribution over log($Hg_T$/TSS). | | | |

Table 6-6. Probability table for annual average $Hg_T$/TSS at gage.

| {Annual Average $Hg_T$/TSS at Gage\| Mine Mitigation Reduces $Hg_T$/TSS? = False, Dry Season} | Probability[1] | | |
|---|---|---|---|
| | Status Quo | Mine Strategy | Geothermal & Mine Strategy |
| Low = 1 ppm | 0 | 0 | 0.95 |
| Nominal = 10 ppm | 0.93 | 0.93 | 0.05 |
| High = 100 ppm | 0.07 | 0.07 | 0 |
| **{Annual Average $Hg_T$/TSS at Gage\| Mine Mitigation Reduces $Hg_T$/TSS? = False, Wet Season}** | **Probability[1]** | | |
| | **Status Quo** | **Mine Strategy** | **Geothermal & Mine Strategy** |
| Low | 0 | 0 | 0.70 |
| Nominal | 0.35 | 0.35 | 0.30 |
| High | 0.65 | 0.65 | 0 |
| **{Annual Average $Hg_T$/TSS at Gage\| Mine Mitigation Reduces $Hg_T$/TSS? = True, Dry Season}** | **Probability[1]** | | |
| | **Status Quo** | **Mine Strategy** | **Geothermal & Mine Strategy** |
| Low | 0 | 0.50 | 0.95 |
| Nominal | 0.93 | 0.50 | 0.05 |
| High | 0.07 | 0 | 0 |
| **{Annual Average $Hg_T$/TSS at Gage\| Mine Mitigation Reduces $Hg_T$/TSS? = True, Wet Season}** | **Probability[1]** | | |
| | **Status Quo** | **Mine Strategy** | **Geothermal & Mine Strategy** |
| Low | 0 | 0 | 0.70 |
| Nominal | 0.35 | 0.77 | 0.30 |
| High | 0.65 | 0.23 | 0 |
| Notes:<br>1) Simulation from published data (RWQCB-CV, 2004b), expert judgment (James J. Rytuba). | | | |

### Probability Distribution Over Annual Median Reactive Mercury in Sediment Upstream of Gage

Reactive mercury in sediment ($Hg_{sed}^{*}$) is an operationally-defined fraction of total mercury in sediment that is used as surrogate for the pool of inorganic mercury that is available for microbial methylation. It is defined more specifically in Chapter 5. The hypothesis is that this fraction is likely available to microbes for methylation, and thus represents a surrogate measure of 'microbially available' Hg(II). Since there are no data on $Hg_{sed}^{*}$ in this watershed, a probability distribution based on the available $Hg_T$/TSS data and observations about the fraction of $Hg_T$ comprised by $Hg_{sed}^{*}$ in other watersheds was elicited from experts at the U.S. Geological Survey, Dr. James J. Rytuba and Dr. Mark Marvin-DiPasquale. The 5$^{th}$ , 50$^{th}$, and 95$^{th}$ percentile values for the percentage of total mercury in sediment (or its surrogate, $Hg_T$/TSS) comprised by $Hg_{sed}^{*}$ for a wide variety of natural environments are 0.01%, 1%, and 5%, respectively (Marvin-DiPasquale 2005). Based on the large uncertainties in the mercury speciation in $Hg_T$/TSS and sediment in the Sulphur Creek and Cache Creek watersheds, a uniform distribution from 0.01% to 5% was used (Bloom 2001; Marvin-DiPasquale 2005; Rytuba 2005c). Table 6-7 presents the probability table for annual median $Hg_{sed}^{*}$ based on the probability distribution over $Hg_T$/TSS, Percent Reactive Mercury in $Hg_T$/TSS, and expert judgment (Rytuba 2005c; Slowey 2005).

### Probability Distribution Over Annual Median Concentration of Methylmercury in Water at the Gage

Table 6-8 shows the probability table for annual median concentration of methylmercury in water at the gage, elicited from Dr. Mark Marvin-DiPasquale of the U.S. Geological Survey. The available methylmercury data for Sulphur Creek, Bear Creek, and Cache Creek were examined by Dr. Marvin-DiPasquale before this elicitation.

Table 6-7. Probability table for annual median reactive mercury in sediment ($Hg_{sed}^*$).

| {Ann. Median $Hg_{sed}^*$ \| Ann. Avg $Hg_T$/TSS = Low} | Probability[1] | |
|---|---|---|
| | **% Reactive Hg in Sediment = Low** | **% Reactive Hg in Sediment = High** |
| Low = 0.0001 ppm | 0.999 | 0.99 |
| High = 5 ppm | 0.001 | 0.01 |
| **{Ann. Median $Hg_{sed}^*$ \| Ann. Avg $Hg_T$/TSS = Nominal}** | **Probability[1]** | |
| | **% Reactive Hg in Sediment = Low** | **% Reactive Hg in Sediment = High** |
| Low | 0.99 | 0.90 |
| High | 0.01 | 0.10 |
| **{Ann. Median $Hg_{sed}^*$ \| Ann. Avg $Hg_T$/TSS = High}** | **Probability[1]** | |
| | **% Reactive Hg in Sediment = Low** | **% Reactive Hg in Sediment = High** |
| Low | 0.90 | 0.0001 |
| High | 0.10 | 0.9999 |

Notes:
1) Simulation from published data (RWQCB-CV, 2004b), expert judgment (James J. Rytuba, Aaron Slowey).

Table 6-8. Probability table for annual median concentration of methylmercury in water at the gage ($MeHg_T$).

| {Ann. Median $MeHg_T$ \| $Hg_{sed}^*$ = Low} | Probability[1] | |
|---|---|---|
| | **Microbial Activity = Low** | **Microbial Activity = High** |
| Low = 0.06 ng/L | 0.93 | 0.20 |
| Nominal = 1 ng/L | 0.07 | 0.80 |
| High = 20 ng/L | 0 | 0 |
| **{Ann. Median $MeHg_T$ \| $Hg_{sed}^*$ = High}** | **Probability[1]** | |
| | **Microbial Activity = Low** | **Microbial Activity = High** |
| Low | 0.05 | 0 |
| Nominal | 0.95 | 0.06 |
| High | 0 | 0.94 |

Notes:
1) Simulation from published data (RWQCB-CV, 2004b), expert judgment (Mark Marvin-DiPasquale).

PROBABILITY DISTRIBUTION OVER ANNUAL METHYLMERCURY LOADING AT THE GAGE

The probability distribution over methylmercury loading at the Sulphur Creek gage ($MeHg_T$) was simulated from the available mean daily flow data, using the median methylmercury concentration in water as the predicted concentration (Table 6-9). As described in Chapter 5, methylmercury was approximately lognormally distributed over the period of record, 2000 – 2003. The median value for the period of record was 0.76 ng/L. The mean daily flow data for 2000 – 2003 was used to simulate annual $MeHg_T$ loadings (g/year) and to explore the relationship between annual discharge and annual $MeHg_T$ loading (g/year). Figure 6-9 shows this relationship for the current estimate of annual median $MeHg_T$ value and for assumed values of 0.06, 1.0 and 20 ng/L. As with the annual $Hg_T$ loading, the simulated $MeHg_T$ load for 2001 was used as the typical dry year. The $MeHg_T$ load for the wet year was predicted from the linear relationships shown in Figure 6-9 using an annual discharge of 1.5 million acre-feet/year for each value of the annual median methylmercury concentration.

Figure 6-9. Relationship between Sulphur Creek annual discharge and the simulated annual methymercury load (kg/year) using a lognormal distribution for predicted $MeHg_T$, current conditions (status quo strategy). In the legend, “m” refers to the hypothetical mean value of the annual $MeHg_T$ distribution.

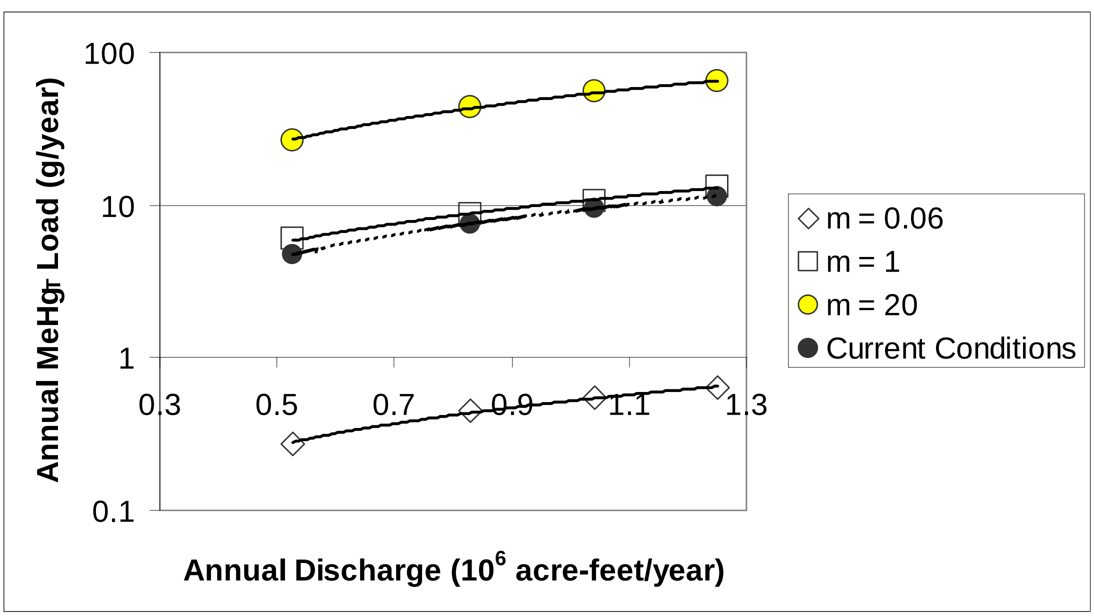


Table 6-9. Probability table for predicted annual methylmercury loading at the gage (g/year).

| {Ann. $MeHg_T$ Load \| Ann. Median $MeHg_T$ = Low} | Probability[1] | |
|---|---|---|
| | **Water Year = Dry** | **Water Year = Wet** |
| Low = 0.25 g/year | 0.995 | 0.89 |
| Nominal = 5 g/year | 0.005 | 0.11 |
| High = 100 g/year | 0 | 0 |
| **{Ann. $MeHg_T$ Load \| Ann. Median $MeHg_T$ = Nominal}** | **Probability[1]** | |
| | **Water Year = Dry** | **Water Year = Wet** |
| Low | 0 | 0 |
| Nominal | 0.989 | 0.89 |
| High | 0.011 | 0.11 |
| **{Ann. $MeHg_T$ Load \| Ann. Median $MeHg_T$ = High}** | **Probability[1]** | |
| | **Water Year = Dry** | **Water Year = Wet** |
| Low | 0 | 0 |
| Nominal | 0.76 | 0.23 |
| High | 0.24 | 0.77 |

Notes:
1) Dry year simulation from published data (RWQCB-CV, 2004b) for 2001. Wet year loading distribution estimated from the relationship shown in Figure 6-9.

