Incorporating Uncertainty into Mercury-Offset Decisions with a Probabilistic Network for National Pollutant Discharge Elimination System Permit Holders: An Interim Report

By Alexander W. Wood,[1*] Richard Bernknopf,[1*] William B. Labiosa,[2] James Rytuba,[1] Donald A. Singer,[1] Robb Kapla,[1,3] and Richard Champion,[1]

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[1]U.S. Geological Survey, Menlo Park, CA 94025, U.S.A.
[2]Stanford University, Civil and Environmental Engineering Department, Stanford, CA 94043, U.S.A.
[3]University of California, Los Angeles, School of Law, Los Angeles, CA 90095, U.S.A.

*Tel: 1-650-329-4229; Fax: 1-650-329-4710
E-mail address: *awood@usgs.gov* (A. Wood).

U.S. Department of the Interior
U.S. Geological Survey

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CONTENTS

FIGURES

TABLES

EXECUTIVE SUMMARY

This interim report describes an alternative approach for evaluating the efficacy of using mercury (Hg) offsets to improve water quality. Hg-offset programs may allow dischargers facing higher-pollution control costs to meet their regulatory obligations by making more cost effective pollutant-reduction decisions. Efficient Hg management requires methods to translate that science and economics into a regulatory decision framework.

This report documents the work in progress by the U.S. Geological Survey's Western Geographic Science Center in collaboration with Stanford University toward developing this decision framework to help managers, regulators, and other stakeholders decide whether offsets can cost effectively meet the Hg total maximum daily load (TMDL) requirements in the Sacramento River watershed. Two key approaches being considered are: (1) a probabilistic approach that explicitly incorporates scientific uncertainty, cost information, and value judgments; and (2) a quantitative approach that captures uncertainty in testing the feasibility of Hg offsets.

Current fate and transport-process models commonly attempt to predict chemical transformations and transport pathways deterministically. However, the physical, chemical, and biologic processes controlling the fate and transport of Hg in aquatic environments are complex and poorly understood. Deterministic models of Hg environmental behavior contain large uncertainties, reflecting this lack of understanding. The uncertainty in these underlying physical processes may produce similarly large uncertainties in the decisionmaking process. However, decisions about control strategies are still being made despite the large uncertainties in current Hg loadings, the relations between total Hg (HgT) loading and methylmercury (MeHg) formation, and the relations between control efforts and Hg content in fish.

The research presented here focuses on an alternative analytical approach to the current use of safety factors and deterministic methods for Hg TMDL decision support, one that is fully compatible with an adaptive management approach. This alternative approach uses empirical data and informed judgment to provide a scientific and technical basis for helping National Pollutant Discharge Elimination System (NPDES) permit holders make management decisions. An Hg-offset system would be an option if a wastewater-treatment plant could not achieve NPDES permit requirements for HgT reduction.

We develop a probabilistic decision-analytical model consisting of three submodels for HgT loading, MeHg, and cost mitigation within a Bayesian network that integrates information of varying rigor and detail into a simple model of a complex system. Hg processes are identified and quantified by using a combination of historical data, statistical models, and expert judgment. Such an integrated approach to uncertainty analysis allows easy updating of prediction and inference when observations of model variables are made. We demonstrate our approach with data from the Cache Creek watershed (a subbasin of the Sacramento River watershed).

The empirical models used to generate the needed probability distributions are based on the same empirical models currently being used by the Central Valley Regional Water Quality Control Cache Creek Hg TMDL working group. The significant difference is that input uncertainty and error are explicitly included in the model and propagated throughout its algorithms. This work demonstrates how to integrate uncertainty into the complex and highly uncertain Hg TMDL decisionmaking process. The various sources of uncertainty are propagated as decision risk that allows decisionmakers to simultaneously consider uncertainties in remediation/implementation costs while attempting to meet environmental/ecologic targets.

We must note that this research is on going. As more data are collected, the HgT and cost-mitigation submodels are updated and the uncertainties may be reduced. Subsequently, the value of using a probabilistic framework for estimating and explicitly stating these uncertainties within a decisionmaking process can be estimated when new data are collected.

Future work includes the design and implementation of a Bayesian network decision support system (BN-DSS) to produce mitigation scenarios for offset-project evaluation in the Cache Creek watershed. The decisionmaker, a wastewater-treatment plant, is expected to evaluate potential Hg-offset programs in terms of changes in HgT load changes, MeHg-production potential, project cost, and other suitability criteria. Subsequently, scenarios can be analyzed by performing sensitivity analyses and ranking environmental and economic uncertainties in terms of the decisionmaker's preferences and risk choices. Such an analysis allows decisionmakers and stakeholders to explore various scenarios and predict the consequences of different stated preferences over outcomes.

ABBREVIATIONS

Au: gold

CWA: Clean Water Act

DOC: dissolved organic carbon

EE/CA: engineering evaluation and cost analysis

EIR: environmental-impact report

EPA: Environmental Protection Agency

Hg: mercury

HgT: total mercury

MeHg: methylmercury

NPDES: National Pollutant Discharge Elimination System

NAWQA: National Water Quality Assessment Program

PBT: persistent bio-accumulative toxic

RWQCB: Regional Water Quality Control Board

SRCSD: Sacramento Regional County Sanitation District

TC (L10): total cost (logarithm base 10)

TMDL: total maximum daily load

TSS: total suspended sediment

VolCY (L10): total volume in cubic yards (logarithm base 10)

I. INTRODUCTION

The United States Geological Survey (USGS)'s Western Geographic Science Center has developed empirical approaches for mercury (Hg) loading, remediation-cost estimation, and probabilistic decision making that can provide decisionmakers support for the analysis of point/non-point source contamination offset. We consider a hypothetical case, using data from the Cache Creek watershed. We develop a probabilistic decision-analytical model consisting of three submodels for total Hg (HgT) loading, methylmercury (MeHg), and cost mitigation.

The HgT-loading submodel is developed for various reaches in a watershed where baseline loadings are treated as random variables with known conditional-probabilistic relations. In addition, linear-regression models for predicting MeHg content in water and total offset-mitigation costs are also developed. A short discussion of each of these models and their role and interrelation provides the context for this report. These empirical models were conceived from past research using linear regression modeling to predict MeHg contents in fish (Brumbaugh, 2001) and offset-mitigation costs (Singer et al., 1998).

The three submodels are all components of a probabilistic Bayesian network framework. The Bayesian network decision analytical model allows the user to evaluate potential Hg-offset programs in terms of changes in HgT (from the HgT-loading submodel), MeHg-production potential (from the MeHg submodel), project cost (from the cost-mitigation submodel), and other suitability criteria. A probabilistic framework composed of the empirical models allows stakeholders to analyze various offset scenarios based on different remediation choices to see determine whether discharge-permit requirements can be achieved at minimal cost.

The impetus for a potential Hg-offset program in the Sacramento River watershed originates from a National Pollutant Discharge Elimination System (NPDES) permit issued on August 4, 2000, to the Sacramento Regional County Sanitation District (2001) (SRCSD). The NPDES permit requires that the SRCSD study the feasibility of Hg-offsets. Offsets, which provide a mechanism to reduce Hg loads in the Sacramento River, can create the assimilative capacity needed to allow for the inevitable contribution from human-population growth. A future offset may be needed for the SRCSD because of potential human-population growth and consequently larger discharge-effluent levels. Currently, the SRCSD discharges below its maximum permit levels.

In preparing its "Hg Offset Feasibility Study," the SRCSD (Sacramento Regional County Sanitation District, 2001) has utilized a collaborative process that includes gathering stakeholders and soliciting their input, identifying potential projects, specifying project selection criteria, calculating creditable load reductions for selected projects, and selecting the most likely feasible study.[1] Although over the past 2 years USGS and SCRSD staff have participated in several joint activities, including attending working- group meetings, reviewing draft documents, and frequently discussing the subject study, the present report should not be seen as a companion document or a derivative of the SRCSD process. As a result of the timing of SRCSD permit requirements and USGS research objectives, communication between the USGS and SRCSD has been more informative than collaborative. However, as the USGS implements these alternative statistical approaches, further collaboration between the USGS and SRCSD seems promising.

The SRCSD decides whether offsets are in the best interest of the public should permit levels be exceeded in the future. The USGS has been funded to research a decision-theoretic approach to estimate the uncertainty in Hg levels and to help provide support for offset issues in future wastewater treatment decisionmaking. Two approaches being considered are (1) a probabilistic approach that explicitly incorporates scientific uncertainty, cost information, and value judgments; and (2) a quantitative approach that captures uncertainty in testing the feasibility of Hg-offsets.

II. PROBLEM DESCRIPTION

Mercury Issues

Since the early 1800s, residual Hg from mining has been transported with sediment downstream into the Sacramento/San Francisco Bay estuary, where it is believed to have contributed to elevated Hg contents in fish, resulting in consumption advisories. Most of the Hg pollution in this area was from placer gold mines, which used Hg to extract gold through hydraulic, drift, and dredging methods (Alpers and

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[1] The SRCSD, along with the consulting firm Larry Walker Associates, initiated the offset discussions by establishing an offset working group composed of various Federal, State, and local agencies to evaluate and obtain consensus on key offset issues as a result of the many uncertainties involved with establishing potential offset projects. Although environmental-advocacy groups did not attend any of the working-group meetings, written input was supplied (See app. A).

Hunerlach, 2000). Gold-enriched gravel deposits within the Sierra Nevada gold belt provided the basis for large-scale mining in California during the mid-1800s until the 1890s. Hg mines in the Coast Ranges of California provided the Hg used in placer mining, as well as contributing tailings to the Hg-enriched sediment in the San Francisco Bay estuary (Bradley, 1918).

MeHg, an organometallic form of Hg, is a potent neurotoxin that accumulates in humans via fish consumption. As a result of its toxicity, numerous environmental studies of Hg contamination have been undertaken by various Federal and State agencies throughout California; many of these studies have focused on the Sacramento River watershed. The California Bay-Delta Authority[2] currently has an Hg program, the CALFED Mercury Project,[3] that assesses the ecologic and human-health impacts of Hg in the bay delta watershed. Past research includes assessments of avian Hg exposure, analysis of the effects of wetland restoration on MeHg production, and studies of the geochemical composition of Hg-rich mineral deposits.

Much Hg research in the CALFED program has focused on the Cache Creek watershed because of its large Hg contribution to the Sacramento River watershed. Recently, the Central Valley Regional Water Quality Control Board (CVRWQCB) released a Cache Creek Hg total maximum daily load (TMDL) report outlining the numeric targets for MeHg, the types of Hg source, the linkage analysis between MeHg contents in water and large fish, and load allocations (Central Valley Regional Water Quality Control Board, 2004). A TMDL is developed under section 303(d) of the Federal Clean Water Act (CWA) to attain water-quality standards to protect beneficial uses. These types of TMDL analysis have significant implications for Hg management in California. Managing Hg, however, is quite complex as a result of physical (sediment dynamics), chemical (MeHg transformation), and biologic uncertainties (food-web dynamics and bioaccumulation).

Despite the fact that Hg research has made great strides, the complexity of Hg speciation and its associated environmental impacts still challenge the scientific community. The scientific understanding of Hg biochemical cycling and transport within California is still incompletely known and contains significant

[2] The California Bay-Delta Authority's mission is to develop and implement a long-term comprehensive plan that will restore ecologic health and improve water management for beneficial uses of the bay-delta.

[3] http://loer.tamug.tamu.edu/calfed/.

uncertainties that are not properly incorporated into the decisionmaking process. The CVRWQCB acknowledges these complexities and uncertainties in their Cache Creek TMDL report through such comments as "it is not possible at present to determine a scientifically defensible sediment mercury concentration that will protect the beneficial uses of Cache Creek" (Central Valley Regional Water Quality Control Board, 2004). As a s result, Cache Creek TMDL numeric targets and linkage relations are based on various deterministic mass- balance assessments, risk reference-dose calculations,[4] and bioaccumulation factors incorporating implicit margin-of-safety factors.

Site-specific fish-tissue water-quality objectives and implementation plans for Hg and MeHg reductions are anticipated for various watersheds throughout California, and so the CVRWQCB grants industrial facilities and wastewater-treatment plants HgT discharge-permit limits on the basis of a TMDL. Historically, improvements to water quality in the Sacramento River watershed have been associated with controlling point sources, such as discharge pipes from industry and water treatment facilities. Although reducing Hg loading to the basin by further controlling point sources (i.e., removing Hg from pipe outflows through additional treatments) may be possible, monitoring data suggest that the Hg content of treated effluent is minimal and that controlling point sources alone is unlikely to lead to significant improvements in reducing Hg loadings. In addition, it is believed that additional point-source-control technologies will be extremely costly. For these reasons, among others, the U.S. Environmental Protection Agency (EPA) and the regulated community have been interested in exploring the feasibility and cost effectiveness of focusing TMDL compliance efforts on controlling diffuse and presently unregulated (i.e., "nonpoint") Hg sources in the Sacramento River watershed through offsets.

Water-Quality Trading and Offsets

Since the 1960s, although considerable progress has been made in reducing point- source pollution, the Nation's water quality has not improved proportionately (Letson, 1992). As a result,

4 Acceptable levels of intake are called reference doses (RfD). An RfD, expressed as an average daily rate (micrograms of Hg per kilogram body weight per day) of Hg intake, is calculated by using studies of exposure in specific populations to determine a threshold level. This level is then divided by arbitrary uncertainty factors to account for differences in metabolism and sensitivity between individuals (Central Valley Regional Quality Control Board, 2004).

regulators have shifted their emphasis to non-point-source-related impairments, such as agriculturally driven nutrient enrichment and toxic contamination of fish tissue (Letson and Crutchfield, 1993). Non-point-source pollution is transported by runoff from rainfall or snowmelt moving over and through the ground and deposited into sediment, soils, and various water bodies, endangering human health and the environment.

A Non-point-source, technically and legally, is defined as any source of water pollution that does not meet the legal definition of a point source in section 502(14) of the CWA. According to the CWA, the term "point source" is defined as any "discernible, confined and discrete conveyance, including but not limited to any pipe, ditch, or channel" (CWA §502(14); see also 33 U.S.C. §1362(7); 40 C.F.R. §122.2). Although diffuse runoff is generally treated as non-point-source pollution, runoff that enters and is discharged from such conveyances as those described above is treated as point-source discharge (some types of stormwater runoff are subject to NPDES permits) and so is subject to CWA permit requirements [(402 (p) (2); (Hoag and Hughes-Popp, 1997)]. In contrast, non-point sources are not subject to Federal permit requirements.

Point-source pollution has been controlled through the application of technology and water-quality-based requirements administered by the States using the NPDES permit program (Stephenson et al., 1998). Almost 87 percent of major municipalities and 93 percent of major industrial facilities were in compliance with NPDES permits by 1990 (U.S. Environmental Protection Agency, 2002). Despite these accomplishments, water- quality problems persist as a result of non-point-source pollution. Natural variations in non-point-source pollution, as well as political and legal issues, have made identifying and locating sources problematic, thereby hindering implementation of efficient regulatory approaches. Interest has been growing among private industries and regulatory agencies in using market-based incentives, particularly trading programs, for non-point- source mitigation to improve water quality in numerous watersheds and produce cost savings.

Since the early 1980s, the EPA has been planning new and innovative schemes to manage and reduce NPS pollution, including trading programs. The EPA issued a broader Policy Statement on Effluent Trading in Watersheds (1996), a proposed water-quality trading policy (2002), and a final water-quality trading policy (2003) establishing a more clearly defined role for water regulation. The EPA supports and encourages water-quality trading programs for many purposes: to reduce the cost of compliance with water-quality-based requirements, to offset growth, to achieve early reductions and progress toward water-quality standards pending the development of such standards, and to establish economic incentives for voluntary reductions (U.S. Environmental Protection Agency, 2002).