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# CHAPTER 7: SULPHUR CREEK MERCURY TMDL DECISION ANALYSIS

This chapter demonstrates the use of the proposed decision analytical approach for TMDL setting. While the level of collaboration with the decision-makers for this case study was not adequate to perform a real-world decision analysis, the intent of this chapter is to *demonstrate the proposed decision analytical approach*. For the purposes of this demonstration, we assume that our somewhat fictionalized decision participants have *fully cooperated* in the creation of the conceptual decision model presented in Chapter 5, trust the expertise encoded in the probability distributions presented in Chapter 6, and agree that the valuation approach (presented below) reflects their preferences. The proposed decision analytical methodology is intended to be adaptable to a real-world TMDL decision-making situation in collaboration with decision-makers and stakeholders, taking into consideration data limitations, knowledge gaps, tight regulatory deadlines, and limited budgets for information collection and modeling.

For this demonstration, I develop and describe a parametric value model that does not require consensus on the desirability of compliance with the various TMDL targets. The approach is designed for use in stakeholder situations in which participants are cooperative, but do not necessarily share the same preferences. This value model is incorporated into a decision model that builds on the mercury mitigation Bayesian network explicated in Chapters 5 and 6.

Decision analytical results from this fully-specified decision model are presented and interpreted. Contingent on the value of non-compliance (as defined below), best strategies are determined, sensitivity to key assumptions and probabilities are evaluated, and the value of clairvoyance (perfect information) for key uncertainties are presented. The decision analytical approach and types of insights generated serve as an example useful for transferring the approach to other TMDL situations.

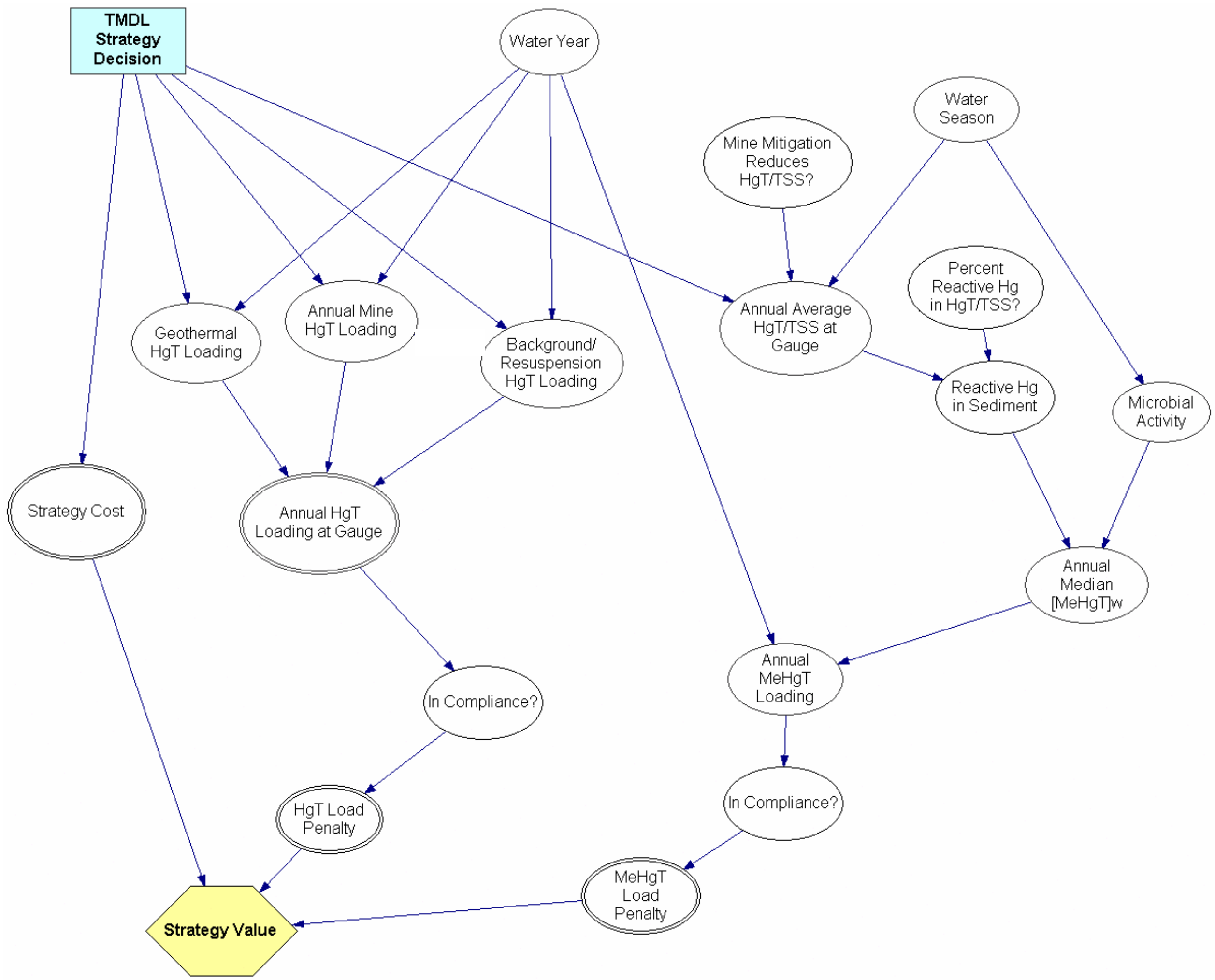
## 7.1 MITIGATION COSTS AND NON-COMPLIANCE PENALTIES: A PARAMETRIC VALUE MODEL

Figure 7-1 shows the Sulphur Creek TMDL decision as an influence diagram with a multi-attribute value model[27] defined as the sum of the expected mitigation cost and non-compliance penalties[28] for a particular strategy. Here, "non-compliance" is in reference to two TMDL regulatory targets, the total mercury loading and total methylmercury loading exported from Sulphur Creek to lower Bear Creek. The total mercury load target can be thought of as a "downstream issue", in that it potentially affects methylmercury concentrations in water and fish downstream (e.g., in the San Francisco Bay delta). The methylmercury load target is more of a "local issue", in that potentially affects methylmercury concentrations immediately downstream in Lower Bear Creek. The variables shown in the model (Figure 7-1) are defined in Chapter 5 and their associated probability tables are presented in Chapter 6. The use of penalty functions in optimization problems like this is standard methodology (Bertsimas and Tsitsiklis 1997; Sundaram 1996).

[27] Multi-attribute value models are defined in Chapter 4. In brief, they can be thought of as a bundle of endpoints or targets that decision-makers are interested in for a particular decision.

[28] In decision analysis, a "penalty function" is a tool that can be used to constrain targeted variables for the purposes of exploring the trade-offs between the risk of violating targets and the costs expended in lowering this risk. In this context, a penalty does not refer to a legal fine that will be imposed upon the decision-makers by a regulatory agency, but rather reflects the social cost of violating the target.

Figure 7-1. Influence diagram for Sulphur Creek mercury TMDL.



The Bayesian network in Figure 7-1 calculates the posterior probabilities of non-compliance conditioned on TMDL mitigation strategy, which is defined as the probability of non-compliance ($p_{NC,Ti}$) for target $T_i$ given all prior data, current scientific understanding, and available expertise about the effects of the various mitigation strategies. The value of the penalty for non-compliance with target $T_i$ is calculated as theproduct of the cost associated with being in the state of non-compliance ($C_{NC,Ti}$) and the probability of non-compliance with $T_i$ ($p_{NC,Ti}$):

$$Penalty_{NC,Ti} = p_{NC,Ti} * C_{NC,Ti} \qquad (Equation \quad 7-1)\,.$$

In the case of a single decision-maker, the value of $C_{NC,Ti}$ could be elicited as a unique value. However, in the case of a social decision, the meaning of $C_{NC,Ti}$ is much more complicated, although one could interpret it as the social disbenefit of non-compliance with regulatory target $T_i$. Such a social disbenefit (or cost) would have a highly uncertain value that could be estimated through a variety of benefit estimation methodologies (observed behavior, surveys, secondary sources, etc.) (Boardman et al. 2001; Heathcote 1998). However, in this work, the value of $C_{NC,Ti}$ is parameterized to evaluate its effect on the identification of the best strategy. This method provides very useful information to decision-makers without the requirement for consensus on preferences. Since the identified best strategy is always contingent on $C_{NC,Ti}$, the approach adopted could be described as "decision analytical support" rather than "decision analysis", since an optimal strategy is not uniquely identified.

The mitigation costs for the mine strategy and the status quo are loosely based on estimates from documents supporting the Sulphur Creek TMDL (RWQCB-CV 2004b; Tetra Tech 2003), but the geothermal & mine strategy mitigation cost is simply assumed to be twice the mine strategy mitigation cost. Note that the purpose of the analysis is to illustrate the Bayesian network-based decision analytical approach and that, while the actual numbers used are reasonable, they do not reflect the beliefs of the actual decision-makers. Table 7-1 summarizes the mitigation costs used and a brief description for each strategy.

Table 7-1. Mitigation costs used in the decision analysis.

| Alternative | Mitigation Cost | Notes[1] |
|---|---|---|
| **Status quo** | $500,000[1] | Educational programs to educate downstream fish consumers, other social controls |
| **Mine strategy** | $3,350,000[1] | Targeted mine waste removal, erosion control at mine sites in watershed |
| **Geothermal & mine strategy** | $6,700,000[2] | High priority mine waste removal, erosion control, and geothermal spring mitigation. |
| 1. (Delta Tribunal Mercury Council 2005). 2. Chosen as twice the mine strategy mitigation cost. | | |

## 7.2 FULLY-SPECIFIED SULPHUR CREEK TMDL INFLUENCE DIAGRAM

Appendix A shows the posterior distributions for all variables for each alternative: status quo, mine strategy, and geothermal & mine strategy. Figure 7-2 shows the posterior distributions for current conditions (status quo alternative) calculated by an implementation of the model in the GeNIe 2.0 Bayesian network programming environment (Decisions Systems Laboratory 2005). This fully specified model is used to determine best strategies conditioned on the value of $C_{NC,Ti}$ (Section 7.4), to perform sensitivity analysis on key uncertainties (Section 7.5), and to determine the value of clairvoyance on these uncertainties (Section 7.6). But first, the total mercury and methylmercury loadings predicted by this model are reported by strategy and water year in Section 7.3.

## 7.3 PREDICTED TOTAL AND METHYLMERCURY LOADINGS BY STRATEGY

The posterior probability distributions over the predicted long-term total mercury ($Hg_T$) loading (Figure 7-3) and the methylmercury loading (Figure 7-4) for each strategy were calculated using the Bayesian network from Figure 7-1. The predicted long-term total $Hg_T$ and $MeHg_T$ loadings for each TMDL strategy, given dry, wet, and any water year are tabulated (Table 7-2). In the case of post-mitigation predictions, "long- term" refers to the new steady state loadings that are predicted to result on the time-scale of years to decades after mitigation. In the case of the status quo, there is no prediction time lag. Table 7-2 also shows the credibility of compliance (COC) with the $Hg_T$ loading and $MeHg_T$ loading targets for each strategy. In this model, the $COC_{HgT}$ is defined as the posterior probability that the annual $Hg_T$ loading at the gage is in state "LLL", which refers to the situation where the annual mine $Hg_T$ loading, annual geothermal HgT loading, and annual background/resuspension $Hg_T$ loading are all in the state "Low". $COC_{MeHgT}$ similarly refers to the posterior probability that the annual $MeHg_T$ loading at the gage is in the state "Low". Other definitions of the credibility of compliance are possible. For example, treating the loadings as continuous variables, $COC_{HgT}$ could be defined as the cumulative distribution for $\{Hg_T \text{ Load} \leq \text{Target}\}$. However, for simplicity of presentation and given the very large uncertainties in the predicted loadings, a discrete representation with targets defined explicitly as states is adequate.

Figure 7-2. Posterior distributions over all variables given no mitigation (status quo strategy).

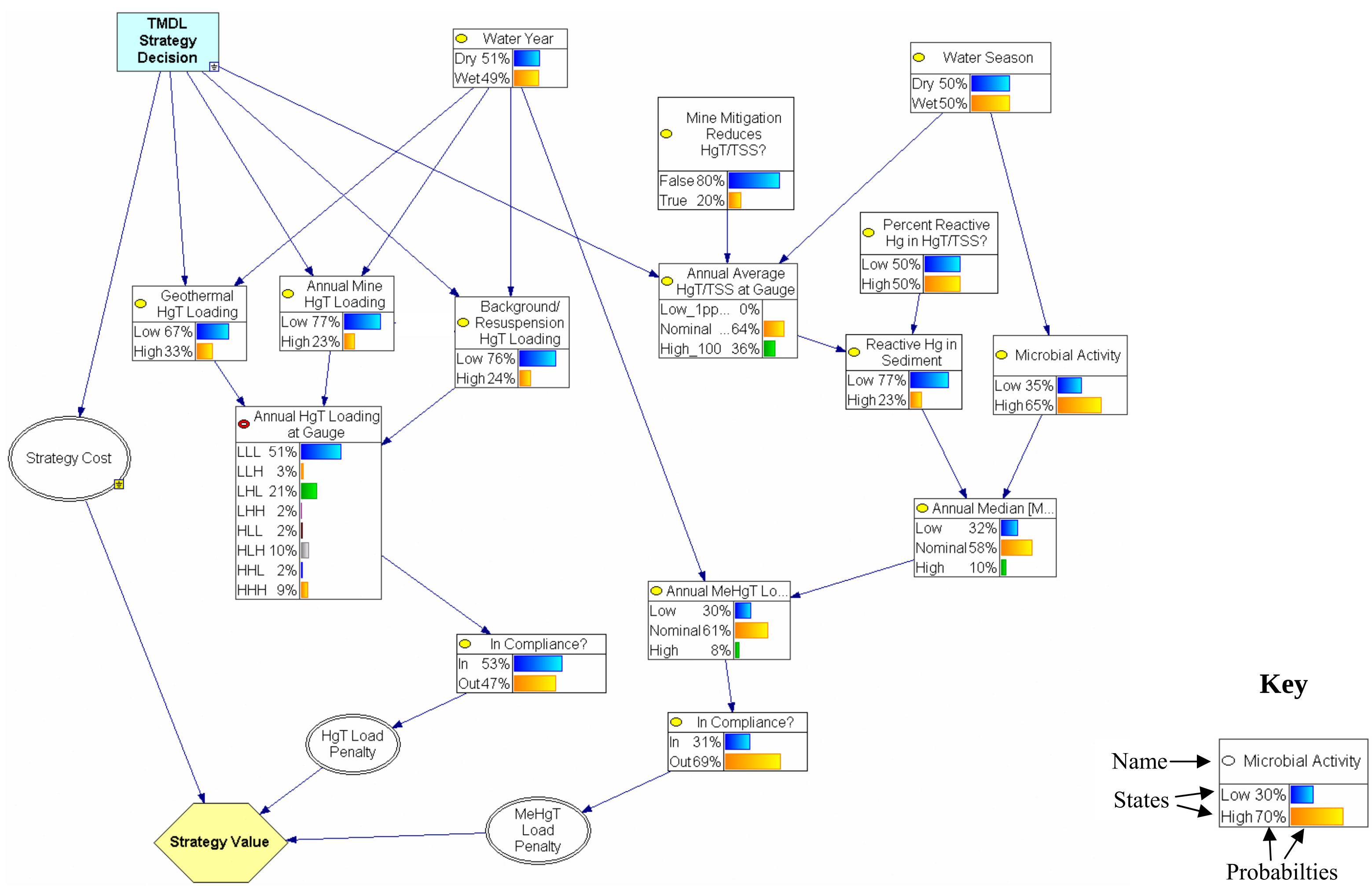


Figure 7-3. Posterior distribution over predicted long-term annual $Hg_T$ loading at gage by strategy.

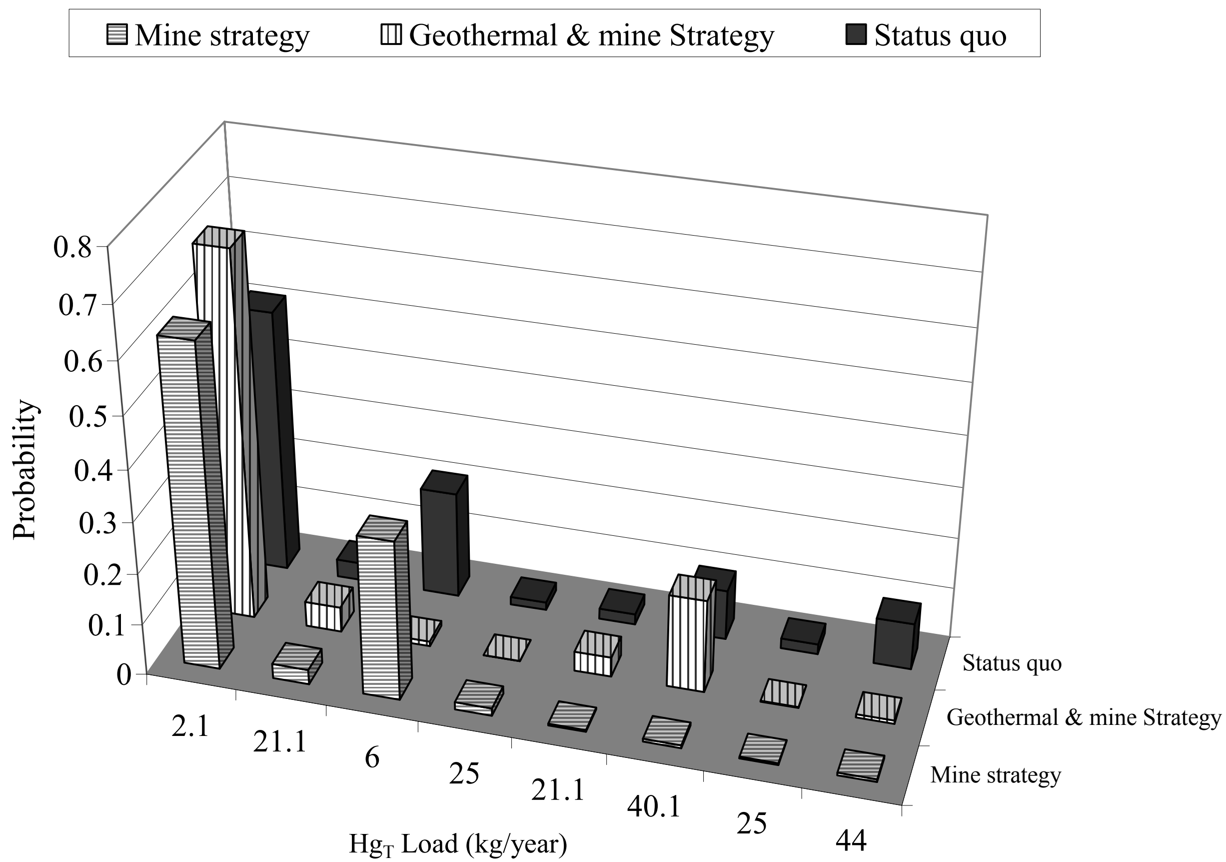


Figure 7-4. Posterior distribution over predicted long-term annual $MeHg_T$ loading at gage by strategy.