Trading programs were first used to provide greater flexibility for emission sources to meet air-quality standards. The first practical application concerned the problem of sulfur dioxide emissions from coal-fired powerplants resulting in acid rain negatively impacting vegetation throughout the Eastern United States and Canada. Established under the 1990 Clean Air Act, the Acid Rain Program is the most widely known and successful trading program. Although cost savings have been difficult to measure because of the proprietary nature of industrial pollution-control/cost data, this program was expected to save more than $2 billion per year in compliance costs within the next decade relative to the cost of preexisting regulations (Jarvie and Soloman, 1998). Watershed-based trading may also provide for cost savings while still meeting the stringent limits expected to result from TMDL development (Borsuk and others, 2002).

Trading programs are founded on the idea that it may be more economically efficient to have high-cost polluters pay low-cost polluters to reduce pollution further, providing more pollution reduction at a lower total cost (Baumol and Oates, 1994). Differences in the marginal costs of pollutant reduction arise because non-point source reduction is generally cheaper on a per-unit basis (relative to point-source control) because point sources commonly require expensive technological methods to control further discharge, whereas non-point sources rely on cheaper nonstructural methods to reduce pollutant loading. In other words, if it costs one entity much more than another entity to reduce the same amount of pollution, then these two entities can trade pollution credits. However, application of this theoretical ideal of marginal-cost differences becomes much more complex because of additional transaction costs (e.g., identifying and negotiating potential projects) that could negate the potential cost savings from trading between sources with different marginal costs.

Under the EPA's proposed policy to create pollution credits to trade or offset, sources must reduce loadings below their applicable trading baseline, which may be technology or water quality based, depending on the situation, in order to potentially create tradable credits. Currently, the EPA does not support trading or offsets of pollutants that are considered to be persistent bioaccumulative toxics (PBTs), such as Hg (U.S. Environmental Protection Agency, 2002). In 2003, the EPA provided funding for this pilot project to assess whether such toxics as Hg could be traded or offset without inflicting irreversible health consequences. Potential offsets may include cleaning up Hg mine tailings, erosion control activities, and Hg-reduction programs (e.g. Hg recycling). An Hg-offset program would be established and succeed only if there was an active participant. Therefore, the approach described in this report evaluates the offset potential for Hg-related projects by integrating Earth science and economic information to identify a wastewater treatment plant's interest in becoming an active offset participant (Wood and Bernknopf, 2003).

III. A DECISION-ANALYTICAL MANAGEMENT APPROACH

In thinking about reducing Hg loads and Hg fish-tissue levels within a watershed, decisionmakers face many uncertainties, both in terms of modeling current and future environmental behavior and in estimating economic outcomes (Labiosa, 2003), included:

- Source and baseline HgT loadings
- Amount of Hg methylated to form MeHg
- Changes in Hg/MeHg downstream loadings as a result of changes in upstream loadings, given the importance of resuspended sediment as a source
- Cost of a particular remediation (offset) program
- Liability for a party paying for such projects in case of non-attainment of load-reduction goals (Labiosa, 2003)

Our study focuses on an alternative decision-analytical approach to the current use of margin of safety factors and deterministic models for Hg TMDL decisionmaking support. The approach uses empirical data and informed judgments to provide a scientific and technical basis for helping NPDES permit holders make management decisions at the regional watershed scale. Empirical submodels for Hg loading, MeHg, and cost mitigation are integrated within a probabilistic decision-support system (DSS) to produce various mitigation scenarios. Subsequently, scenarios can be analyzed by performing sensitivity analyses and ranking environmental and economic uncertainties in terms of a decisionmaker's preferences and risk choices. In the following sections, we describe these submodels, how they relate to decision analysis, and how they can be integrated into a DSS to support Hg-offset program-evaluation and selection. Conceptual development of the DSS for the Cache Creek watershed is discussed in the section below entitled "Future Research."

Hg-program studies by the USGS' National Water Quality Assessment (NAWQA) in the Sacramento River/San Joaquin Delta and San Francisco Bay, CALFED studies, and other additional Hg-related projects in the region, suggested that the Cache Creek watershed, a major contributor to the annual Hg load of the Sacramento River, be selected as a pilot study (Foe and Croyle, 1998; Domagalski, 2002; Churchill and Clinkenbeard, 2003). The Cache Creek watershed (figure 1), which encompasses an area of approximately 3,000 km^2 within the Coast Ranges (upstream areas consist of low, forest, and grazing hills) and the Sacramento Valley of California (downstream flatter areas are used mostly for crop production) (Domagalski et al., 2004) is considered a significant Hg source, both from anthropogenic sources of inorganic Hg (abandoned and inactive mine sites) and natural sources (geothermal springs and native soils), to the Sacramento River/San Joaquin Delta and San Francisco Bay. As a result of deposition over the past 100-150 years by stormwater runoff, abandoned mines, and geothermal sources, streambed sediments is a significant source of Hg and MeHg in the Cache Creek watershed (Foe and Croyle, 1998; Domagalski et al., 2004). In the following sections, we describe our approach to water-quality-management decisions for the Cache Creek watershed.

Figure 1. Cache Creek watershed in north-central California

Decision Analysis for Water Quality Management

Although decision analysis for water-quality management could be done by using a wide variety of approaches to water-quality/natural-system forecasting approaches, the research outlined here uses Bayesian network models to forecast water-quality and ecologic responses to mitigation strategies. Such models are probabilistic representations of a system (Shachter, 1988; Jensen, 2001) in which related variables represent a water quality management problem (Varis, 1995; Reckhow, 1999; Borsuk et al., 2003). Bayesian networks are structured in terms of cause-and-effect relations between random variables that describe environmental end points of interest. The probabilistic method contrasts with the deterministic approaches currently in use that model system behavior on the basis of mathematical representations of the underlying mechanisms and on deterministic approaches that ignore uncertainty. A Bayesian network decision-analytical tool has distinct advantages over other decision frameworks, including:

- Representation and propagation of uncertainty in a computationally efficient manner;
- Integration of diverse information, including the results from, e.g., science-and- engineering models, cost-benefit analysis, empirical data summaries, decisionmaker preferences, and expert judgment;
- Integration of predictions of mitigation consequences into a model that evaluates the various possible consequences; and
- Inclusion of sensitivity analysis and evaluation of "decision robustness."

Because the uncertainties involved in estimating HgT loading and predicting the environmental impacts of load-reduction projects are significant, an approach that explicitly treats uncertainty is useful for decision-support activities (Varis, 1994). The discussion in the rest of this section is largely based on previous work (Labiosa, 2003).

The proposed decision-analytical approach utilizes Bayesian rules and allows the decisionmaker to combine various types of information into a unified probabilistic framework. For decisions that involve perturbations to complex natural systems, Bayesian networks that are built from the best available scientific models, data, and expert judgments can be used to predict the probabilities of the various outcomes of those decisions (Reckhow, 1999; Borsuk et al., 2001, 2002; Stow et al., 2003). In practice, empirical models and expert judgment are straightforward means to create the needed probabilistic relations.