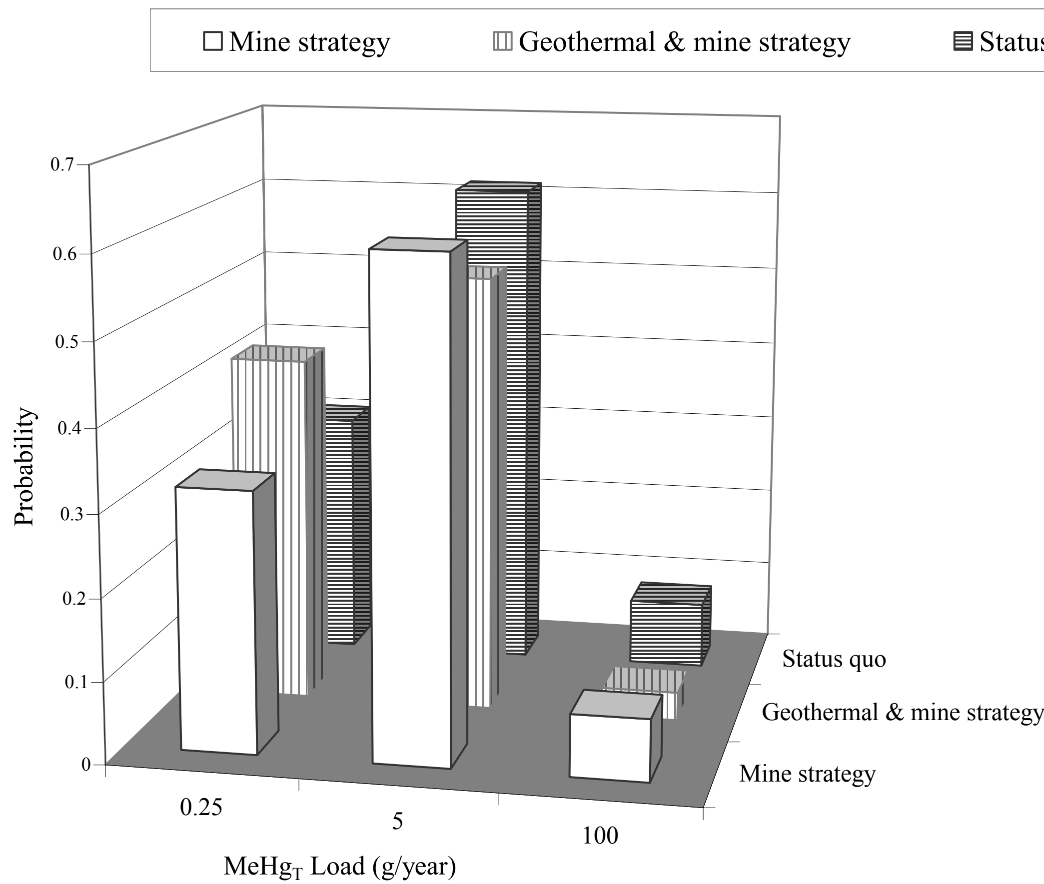


Table 7-2. Predicted annual $Hg_T$ and $MeHg_T$ loadings at the Sulphur Creek gage and the associated credibility of compiance (COC), by strategy and water year.

| | **Mine Strategy** | **Geothermal & Mine Strategy** | **Status Quo** |
|---|---|---|---|
| Annual Loading \| &[1] | | | |
| Average $Hg_T$ Loading (kg/year), COC[2] | 4.8, COC = 0.64 | 11, COC = 0.71 | 12, COC = 0.52 |
| Average $MeHg_T$ Loading (g/year), COC | 11, COC = 0.33 | 6.3, COC = 0.43 | 11, COC = 0.31 |
| Annual Loading \| Dry Year | | | |
| $Hg_T$ Loading (kg/year), COC[2] | 3.7, COC = 0.79 | 3.5, COC = 0.93 | 4.2, COC = 0.77 |
| $MeHg_T$ Loading (g/year), COC | 5.8, COC = 0.34 | 3.5, COC = 0.46 | 6.1, COC = 0.33 |
| Annual Loading \| Wet Year | | | |
| $Hg_T$ Loading (kg/year), COC[2] | 5.9, COC = 0.49 | 19, COC = 0.48 | 21, COC = 0.27 |
| $MeHg_T$ Loading (g/year), COC | 16, COC = 0.31 | 9.2, COC = 0.41 | 17, COC = 0.29 |

Notes: 1) "&" designates the "background state of information". In this case, this means that the loading prediction includes the uncertainty about the future state of the water year.
2) Credibility of compliance, defined as the posterior probability that the compliance target is met.

## 7.4 DETERMINING THE BEST STRATEGY

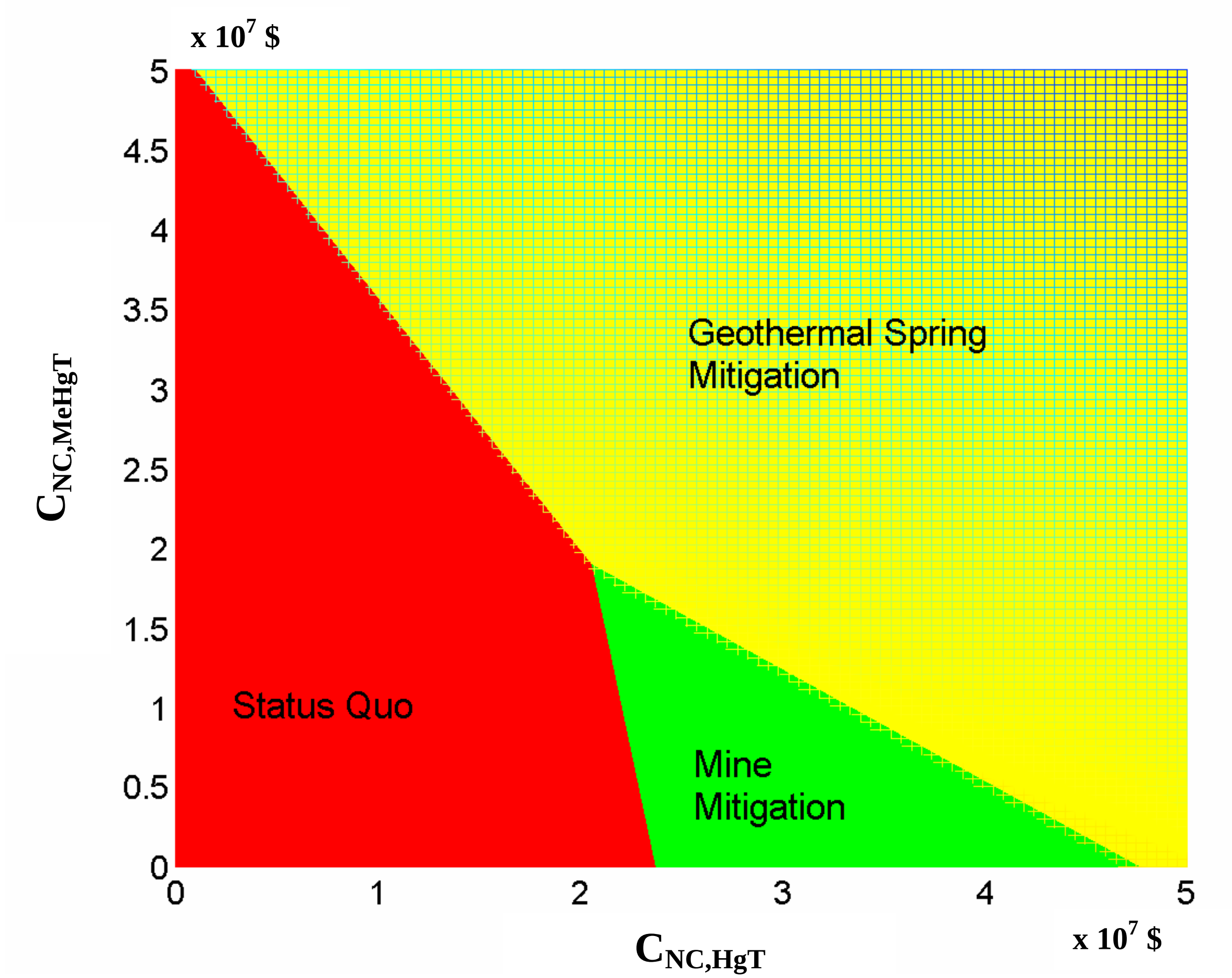
Using the model shown in Figure 7-2, a best strategy can be determined for the background state of information contingent on the non-compliance costs, $C_{NC,HgT}$ and

$C_{NC,MeHgT}$. When the non-compliance costs are assigned values, a best strategy is determined from the expectation of the value model, E[Mitigation Cost + Penalty]. There are several exact and approximate algorithms used for solving influence diagrams (Jensen 2001; Pearl 1988; Shachter 1986). The computational requirements for solving a particular probabilistic problem using a given algorithm can be estimated beforehand. When exact algorithms are predicted to consume an unreasonable amount of computational resources (storage and/or time), approximation algorithms (e.g., stochastic simulation) can be used. For this work, the clustering algorithm[29] was used in the GeNIe 2.0 environment, which provides an exact solution for belief updating and is feasible for relatively small models (Decisions Systems Laboratory 2005). The "policy evaluation" mode was used to solve influence diagrams, which is an implementation of the algorithm proposed by Cooper (Cooper 1988). The policy evaluation algorithm solves the influence diagram by transforming it into a Bayesian network and then determining the expected utility for each of strategy. The algorithm can be computationally intensive for large influence diagrams, but is very fast for the model shown in Figure 7-2. See Shachter (1986), Jensen (2001), and Pearl (1988) for further discussion on the details and trade-offs among the various Bayesian network and influence diagram solution algorithms.

[29] The clustering algorithm often uses a two phase process. First, the directed acyclic graph (DAG) is compiled into a junction tree. Then, probability updating is performed in the junction tree representation. However, the compilation phase is not necessary for many models. The clustering algorithm in GeNIe 2.0 does not use a compilation phase. For more information on the details of the clustering algorithm and other exact algorithms, see Jensen (2001) and Pearl (1988).

Figure 7-5 shows the best strategy regions given the values of the non-compliance social cost parameters ($C_{NC,HgT}$ and $C_{NC,MeHgT}$), ranging from \$ 0 to \$ 50,000,000. This figure can also be thought of as an analysis of the decision sensitivity to the non-compliance social cost parameters, in the sense that any particular combination of $C_{NC,HgT}$ and $C_{NC,MeHgT}$ values uniquely determines an optimal decision, given those values. Performing a standard decision sensitivity analysis on $C_{NC,HgT}$ and $C_{NC,MeHgT}$ is then equivalent to treating $C_{NC,HgT}$ and $C_{NC,MeHgT}$ as unknown parameters. Note from Figure 7-5 that there are regions in which each of the three alternatives is the best strategy. This suggests that decision-makers should carefully evaluate where they think they are in terms of this "non-compliance cost map". As will be seen, the cost of non-compliance is one of the most important factors for decision-makers to consider in making this decision. In the actual Sulphur Creek TMDL decision situation, this factor is only implicitly considered (RWQCB-CV 2004b). The fact that the real world decision-makers will probably choose either the mine strategy or geothermal & mine strategy reveals that their cost of non-compliance values are in either area "1" or "2" of Figure 7-5.

Figure 7-5 . Best strategy contigent on $C_{NC,HgT}$ and $C_{NC,MeHgT}$. Labeled areas denote the best strategy for regions of $C_{NC,HgT}$ , $C_{NC,MeHgT}$



## 7.5 SENSITIVITY ANALYSIS

The influence diagram implementation can be used to perform sensitivity analysis in a simple manner by adding a "sensitivity variable" to the model from Figure 7-2. Figure 7-6 demonstrates this method for performing sensitivity analysis using the variable "Percent Reactive Hg in $Hg_T$/TSS" (PRHg). A conditioning arc is added from the sensitivity variable to the variable of interest and an informational arc is added from the sensitivity variable (PRHg) to the decision variable (TMDL Strategy Decision). The sensitivity variable has states "Low", "Nominal", and "High", assumed to have a uniform marginal distribution. The PRHg is no longer marginal and is now described by the probability table (Table 7-3):

Table 7-3. Probability table over the sensitivity variable.

| **Sensitivity States →**<br>Percent Reactive Hg in $Hg_T$/TSS States ↓ | Low Case | Nominal Case | High Case |
|---|---|---|---|
| Low | 0.1 | 0.5 | 0.9 |
| High | 0.9 | 0.5 | 0.1 |

The nominal case (Sensitivity state = Nominal) is the uniform distribution over the PRHg variable. The low case has a probability of 0.1 for the PRHg variable having a state of Low (PRHg = Low) and the high case has a probability of 0.9 for PRHg = Low. This reduces the sensitivity analysis to solving the influence diagram for the expected value for the TMDL Strategy Decision variable now that it is conditioned by the sensitivity variable. Table 7-4 shows that results of the sensitivity analysis for the

Figure 7-6. Sensitivity to the probability distribution over percent reactive Hg in $Hg_T$/TSS.

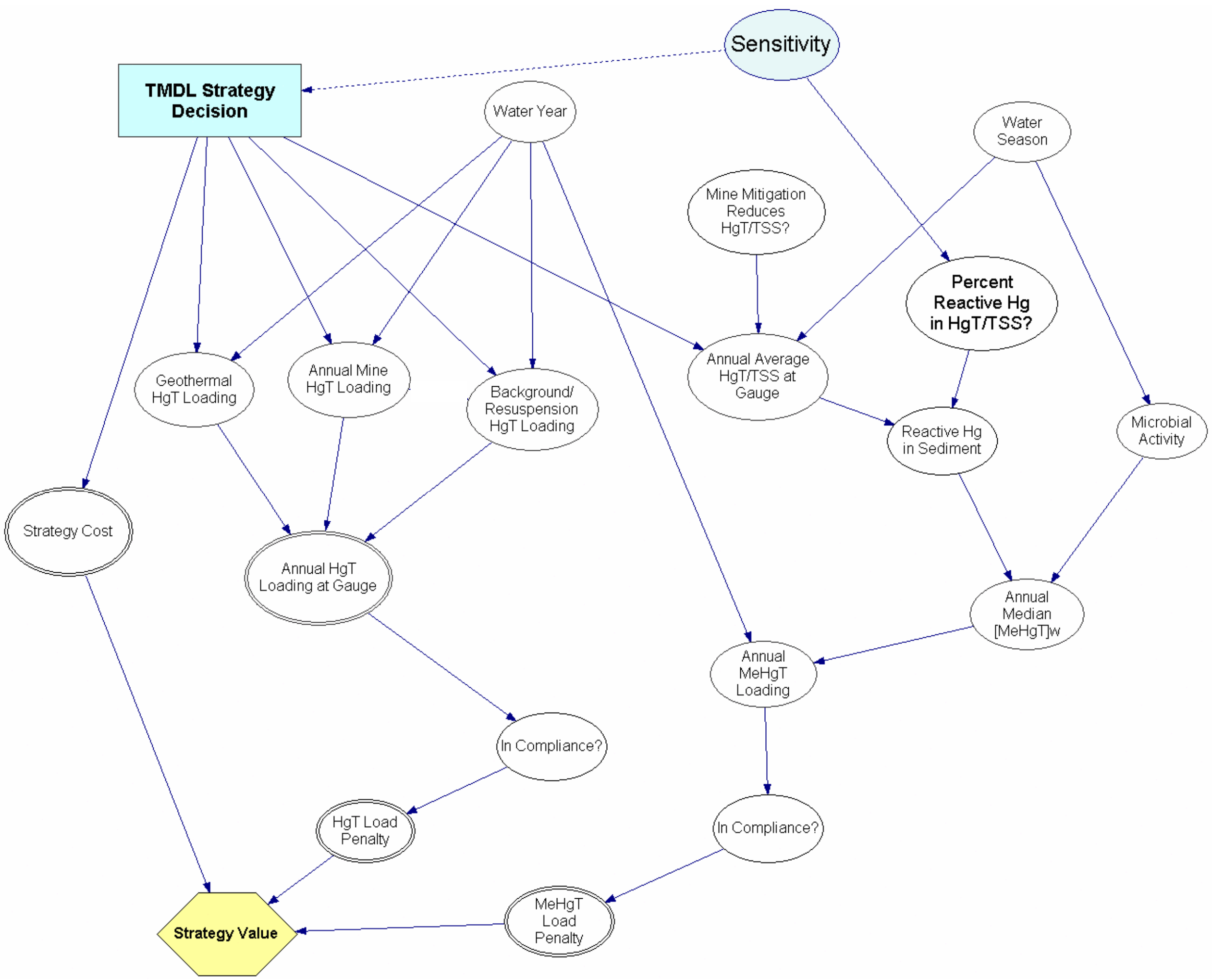


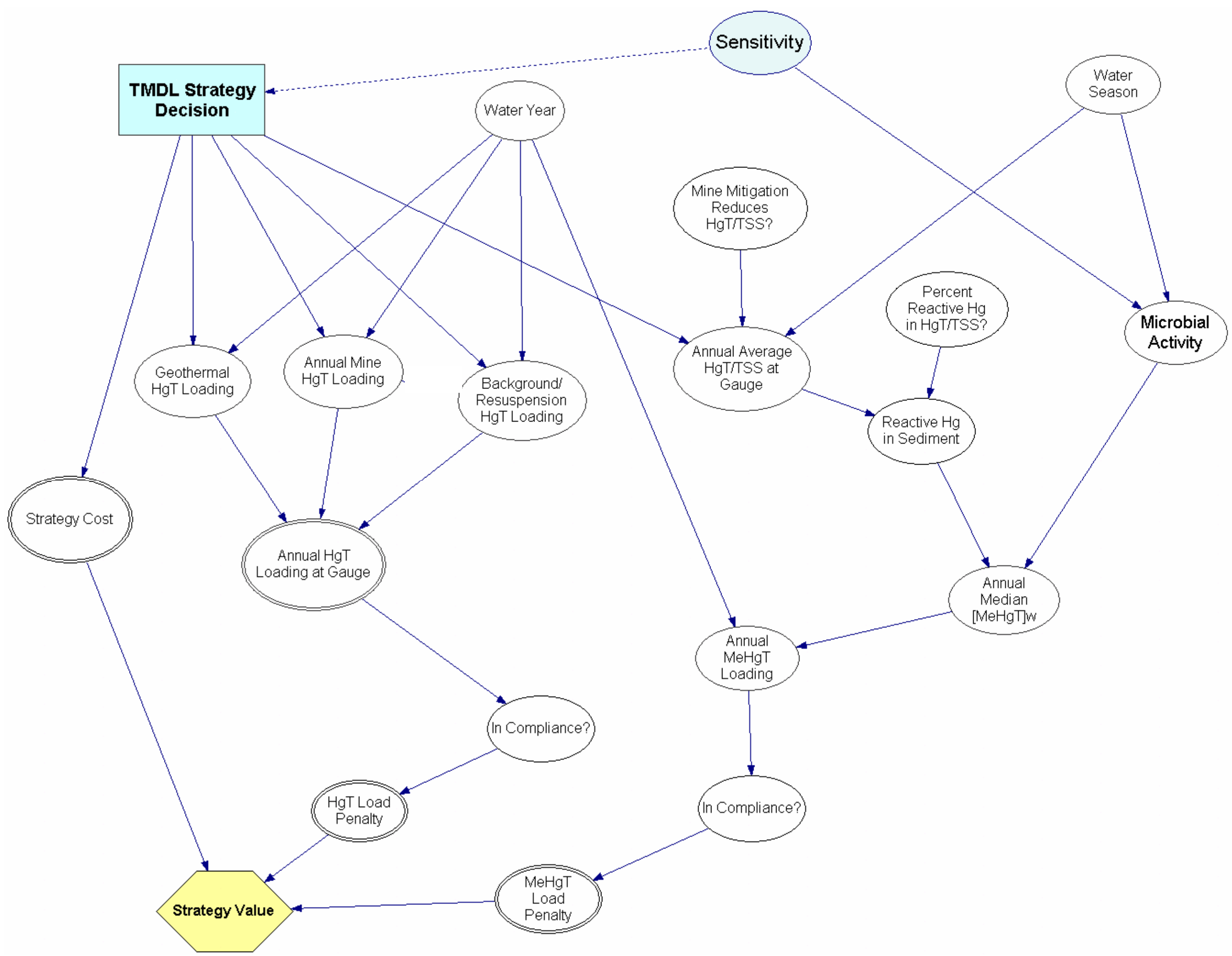
Table 7-4. Sensitivity analytical results for the Percent Reactive Hg in $Hg_T$/TSS (PRHg) variable. The value for the best strategy is shown in bold for each state of the sensitivity variable. The values shown are the expected costs (mitigation cost + penalties) for each strategy, given the effect of sweeping through the probability distribution for the PRHg variable on the credibility of compliance, calculated using the Bayesian network model. The mitigation costs used are from Table 7-1 and the assumed values for the social costs of non-compliance for the HgT and MeHgT load targets ($C_{NC,HgT}$, $C_{NC,MeHgT}$) are each $30,000,000.

| Sensitivity States → | **Low** | **Nominal** | **High** |
|---|---|---|---|
| Expected Value of the Decision | ↓ | ↓ | ↓ |
| Mine strategy | -$35,464,000 | -$33,637,000 | **-$31,809,000** |
| Geothermal & mine strategy | **-$32,500,000** | **-$32,359,000** | -$32,218,000 |
| Status quo | -$38,011,000 | -$35,478,000 | -$32,945,000 |

PRHg variable assuming that $C_{NC,HgT} = C_{NC,MeHgT} = \$30,000,000$. The fact that the best strategy is "Spring Mitigation" for the low and nominal states and the "Mine strategy" for the high state indicates potential value to gathering information on this variable, given the assumed values of $C_{NC,HgT}$ and $C_{NC,MeHgT}$. By varying $C_{NC,HgT}$ and $C_{NC,MeHgT}$ and repeating this procedure, sensitivity to probability for the PRHg variable can be explored without assuming particular non-compliance costs.