A decision-analytical approach recognizes and frames the decisionmaking problem in terms of *alternatives*, *information*, and *preferences*. Within the context of environmental decisionmaking that affects diverse stakeholders, these terms could be cast as (1) decision framing and strategy generation; (2) data interpretation, environmental modeling, and forecasting; and (3) group-preference elicitation (e.g., multiattribute utility analysis), negotiation among stakeholders and decisionmakers, or other methods of eliciting and representing preferences. The goal of decision analysis is to create clarity of action in a complex decision situation, in spite of significant uncertainty (Howard, 1984). Decision analysis is a theoretically sound approach for making decisions under uncertainty (e.g., Howard, 1968; 1988; Keeney and Raiffa, 1976; Clemen, 1996; Merkhofer, 1999).[5]

A Bayesian network approach estimates best decisions, given the decisionmakers' consensus on information, alternatives, and preferences and allows the modeler to focus on predictive accuracy over the temporal and spatial scales desired for the variables of interest to the decisionmakers, removing details that

[5] Many examples of the use of decision analysis for environmental decisionmaking exist in the literature, generally in the area of site selection or choice between remediation, restoration, or technology (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; Labiosa 2003). In addition, more recent work has demonstrated that water quality can be effectively modeled by using Bayesian networks, producing results that are comparable to those from more complex mechanistic models (e.g., Reckhow, 1999; Borsuk et al., 2001, 2002; Stow et al., 2003).

are determined to be extraneous to the decisionmaking problem. All decisionmaking is subjective, and so any decision- analytical tool must be modified to reflect the beliefs and preferences of the decisionmakers before use. As Reckhow (1999) pointed out, this approach generally leads to superior predictive accuracy compared to complex mechanistic scientific models of water quality impacts at the temporal and spatial scales of interest to decisionmakers. The loss of mechanistic descriptive power is compensated by the ability to perform sensitivity analyses, explore scenarios probabilistically, and estimate the probability that water-quality indicators will meet targets, all of which provide useful information to decisionmakers. Because compliance is predicted probabilistically, the procedure of using arbitrary margin-of-safety factors to hedge against uncertainty can be replaced by an explicit consideration of uncertainty and its consequences for mitigation decisions.

From a decision analytical perspective, the tradeoff between mitigation costs and the probability of compliance (a measure of decision uncertainty) with various environmental/ecologic targets can be explicitly modeled with no need for safety factors or other arbitrary hedges against risk (Labiosa, 2003). This concept, a basic economic preference, may prove useful for evaluating mitigation strategies because strategies that yield higher probabilities of success would naturally be more appealing at a given cost.

The proposed approach recognizes that the uncertainties in model inputs and propagated through the relations between system variables may result in large uncertainties in the relations between mitigation efforts and effects on the environmental end points of interest, e.g., HgT loadings and MeHg contents in water and fish tissue. A decision-analytical approach is used so that these large uncertainties can be meaningfully interpreted within the decisionmaking context. Current models incorporate uncertainty unsystematically, commonly through consideration of liability and risk outside the analytical framework, or by using safety factors and other hedges in the analysis to accommodate uncertainties. As pointed out in the literature, probabilistic forecasting approaches are superior to deterministic approaches for supporting complex decisions (Howard, 1968; Morgan and Henrion, 1990; Clemen, 1996; Clark et al, 2001).

Total-Mercury-Loading Submodel

The first submodel is a probabilistic HgT-loading model for the Cache Creek watershed that allows the user to predict, on the basis of available data and best understanding of the system behavior, how HgT-reduction projects will affect downstream water quality at several points of interest. This submodel was designed and researched this past year in collaboration with researchers at Stanford University (William Labiosa, James Leckie, and Ross Shachter, written commun., 2003) for a Bayesian network (see app. B) that treats HgT loading and streamflow within the various defined stream segments of the Cache Creek watershed (fig. 2) as random variables with known conditional probabilistic relations. Data, received from the CVRWQCB TMDL working group, included sampling-site name, date of sample taken, HgT and MeHg contents, total-suspended-sediment (TSS) concentration, and streamflow data. The HgT-loading submodel is developed by estimating the conditional probabilities for various stream segments in the Cache Creek watershed, using a log-log (base e) empirical-linear regression model relating Hg load to streamflows (flow range, e.g., {<X, [X,Y], >Y}) and season (water season: {wet, dry}) in each stream segment.

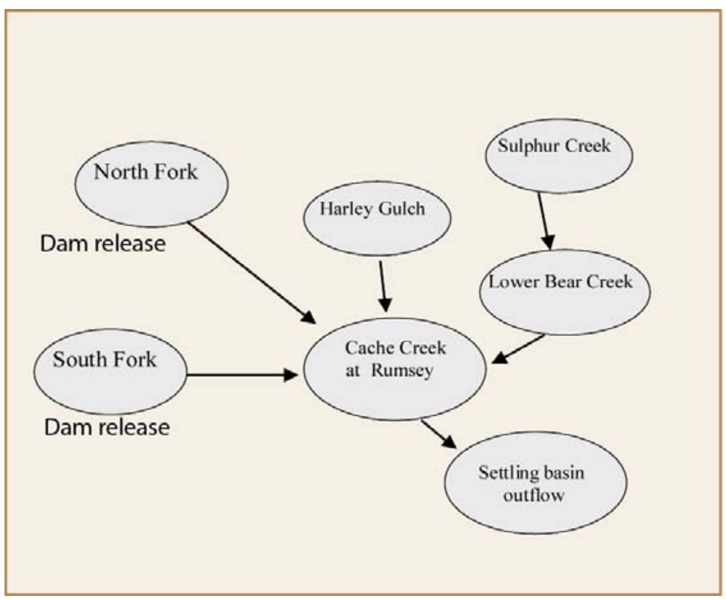

Figure 2. Defined stream segments of the Cache Creek watershed, north-central California (fig. 1), showing data flow

Streamflow data are partitioned by range and season to achieve approximately Gaussian HgT loadings in logarithmic space. Flows are simulated by bootstrapping (repeated sampling with replacement) the available streamflow data for each partition. Model error is represented as a random log normally distributed additive term. The HgT probability distribution, {HgT load|season, flow}, is simulated by using Monte Carlo analysis that samples from bootstrapped flows and the random-error term. The HgT loadings for each partition are combined by using standard Bayesian-network algorithms to generate the HgT distribution over the water year; e.g. the regression equation developed for the Sulphur Creek segment is:

$$\mathbf{\ln(\text{HgT load, in grams per day}) = {}_{0} + {}_{1} * \ln(\text{streamflow, in cubic feet per second}) + \ ,} \quad \mathbf{(1)}$$

where   is an error term that is assumed to be normally distributed around the predicted value with a constant variance. Loading regression equations for the various stream segments differ in dependence on Hg-loading contributions from upstream segments. A conceptual Hg-loading submodel for the Sulphur Creek and Lower Bear Creek segments is illustrated in figure 3.

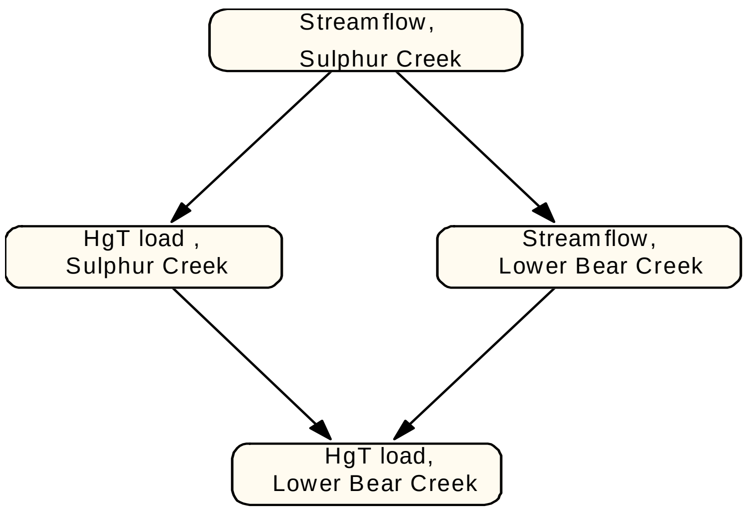

Figure 3. HgT-Loading Bayesian Network Sub model for Sulphur Creek and Lower Bear Creek segments of the Cache Creek Watershed, north-central California (figs. 1,2).

The overall HgT-loading submodel for the Cache Creek watershed is composed of similar submodels for the various stream segments and can be shown at the level of detail for individual stream segments or aggregated at a watershed-level loading model. Fitting parameter nodes are probabilistically absorbed into the network (i.e., their contribution to the overall uncertainty is incorporated into the remaining nodes), leaving only the variables of interest to decisionmakers. These probabilistic relations are based on available data and can be adjusted as necessary with new sample observations or expert judgment. Hg-loading Bayesian network models for the various stream segments of the Cache Creek watershed are currently being developed by using this procedure.