Figure 7-7 shows a model for performing sensitivity analysis on the Microbial Activity variable from the model shown in Figure 7-2. Using the procedure just described and again assuming that $C_{NC,HgT} = C_{NC,MeHgT} = \$30,000,000$, it turns out that the best strategy is "geothermal & mine strategy" for all states of the sensitivity variable. For the assumed non-compliance costs, this implies that there is *no value* to gathering more information on this variable. This procedure demonstrates the use of sensitivity analysis as a tool for exploring which uncertainties are most important for supporting the TMDL decision. Determining which uncertainties have the potential to

Figure 7-7. Sensitivity to the probability of Microbial Activity = Low.



change the best strategy to prioritize future information collection activities is a potentially important application for the proposed decision analytical approach. While this procedure could again be repeated for a range of non-compliance costs to map out regions in which the best strategy changes, there are easier methods for exploring the value of perfect information using influence diagrams, as described in the next section.

## 7.6 VALUE OF CLAIRVOYANCE (PERFECT INFORMATION)

The influence diagram implementation of the model shown in Figure 7-2 can be directly used to calculate the value of clairvoyance (VOC) for the variables in the model. The value of clairvoyance is based on the abstraction of the "clairvoyant", which is a convenient fictional character that omnisciently knows the future outcome of any decision, but cannot change that future. For the clairvoyant to be able to answer a query about a future outcome, the possible decision outcomes be clearly defined in terms of unambiguous events[30]. The clairvoyant cannot tell you, even in theory, anything about your preferences, but could tell you exactly how a particular uncertainty will be resolved in the post-decision future. For outcomes that can be valued in terms of money, this useful abstraction allows us to formulate the idea of the value of clairvoyance (perfect information), which serves as the *upper limit to the value of any information gathering activity* (Clemen et al. 1996; Howard 1996; Howard et al. 1972).

Clairvoyance (knowing the future state of an uncertain variable before the decision is made) can be expressed using the notation of influence diagrams. In this notation, clairvoyance on an uncertainty is equivalent to the presence of an informational arc from that uncertainty to the decision variable, which denotes that its state is known before the decision is made. This is semantically equivalent to flipping the decision tree described by an influence diagram such that the uncertainty in question precedes the decision variable in the tree. Since we do not know what the

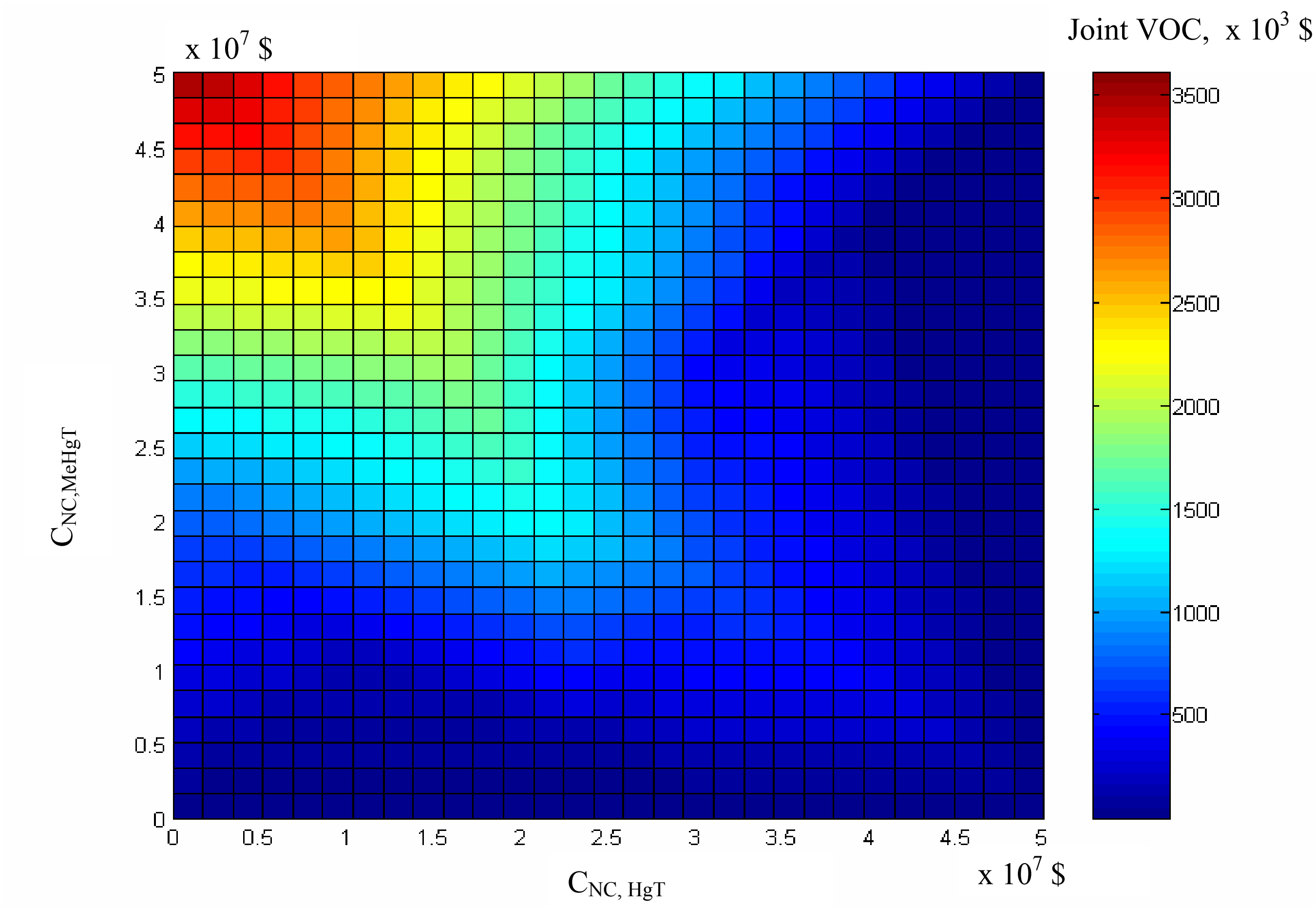
[30] In other words, the events must be mutually exclusive and collectively exhaustive.

hypothetical clairvoyant would reveal beforehand, the probability distribution over the Clairvoyant's response is the same as the marginal distribution over the uncertainty. In essence, this allows us to explore whether or not perfect information would change the best strategy and, for monetized outcomes, allows us to calculate what that perfect information would be worth to us before the decision is made. Assuming that the decision-maker is risk neutral, the value of clairvoyance is simply the difference of the value of the decision[31] with clairvoyance and without clairvoyance (Clemen et al. 1996; Howard 1996). This work assumes risk neutrality over monetized outcomes, which is appropriate for many public decisions (Merkhofer 1987). A detailed introduction to the value of clairvoyance can be found in an introductory decision analysis text, e.g., Clemen (1996) or Howard (1996).

The GeNIe Bayesian network programming environment allows the value of clairvoyance to be easily calculated for an influence diagram for a risk neutral decision-maker, automating the steps of comparing the decision value with and without clairvoyance. Figure 7-8 shows the joint value of clairvoyance on Percent Reactive Hg in $Hg_T$/TSS (PRHg) and Microbial Activity (MA) for several combinations of $C_{NC,HgT} = C_{NC,MeHgT}$. These two variables were not picked haphazardly. They are the only uncertainties with significant VOC over the range of non-compliance costs. This means that collecting information on these uncertainties could potentially change the choice of strategy, while collecting information on the

[31] In this case study, the "value of the decision" is the expected value of the best strategy. This corresponds to the strategy with the minimum cost function (mitigation cost + penalties). For at least one of the clairvoyant's responses, the best strategy changes from the best strategy without clairvoyance. This *potential* change generates value for the decision with clairvoyance.

Figure 7-8 . Joint value of clairvoyance (VOC) on microbial activity and percent reactive mercury in $Hg_T$/TSS as a function of the cost of non-compliance with the $Hg_T$ load ($C_{NC,HgT}$) and the $MeHg_T$ load ($C_{NC,MeHgT}$).



other uncertainties will not change the best strategy for a given set of non-compliance costs.

Joint VOC refers to perfect information on more than one uncertainty simultaneously and is calculated as the difference between the decision value with perfect information on the set of uncertainties and without this information. Note that the joint VOC on two or more variables does not have to be the sum of the VOC on the individual uncertainties. In fact, two variables with zero VOC can jointly have a significant VOC, indicating that the clairvoyance on both variables may change the best strategy while clairvoyance on each individual variable never changes the best strategy. For example, when $C_{NC,HgT} = C_{NC,MeHgT}$ = \$10,000,000, the individual VOCs on the PRHg and MA variables are zero, but the joint VOC is \$176,000. Figure 7-8 also shows that the joint VOC varies considerably depending on the particular values of $C_{NC,HgT} / C_{NC,MeHgT}$. This suggests that exploring the magnitude of non-compliance costs would be also be useful to decision-makers for its implications regarding the value of clairvoyance on Percent Reactive Hg in $Hg_T$/TSS and Microbial Activity.

## 7.7 SUMMARY

This chapter presents the decision analytical results for the Sulphur Creek mercury TMDL strategy decision using the Bayesian network (influence diagram) model created in Chapters 5 and 6. It presents a parametric value model based on the unknown social costs of non-compliance with two TMDL targets. The model was designed such that it does not require consensus among decision-makers and stakeholders. This approach allows decision-makers to separate the importance of scientific uncertainties from the importance of preferences over possible decision outcomes. Best strategies are shown as a function of the social costs of non-compliance with the total mercury ($Hg_T$) and methylmercury ($MeHg_T$) load targets through the use of “decision maps”. Sensitivity analysis is used to demonstrate which uncertainties are most important for TMDL decision support. For choosing between a “mine mitigation strategy” and a “geothermal and mine mitigation strategy”, only studies concerning the percent reactive mercury in HgT/TSS from mine run-off versus geothermal springs and the ability to model microbial activity (related to mercury methylation efficiency) should be conducted. Value of perfect information analysis is used to determine the upper limit on money spent for future decision support information collection activities. A value of perfect information map is also provided as a function of the social costs of non-compliance with the $Hg_T$ and $MeHg_T$ load targets. This demonstration is meant to show the capabilities of a decision analytical approach for identifying and exploring important scientific uncertainties in a complex TMDL decision problem, to separate informational concerns from value judgments, and to prioritize information collection activies to support the TMDL decision-making process.

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# CHAPTER 8: CONCLUSIONS AND SUGGESTIONS FOR FUTURE RESEARCH

## 8.1 SUMMARY

The typical current approach to the complexities and uncertainties surrounding TMDL decision-making is to build deterministic predictive models that characterize the situation as well as possible and then depend heavily on these models to help make and support decisions. Uncertainty is currently handled through the use of *ad hoc* methods for "doing away" with uncertainty by adopting conservative TMDL targets (margins of safety) and/or employing conservative modeling choices. The recognition that TMDL uncertainties are much larger than deterministic thinking warrants is reflected in the wide adoption of adaptive management as the planning framework. Answering the question of "how conservative should we be" should be approached by thinking carefully and strategically about the uncertainties involved and the values at stake.

To address this problem, this research has a re-framed a real-world mercury TMDL decision problem from a decision analytical perspective. This paradigm shift introduces concepts and modes of thinking not currently used in TMDL decision-making, including outcome-based strategy evaluation, value of clairvoyance (perfect information), and the explicit separation of scientific uncertainty from decision-maker preferences. It also provides a formal context for considering the importance of uncertainty in TMDL decisions, for prioritizing information collecting activities, and for considering and representing hypotheses within a TMDL decision-modeling framework. Very importantly, the Bayesian perspective of decision analysis allows decision participants to interpret new information (monitoring and knowledge) in light of previous information and knowledge. The proposed decision model frames the TMDL setting process as a set of related regulatory (scientific, engineering, and economic) decisions that may involve large uncertainties (limited data bases and incomplete knowledge) subject to tight regulatory deadlines and small decision process budgets. Poor TMDL decisions avoid the hard work of considering trade-offs between scientific uncertainties and decision-maker values, which may result in a higher risk of a bad future outcome. An example of a poor TMDL decision would be the choice of a strategy that has both high expected compliance costs and a low probability of achieving compliance within the desired time-frame. Current TMDL decision-making only considers such possible outcomes implicitly using deterministic models and margins of safety to "ensure compliance". In many TMDL situations, including the mercury TMDL case study used in this research, compliance is not a certainty for feasible mitigation strategies. Good TMDL decision-making explicitly considers the important (and often large) uncertainties that may be the difference between "success" and "failure" for a strategy, recognizes differing decision participant preferences over possible outcomes, and considers the trade-offs between the uncertainty of meeting targets and the costs associated with compliance for a strategy. Ultimately, a good TMDL decision should result in a better chance of achieving the successful restoration of a water body's beneficial use at a socially acceptable cost. From the decision analytical perspective, a good outcome happens to the lucky decision-maker. A good decision is the result of the quality of the processes used by decision participants to define and analyze the decision problem.

This research has resulted in a decision model that represents the current understanding of the uncertain relationships between potential mercury TMDL mitigation strategies and the environmental targets of interest, total mercury and methylmercury loads exported from a small mine-impacted Northern California watershed (Chapter 2). These complex relationships are broken down into probabilistic causal relationships between variables, in which each variable has an associated conditional probability table that describes the probability distribution over its value conditioned on the values of its parent[32] variables (Chapters 3 and 5). The

[32] As described in Chapter 3, causally related variables can be thought of in terms of structural equations, in which a child variable (C) is predicted from the states of its various parent variables (Pa(C)). The exact states of the parent variables may themselves be uncertain and the value of the child variable given the exact states of its parents may also be uncertain (random error, $\varepsilon$). This can be represented by: $C = F(Pa(C), \varepsilon)$, where F is a function that predicts C from the states of its

purpose of the model is to generate posterior probabilities that the targets of interest will be met in the future, given a particular mitigation strategy (Chapters 5, 6, and 7). The value of the strategy is modeled as a simple net benefits model (Chapter 7):

$$Strategy\ Value = Strategy\ \ Cost + Penalties \quad (Equation\ 8-1),$$

where the penalty[33] for violating a particular target is modeled as the product of the posterior probability that the target "i" will be violated ($p_{NC,Ti}$) and the social cost of non-compliance with target "i" ($C_{NC,Ti}$). To avoid the need for decision participant consensus on the value of the social cost of non-compliance, $C_{NC,Ti}$ is treated as a parameter. This approach allows the decision participants to explore pair-wise value trade-offs between targets, to explore the sensitivity of the best strategy to important informational uncertainties, and to estimate the upper-limit of the value of collecting new information before the decision is made (Chapters 4 and 7).

Contrary to typical water quality model development practice, the purpose of the water quality sub-model is not to replace *less realistic* models, but rather to provide an alternative causal modeling framework specifically designed for decision support. In addition to providing a causal understanding of a complex environmental system, modeling for decision support should provide decision-makers with an understanding of the *meaning* of predictive uncertainty in the context of the decisions being made and in terms useful to decision-makers (Chapters 1, 4, and 7). This obviously goes beyond the purposes and methods of traditional water quality modeling and potentially enters into the many sub-fields that make use of results from the decision sciences, including "decision support", decision analysis, multi-criteria decision-making, multi-attribute utility analysis, etc. In short, the burden becomes

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parents, Pa(C). The uncertainty in this functional relationship is represented by the random error term, ε. See Pearl (2000) for a detailed explication of causal networks and structural equation models.

[33] In decision analysis, a "penalty function" is a tool that can be used to constrain targeted variables for the purposes of exploring the trade-offs between violating targets and expending resources to meet them. In this context, a penalty does not refer to a legal fine that will be imposed upon the decision-makers by a regulatory agency, but rather reflects the "cost" of violating the target to the decision-participants.

scientific modeling for decision support in the face of both significant informational uncertainty and disputes over preferences and values.

This dissertation proposes an approach for meeting the needs of decision-makers, while faithfully representing what is currently known about the behavior of a complex environmental system subject to possible interventions, given the available data, models, and expert judgment. The approach is based on the use of influence diagrams, since this tool allows probabilistic modeling of complicated knowledge systems in the context of decision-making and can be used to perform the full range of decision analysis. The approach also addresses the complex institutional aspect of group decision-making by using a parametric penalty value model to model decision-maker preferences, without requiring consensus. This results in a methodology that could be described as "decision analytical support" rather than decision analysis, since best strategies are contingent on the penalty parameter and hence are not uniquely identified. In essence, this maps out the "decision space" along the dimensions of social costs on targets of interest to decision-makers.

This research presents a decision analytical approach for handling uncertainty and balancing trade-offs in a mercury TMDL decision situation. Current decision-making based on the highly uncertain results from deterministic models of complex systems makes use of potentially flawed heuristics, subject to many potential errors. By using a conservative deterministic approach, decision-makers cannot determine whether they are being overly conservative or not conservative enough. Just as importantly, by not explicitly separating values and preferences from information about scientific uncertainty, a conservative deterministic approach avoids the important question, "conservative for whom?". The trade-off framework presented in Chapter 7 explicitly separates these dimensions and allows decision-makers to consider the importance of scientific uncertainty separately from the importance of differing stakeholder preferences.

## 8.2 CONCLUSIONS AND MAJOR FINDINGS FOR MERCURY TMDL CASE STUDY

- The Regional Water Quality Control Board staff should focus their future Suphur Creek mercury TMDL data collection efforts on identifying and modeling zones of high microbial activity for mercury methylation and on characterizing the reactive[34] fractions of mercury inputs from mine-related run-off and geothermal springs (Chapter 7, Section 6). Figure 7-8 could be used by decision-makers to estimate the upper limit on collecting data on these two uncertainties. It is important to note that this upper limit depends on the social costs of non-compliance for the total mercury and methylmercury TMDL targets.

- The consideration of decision participant preferences strongly influences the best strategy. Depending on the exact values of the social costs of non-compliance for the total mercury load target and methylmercury load target, any of the three alternatives considered (status quo, mine strategy, geothermal & mine strategy) could be the best strategy, given current scientific understanding (see Table 7.1 for descriptions of the strategies).

- The choice of mine strategy versus the geothermal & mine strategy depends strongly on whether the "local mercury problem" (methylmercury load exported to Lower Bear Creek) is more important than the "downstream mercury problem" (total mercury exported further downstream). If the local problem is more important, the geothermal & mine strategy is superior to the mine strategy. Only if the downstream mercury problem is more important could the mine mitigation strategy be superior. However, depending on the exact social costs of non-compliance and the results of new data collections on reactive mercury and high microbial activity locations, the combined

[34] Reactive mercury in sediment ($Hg_{sed}^{*}$) is an operationally-defined fraction of total mercury in sediment that is used as surrogate for the pool of inorganic mercury that is available for microbial methylation.

mine/geothermal mitigation strategy could still be superior. This means that, in this case, further decision-modeling could be in order (Chapter 7, Sections 4 – 6).

## 8.3 FUTURE RESEARCH

I have developed a simple decision model for a very complicated water quality problem for a small watershed. There are, of course, many other possible approaches. Carefully exploring and comparing the applicability, strengths, and weaknesses of the possible approaches could be the subject of much useful future research. This decision model could be extended in a number of ways, including expanding the decision frame to include the TMDL decisions for Cache Creek, Bear Creek, and Harley Gulch. This would allow these TMDLs to be considered simultaneously, to consider the uncertain relationships between upstream and downstream mercury loadings and to think about integrated mitigation strategies. The relationship between mercury in water and mercury in biota could be modeled at various points in the watershed, and a penalty for a fish tissue target could be incorporated.

The model could also be extended to explicitly consider information gathering decisions for various uncertainties, incorporating expert judgment over the likelihoods of experimental results given the possible states of the uncertainty. For example, an information gathering strategy for reducing uncertainty in the percentage of reactive mercury in various erodible materials from mines and geothermal springs could be devised by considering which materials and sites to sample and how many samples to analyze. This decision could be modeled as an influence diagram treating the choice of information collection strategy as a decision.

This approach could also be tested in a real TMDL decision-making situation and/or in a decision laboratory situation, in which the decision situation is simulated under controlled conditions. This research could explore and compare the usefulness of various methods for presenting decision insights, for talking about the uncertain causal linkages, and, in exploring the usefulness of modeling preferences using a parametric penalty function. Simple formulations of this and related approaches could prove useful to decision-makers in real water quality management decisions, allowing decision-makers to consider the meaning of uncertainty in terms of possible preference structures.

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# APPENDIX A - ADDITIONAL BACKGROUND ON THE FEDERAL WATER QUALITY PROTECTION AND THE TMDL REGULATORY PROGRAM

Since the 1972 Clean Water Act, water quality protection has been driven by the control of point source pollution through the promulgation of effluent-based water quality standards (NRC 2001). These regulations require that point dischargers comply with effluent-based standards for criteria pollutants through a permitting system, the National Pollutant Discharge Elimination System (NPDES). State agencies issue these permits to individual dischargers subject to the oversight of the U.S. Environmental Protection Agency (USEPA), as authorized by the Clean Water Act. The NRC (2001) points out that the NPDES program has been successful in reducing point source pollution, but has not resulted in the achievement of the nation's water quality goals of "fishable and swimmable waters" in large part because of pollutant contributions from nonpoint sources, like runoff from agriculture, mining operations, and urban environments.