Methyl-mercury Submodel

The MeHg submodel uses linear regression to predict MeHg content in water, which have been shown by various field-based studies to be an important indicator for predicting Hg uptake in biota (Slotton et al., 2004). The chemical transformations of Hg into MeHg have challenged researchers for many years. Although scientists have identified some of the critical processes and variables that may be important for MeHg production [e.g., temperature, sulfate, dissolved organic carbon (DOC), pH, and wetland density] (Marvin-Dipasquale, 2000) the complexity of these processes in various aquatic environments has precluded defining general controls on MeHg formation in all types of ecosystems.

Because no generally agreed-upon approach exists, our effort began with testing different statistical approaches for estimating MeHg content in water (see app. C). On the basis of scientific expert judgment, a linear regression is calculated by using variables believed to be significant in the Cache Creek watershed to predict MeHg content in water. This method was previously by Brumbaugh (2001) to estimate the MeHg contents of fish in watersheds throughout the United States. Again, those data were collected from by the Cache Creek CVRWQCB TMDL working group. Sampling sites were categorized on the basis of data availability and past studies (fig. 4).

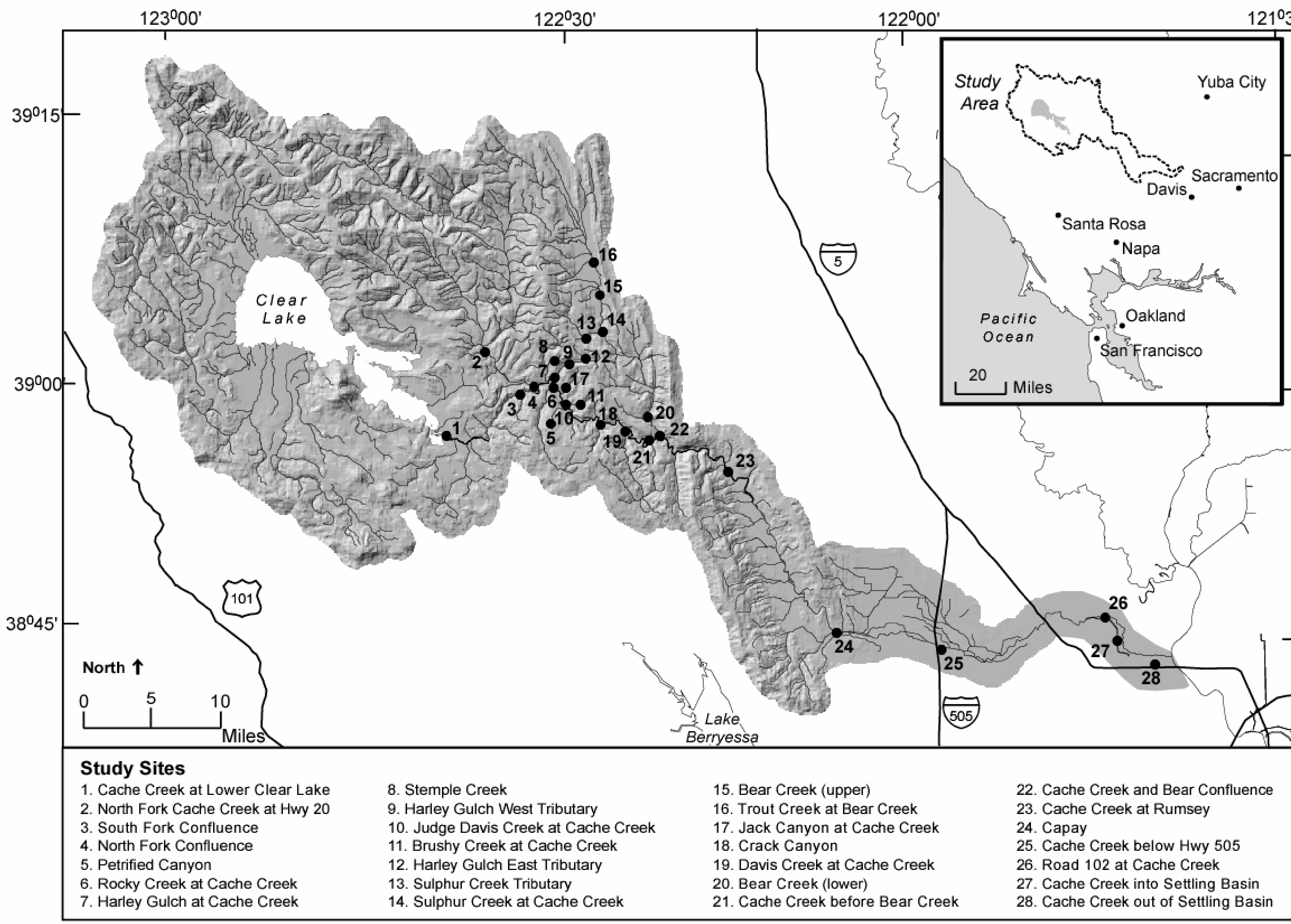

Figure 4. Cache Creek watershed in north-central California (figs. 1,2) showing locations of sampling sites (numbered dots).

Several quantitative (HgT content, streamflow data, TSS concentration, and elevation) and qualitative [seasonal effect (dry/wet) and a natural sulfur effect] variables were tested to predict MeHg content in water. Qualitative variables were those that were deemed important by expert judgment, as indicated by a one (1) if the variable is present and a zero (0) if the variable is absent.

Seasonal variation is an important indicator to take into account in measuring HgT and MeHg contents and loadings in the Cache Creek watershed (figs. 1,4). The seasonal effect is indicated by the "dry" season (1 in the regression), which is synonymous with the irrigation season that begins on April 1 and ends on October 31 each year.[6] The implication is that "dry"-season flows are generally comparable to or greater than "wet"- season (0 in the regression) flows in the North and South Forks. Indian Valley (North Fork) and Clear Lake (South Fork) are the major sources of water in the basin, averaging 24% and 58%, respectively, of the measured streamflow during the 5-year sampling period (Central Valley Regional Water Quality Control Board, 2004).

Downstream flows from Clear Lake and Indian Valley Reservoir are controlled for release during the summer irrigation season for Yolo County (Schwarzbach et al, 2001; Central Valley Regional Water Quality Control Board, 2004; Domagalski et al., 2004). During this period, downstream irrigation usage removes most of the water volume, diverting flow at Capay Dam into irrigation canals, resulting in minimal flows at the outlet of the Cache Creek watershed (CVRWQCB, 2004; Slotton et al., 2004). The point is, however, that the flows are managed in much of the watershed north of Rumsey according to a particular calendar. Finally, the CVRWQCB Cache Creek TMDL report (Central Valley Regional Water Quality Control Board, 2004) states that MeHg contents are observed to be higher in the early, "dry" summer, when in place production is greatest, and after the first storms, when MeHg produced in the tributaries is flushed downstream (Slotton et al., 2004).

An additional fixed-effect variable that was insignificant at the p=0.05 (95%- confidence) level for the regression model is a sulfate effect, which is important in MeHg production (a statistically positive relation) through sulfate-reducing bacteria. Bear Creek and Sulphur Creek are both "hotspots" for sulfate derived from geothermal and mineral springs. Sulphur Creek during low flow conditions is dominantly hot spring effluent water that differs considerably from water in the other Cache Creek tributaries because of

[6] Adopting a fixed-effect variable of dry/wet season for this regression is watershed site specific because of geography and watershed resource-management needs.

high salinity (Hg chloride complexes are more bioavailable), sulfate, boron, and organic acids. In addition, this continuous source of sulfate from Sulphur Creek becomes available for the growth of sulfate-reducing bacteria and subsequent MeHg production. These bacteria are active in anaerobic sediment, not in the river, within an anoxic environment.

Hg loads in Bear Creek are largely influenced by Sulphur Creek, a tributary to Bear Creek (figs. 1,2). Sulfur Creek drains the Wilbur Mining District which includes the Elgin Mine, the Wide Awake Mine, the Abbot Mine and the Empire Mine (Suchanek et al., 2002). Bear Creek receives recently deposited Hg - sulfide and Hg-enriched pyrite that is being deposited from hot springs which vent in and near Sulphur Creek, as well as higher-sulfate water discharged from the hot springs in Sulphur Creek and cold carbon dioxide high-sulfate springs that vent along Bear Creek (Oscarson et al., 1992). Therefore, Bear Creek and Sulphur Creek distinguish themselves from most other tributaries to Cache Creek because of this direct input of recently deposited Hg and sulfate. Bear Creek loads are typically a smaller part of the Cache Creek load in general, but Bear Creek may contribute more of the Hg load in early season storms (Central Valley Regional Water Quality Control Board, 1998), when the other two tributaries with reservoirs are in storage mode (Schwarzbach et al., 2001).

The linear regression MeHg submodel was estimated by using the S-plus statistical data analysis software of Insightful Corp. Many different models were examined with alternative combinations of independent variables. The results for the MeHg submodel are expressed as:

$$\mathbf{y = -0.817 + 0.43*HgT(log\ 10) - 0.072*\ FL(log\ 10) - 0.19*Elev\ (log\ 10) + 0.45*DRY} \qquad \mathbf{(2)}$$

All the independent variables in equation 2 were significant at the $p = 0.05$ (95%-confidence) level where y is the logarithm of total MeHg content in water, HgT is the HgT content in water at a particular sampling site, FL is the streamflow (in cubic feet per second), Elev is the elevation (in feet), and DRY is the dry season (1 = yes, 0 = no). The linear regression had 122 degrees of freedom [the number of samples tested (127) minus the number of terms estimated (5) (independent variables and intercept)]; a standard error of 0.37, and an r^2 factor of 0.63 (an r^2 factor measures the proportion of the total variation of log MeHg that is explained by the model). In other words, about 63% of the variation in MeHg content can be explained by equation 2.

Given these specifications, we might include expecting a higher MeHg content in water at higher HgT content (larger potential for HgT methylation), at lower streamflow levels (slow-moving waters, allowing methylation), lower elevation (areas containing more organic material), and in a “dryer” season (more organic material available for reactions). On the basis of these relations, our results agree with those of previous field- based studies (Domagalski et al., 2002).

Regression results for MeHg content in water are mapped in figure 5 to provide decisionmakers with a geospatial visual resource showing areas of high methylation potential and subsequently potential offset-mitigation projects if target reductions include MeHg reduction. The predictions at each sampling site consist of two types of estimated MeHg content: (1) predictions using the same variables from the regression (127 samples), and (2) predictions based on other samples without measured MeHg content but using the input variables from the regression (196 samples).

The regression results for MeHg content in water mapped in Figure 5 agrees with observations from CALFED studies and past Hg research in the Cache Creek watershed (figs. 1,2). The highest MeHg contents are predicted for the tributaries to Sulphur Creek, the main stem of Sulphur Creek, and the tributary to Harley Gulch West –all areas that are known to have Hg sources with high levels of HgT and sulfate which contribute to MeHg formation. The CVRWQCB Cache Creek TMDL report (Central Valley Regional Water Quality Control Board, 2004) states that the “watershed above Rumsey was the major source of MeHg. The highest concentrations and production rates were observed below the Hg mines in Harley Gulch, and Sulphur Creek and Bear Creeks and in the canyon above Rumsey.”

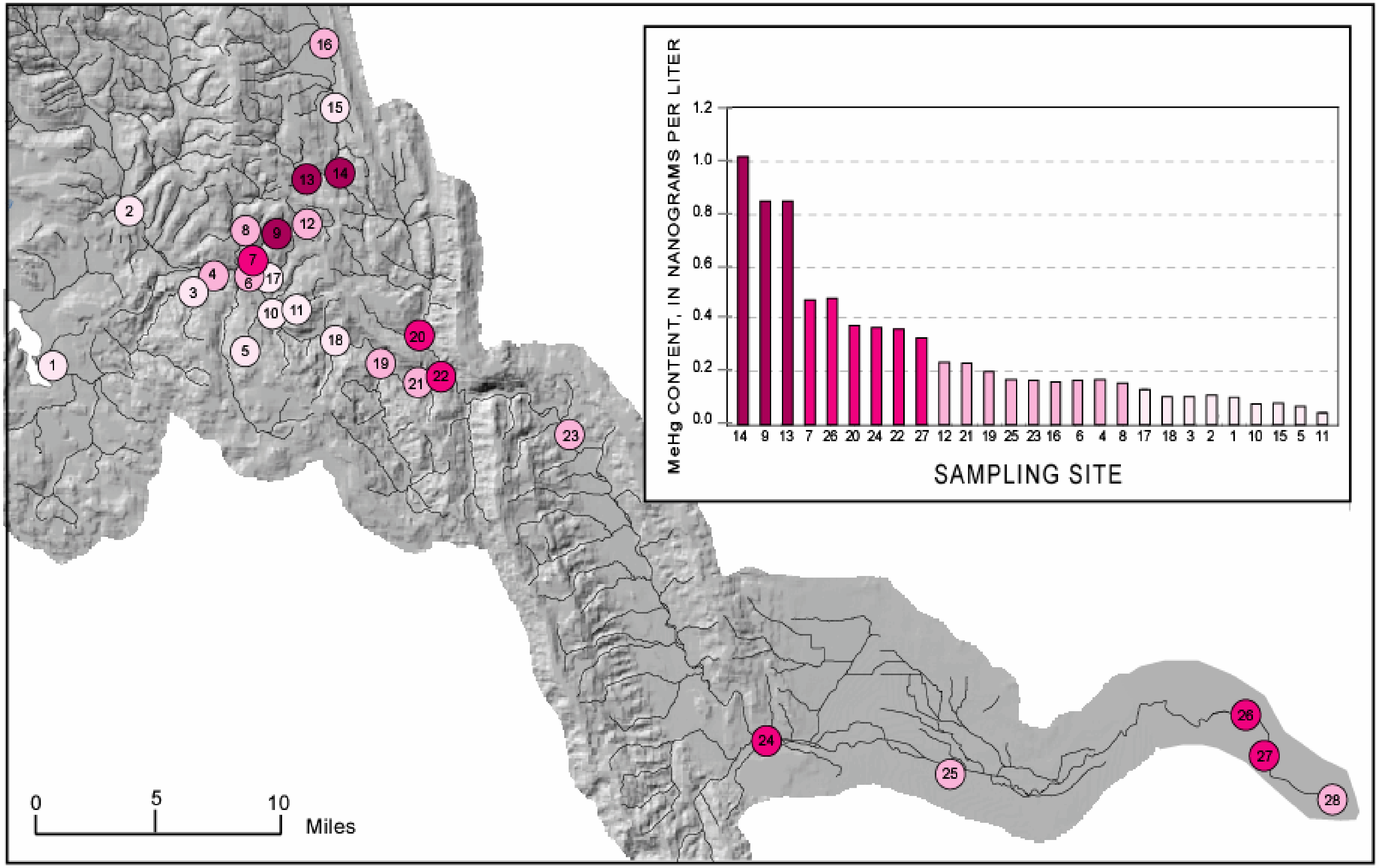

Figure 5. Cache Creek watershed in north-central California (figs. 1, 2), showing locations of sampling sites (numbered circles) correlated with median MeHg content at each sampling site as predicted from equation 2.

The higher MeHg concentrations downstream at the settling basin are attributable primarily to resuspension of previously deposited Hg in the bottom sediment because of the managed flows (Domagalski et al, 2004). The broad, flat flood plain between Capay Dam and the settling basin is undergoing continuous streambed erosion and redeposition of Hg-enriched sediment during all but the highest streamflows (Central Valley Regional Water Quality Control Board, 2004). Downstream irrigation usage (as well as evaporation, ground-water recharge, and consumption by riparian vegetation; Central Valley Regional Water Quality Control Board, 2004) removes most of the water volume, resulting in minimal flows at the outlet of the Cache Creek watershed and providing suitable conditions for methylation (Foe and Croyle, 1998; Slotton et al., 2004).