These on-going water quality challenges have resulted in a shift in focus from effluent standards to ambient water quality standards and the Total Maximum Daily Load (TMDL) program. The goals of the TMDL program are to attain ambient water quality standards through controls of both point and nonpoint sources of pollution, channel modification, and other potential controls. Although the legislative authority for the TMDL program dates back to the 1972 Clean Water Act, it was underutilized until citizen lawsuits in the 1980's prompted the USEPA to focus on the TMDL approach to managing ambient water quality (Houck 2002; NRC 2001).

SEVERITY OF THE PROBLEM FACING STATES

At present, over 40% of assessed waterbodies do not meet ambient water quality standards for their designated beneficial uses. Impaired waterbodies comprise over 20,000 individual river segments, lakes, and estuaries, affecting approximately 300,000 miles of rivers and shorelines and approximately 5 million acres of lakes. The most common contaminants are excess sediments, nutrients, and pathogens. A majority of the population of the United States (ca. 220 million, or 78%) live within 10 miles of an impaired waterbody (USEPA 2005). Since a waterbody may be impaired by more than one contaminant, there are actually more than 40,000 TMDLs that need to be set in the near future (NRC, 2001).

TMDL regulations promulgated by USEPA in 1992, and in specific cases terms of lawsuit settlements, require States to meet deadlines of 8 to 13 years for completion of TMDLs. Many TMDLs are imminently due and many TMDL workgroups are in the process of performing information collection activities and making TMDL setting decisions. The Government Accounting Office reports that there is a pervasive lack of data (especially for nonpoint sources) at the State and watershed level for supporting water quality determinations and TMDL development (GAO 2000). NRC (2001) reports claims by Federal, State, and local government officials, representatives of regulated and potentially regulated parties, and concerned citizens that untested analytical and decision-making procedures will be required to meet the "unrealistic" deadlines and resource limitations.

The original focus on point source controls through the NPDES program in the 1972 Clean Water Act was largely in response to concerns about the infeasibility of determining causes of impairment and assigning responsibility to the various sources (Houck 1999; Houck 2002; Ortolano 1997a). The return to a focus on ambient water quality standards presents and will continue to present significant challenges to States as they attempt to implement the TMDL requirements under Section 303(d) of the Clean Water Act.

As I hope to demonstrate with this research, the use of Bayesian network water quality modeling and TMDL decision influence diagrams addresses these needs, at least in part. Specifically, the approach presents a feasible and useful decision analytical framework that makes the best use of available information (scientific, economic, and social), allows for comprehensive planning of information gathering activities, allows for rigorous updating of existing models when new evidence is presented, and can be designed in terms of adaptive management approaches that balance information needs with water quality goals.

# APPENDIX B – LOGNORMAL PROBABILITY PLOTS FOR TOTAL MERCURY CONCENTRATION IN FINE SEDIMENT DATA

This appendix shows the normal probability plots (in log space) for the available $Hg_T$/TSS data for Sulphur Creek, by water season and flow regime.

Figure B.1. Normal probability plot, $Log(Hg_T/TSS)$, dry season, all data.

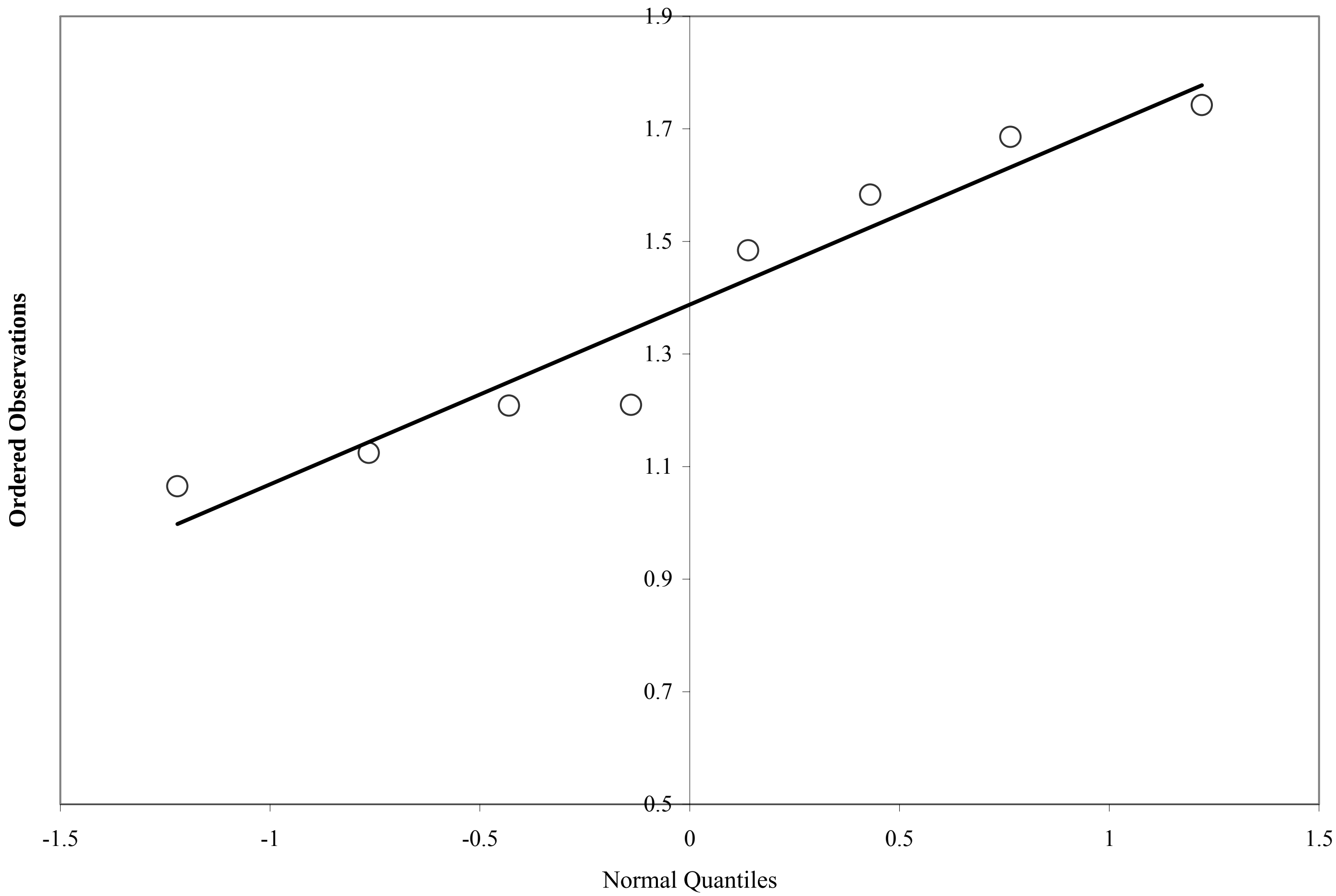

Figure B.2. Normal probability plot, Log($Hg_T$/TSS), wet season, flow < 55 cfs.

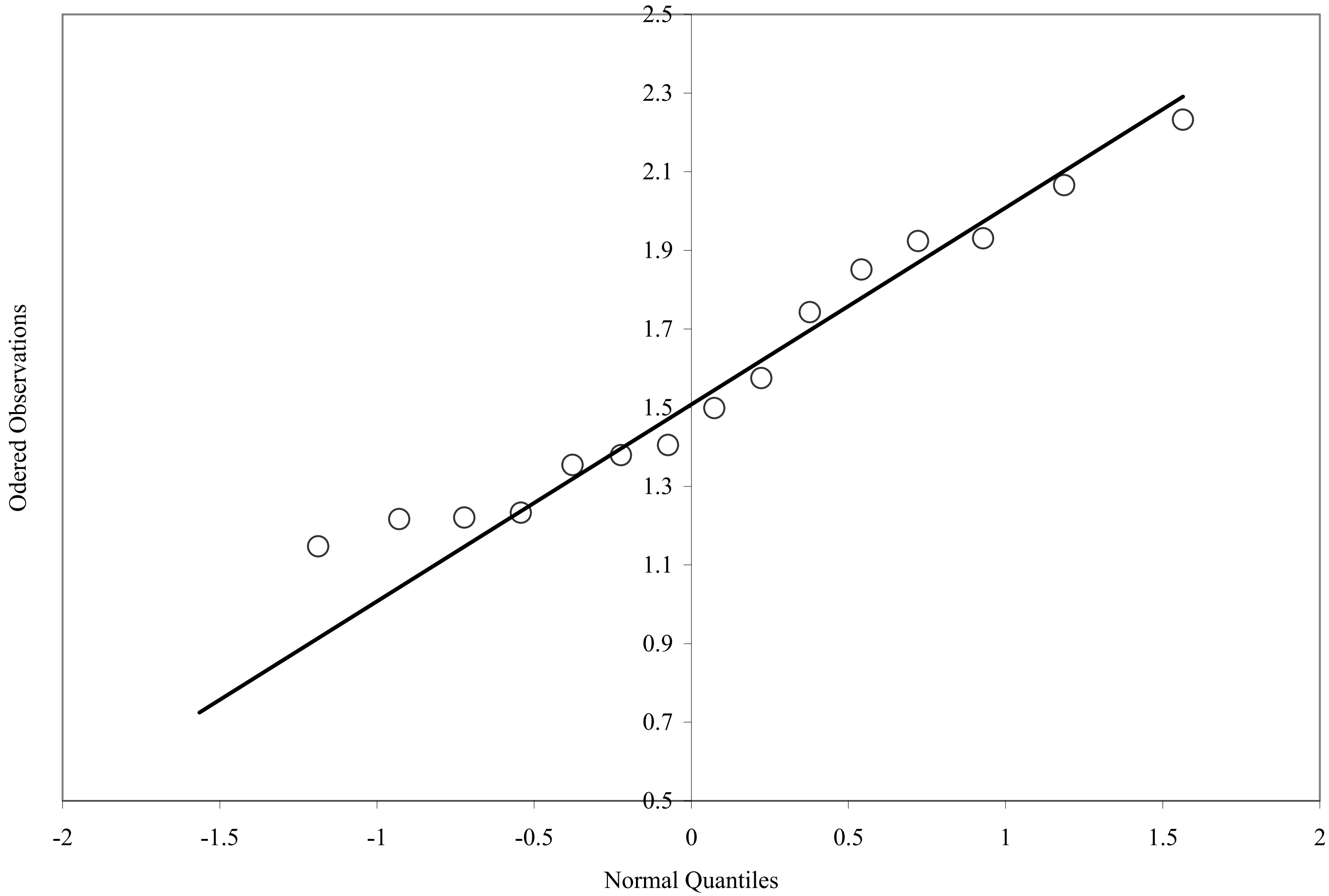

Figure B.3. Normal probability plot, Log($Hg_T$/TSS), wet season, flow > 55 cfs.