The uncertainty in the predicted MeHg content at sampling sites in the Cache Creek watershed is illustrated by a plot of minimum, maximum, median, and 25th and 75th percent in figure 6. Consideration of the variation or uncertainty in outcomes is essential when analyzing various remediation scenarios. As more data become available for each of the sampling sites over various seasons, seasonal aspects (by calendar) of MeHg production could be more thoroughly tested and incorporated into the model if significant (Slotton et al., 2004).

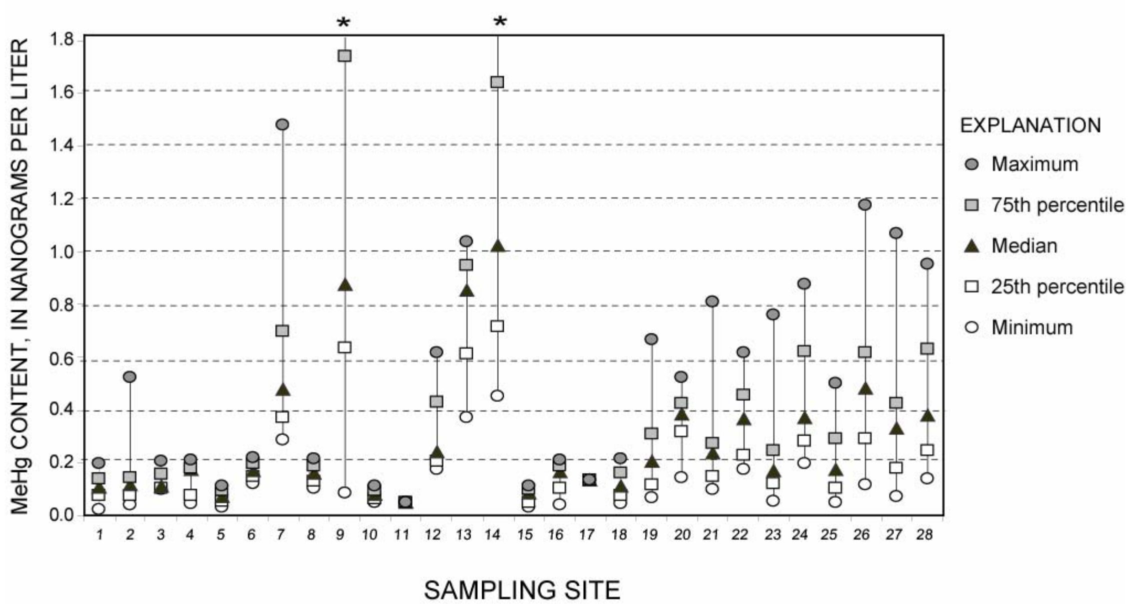

Figure 6. Predicted MeHg Contents in Water at sampling sites in the Cache Creek Watershed, north-central California (figs. 1,2). Maximum value was 8.8 ng/L at sampling site 9 and 2.6 ng/L at sampling site 14.

The date in figures 5 and 6 provide decisionmakers with visual resources to assess areas of the Cache

Creek watershed that may contain high MeHg contents in water (e.g., Sulphur Creek, Sulphur Creek tributaries, Harley Gulch, fig.2), as well as indicating where MeHg contents are high and targeting those areas for offset projects (again, if the permit requirements target MeHg-content reductions). The considerable uncertainty in MeHg content at particular sampling sites is also evident. Subsequently, these results can be used as inputs to the Bayesian probabilistic framework. We note that the regression equation does not address other factors affecting total MeHg content in water, such as demethylation processes (Marvin-Dipasquale et al., 2000).[7]

The difference between predicted and observed MeHg contents at various sampling sites in the Cache Creek watershed in the linear regression model are plotted in figure 7. Two observations can be gained from such a plot. The observed MeHg contents in most of the samples from the North Fork at Highway 20 are overpredicted suggesting a seasonal effect. Newly flooded impoundments are known to increase the methylation rates, but Indian Valley Reservoir (at the headwaters of the North Fork) has been in operation since 1975 and should therefore act as an environment for decreasing MeHg contents (Domagalski, written commun., 2004). In contrast, the observed MeHg contents in the samples from Upper Bear Creek are underpredicted, suggesting an unmeasured "sulfate effect." MeHg contents are expected to be higher at Rumsey than at Clear Lake because of runoff from geothermal sources and because of naturally occurring Hg in upstream soils (Domagalski et al., 2004). Although these effects were not statistically significant in the regression model, the plots in figures 6 and 7 suggest the importance of these effects and may be used to direct additional sampling in the future.

[7] See app. D for summary statistics of the MeHg submodel

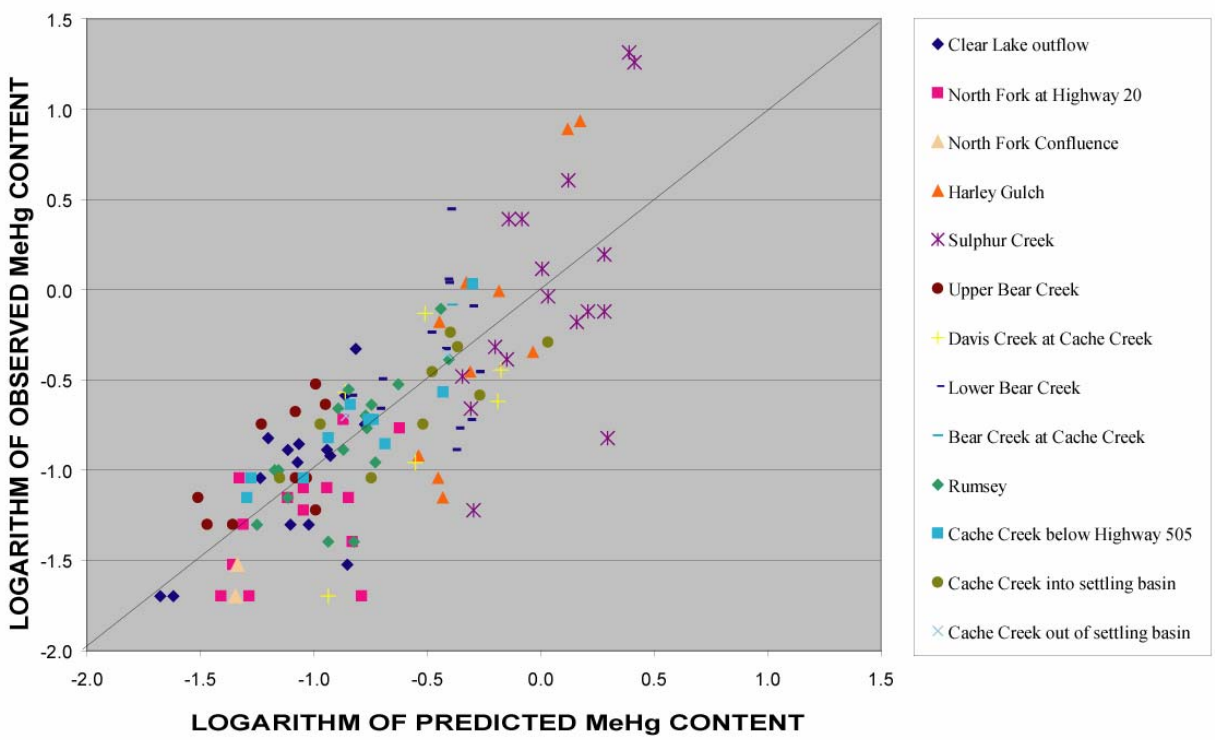

Figure 7. Logarithms. The diagonal line is used to illustrate which observed samples are over and under-predicted from the regression equation. Samples above the line are under-predicted and those below the line are over-predicted.

Though equation 2 may provide suitable results for the Cache Creek watershed, the terms used in the equation may not necessarily provide suitable predictive power for other watersheds, within the Sacramento River basin or elsewhere, because of uncertainties in the factors promoting methylation and demethylation. Further testing of the regression model will be conducted after additional data have been collected (see app. E).

Cost-Mitigation Submodel

The cost-mitigation submodel uses a multivariate-regression approach to predict a remediation cost based on environmental and locational attributes and a series of fixed-effect variables to help wastewater treatment plants decide whether offsets are cost effective, and whether a financial incentive of implementing an offset exists. For example, remediation costs could be minimized by cleaning up mine tailings instead of building a new treatment plant or installing tertiary controls.[8] Total offset costs are composed of remediation costs and transaction costs: remediation costs include capital (investments in plant and equipment) and operating costs (regular and periodic expenditures on labor and materials) and generally are estimated through standard engineering procedures; transaction costs include time searching for offset partners, bargaining and negotiating, administrative costs, and liability costs (costs to gain liability protection for mine remediation).

An alternative approach for estimating remediation costs is to use statistical methods, similar to how mining costs have been estimated (Singer et al., 1998). Several different potential offset-remediation projects (e.g., abandoned mines, best management practices) may be undertaken with different costs (Wood, 2003) Because hundreds of potential remedial solutions for Hg control exist, a simple and consistent approach could be used to estimate the expected total cost for each of these potential controls without spending large amounts of time and money. In our empirical approach, transaction costs are estimated on the basis of a literature review of liability issues.

Remediation Costs

Engineering cost estimates are typically made through methodical steps based on standard engineering practice. Project costs are site specific. Site variables commonly include type of contaminant, type of remediation technology selected, size of affected area, characteristics of the contaminants, and required cleanup standards (Federal Remediation Technologies Roundtables, 1998). Costs are estimated on the basis of various worksheets under such categories as source control, active treatment, passive treatment, general treatment and polishing, and discharge methods (Tetra Tech, Inc., 2000). Costs are generally broken down into capital (one-time costs typically occurring at the beginning of a project: construction, equipment, and installation) and operating costs (recurring costs: costs associated with doing the work necessary to maintain required remediation levels, labor, etc.). Use of these worksheets, though consistently practices by engineers, is time and resource intensive. For selecting an Hg-offset program, these approaches would have substantial upfront costs requiring estimation for hundreds of various sites.

One example of such an evaluation is the Engineering Evaluation and Cost Analysis (EE/CA) for remediation of Hg associated with multiple abandoned mines and geothermal springs within the Sulphur Creek

[8] These are only hypothetical examples of what WWTP could do; however, it is not known for certain what the WWTP would have to do, if anything, in order to meet current or future discharge permit requirements.

Mining District, a subbasin of the Cache Creek watershed (Tetra Tech, Inc., 2003). The purpose of the EE/CA is to present a detailed analysis of remediation alternatives that regulatory agencies and the scientific community can use for decision-making. Although the EE/CA provides a comprehensive assessment of specific engineering controls and mine-remediation alternatives, the process was time and resource intensive (~2 years). In addition, the actual remediation decisions that are made under the recommendations of the engineering analysis may take additional time and resources. Under this EE/CA, the selection of the appropriate remediation alternative(s) for mines throughout the entire Sulphur Creek Mining District depended on six different categories subject to three phases of screening and evaluation (Churchill and Clinkenbeard, 2003; Tetra Tech, Inc., 2003). This process itself may prevent decisionmakers from identifying and selecting the solution in a timely manner. Given the nature of TMDL analyses, permit requirements, and budget limitations, decisions need to be swift and expeditious.

A regional multivariate-regression model can provide decisionmakers with an initial indication of what a mitigation project may cost on the basis of the physical and locational attributes of existing projects. Once a group of projects are identified as being possibly cost effective, a refined EE/CA could then be performed for a few selected sites. Quantitative attribute data collected include total cost, total soil volume treated/collected (in cubic yards), and elevation (in feet) of the site; qualitative data include ownership of the property (private or public), location in California or not, project area containing acid mine drainage or not, high or low slope of the remediation area, and type of mineral deposit in the remediation area (e.g., silica-carbonate Hg, epithermal gold, gold, porphyry copper, massive sulfide, industrial).

A national database was developed, primarily of mine sites, for this regression to provide as large a dataset as possible (see app. F). Numerous project managers from local, State, and Federal agencies provided cost and attribute data for various past, current, and proposed projects. In addition, data were collected from the EPA's Superfund database. Results are based on currently available data.[9] A subsidiary USGS report (Wood, 2003) describes how the database was developed and how the remediation-cost estimates were normalized into same-year costs. These results show that the following three variables were significant: porphyry copper (PoCu) (a type of mineral deposit), whether the site is in California (CA) or not, and the logarithm of volume in cubic yards (VolCY L10). The coefficient of determination, r^2, is 0.76. About 76% of the variation in total costs can be explained by the three-variable regression equation. The cost mitigation submodel produced the following

[9] Linear-regression analysis was conducted by using S-plus software.

equation based on 30 data points (see app. G):

$$\mathbf{y = 5.05 + 0.77PoCu - 0.62CA + 0.39VolCY\ L10} \qquad \mathbf{(3)}$$

All the independent variables in equation 3 were significant at the p = 0.05 (95%-confidence) level where y is the predicted total cost (logarithm) for any type of remediation project.[10] This empirical approach can provide decisionmakers with a screening tool to identify potential cost-effective mitigation scenarios by using the coefficients to estimate a dollar cost.

Testing the Cost Mitigation Submodel

Although the cost mitigation submodel was developed from a national database that included variables which may not be relevant on a regional and (or) local scale, these cost estimates are tested against those in Tetra Tech, Inc.'s (2003) EE/CA report for the Sulphur Creek Mining District. The attribute inputs -- offset project site, total volume (in cubic yards) of mine waste mitigated, location of offset project site, and deposit type – are listed in table 1, and the USGS and Tetra Tech, Inc. cost estimates based on these input values are listed in table 2[11] (Tetra Tech, Inc., 2003, table 9-11). The cost estimates for these sites are based on the selected mitigation strategy and waste medium at each site. The linear-regression total-cost outputs are listed in table 2 along with Tetra Tech, Inc.'s cost estimates and the differences between the two estimates. The USGS regression-cost model is compared with Tetra Tech, Inc.'s engineering estimates in figure 8. Appendix H verifies that the cost mitigation submodel passes all the requirements of linear regression models.

Table 1. Environmental and Locational Attributes

Vol. CY = volume in cubic yards, CA = California,

Table 2. Total-Cost Estimates

USGS = U.S. Geological Survey,

[10] We note that the development of this submodel is on going. The analysis depends on the availability and accuracy of the data attributes. Updating the database may cause some attributes to be added to or dropped from equation 3.

[11] Only final mitigation strategy cost estimates were used for this example. Transaction costs are omitted in this comparison because Tetra Tech, Inc. cost estimates are based strictly on remediation engineering controls. However, the decisionmaker, a point source, can substitute their own assumptions about the transaction costs using their own risk preferences and applying percentages or specific values that they believe are fair for specific cost runs.

PoCu= porphyry copper

Offset Site	Vol. CY	Logarithm of Vol. CY	CA	PoCu
Abbott	174,022	5.241	1	0
Turkey Run	13,424	4.128	1	0
Wide Awake	10,014	4.001	1	0
Elgin	4,227	3.626	1	0
West End	3,722	3.571	1	0
Cherry Hill	811	2.909	1	0
Central	166	2.220	1	0
Manzanita	150	2.176	1	0
Rathburn	6,546	3.816	1	0
Rathburn-Petray	95,896	4.982	1	0
Petray-North	4,980	3.697	1	0
Petray-South	400	2.602	1	0

RPD = Relative Percent Difference[12]

Offset Project	Logarithm of Cost Estimates		
Site Name	USGS	Tetra Tech	RPD
Abbott	6.47	6.69	-3.29
Turkey Run	6.04	5.96	1.36
Wide Awake	5.99	6.01	-0.28
Elgin	5.84	5.79	0.91
West End	5.82	5.58	4.18
Cherry Hill	5.57	5.30	4.90
Central	5.30	5.47	-3.30
Manzanita	5.28	5.55	-5.08
Rathburn	5.92	5.56	6.18
Rathburn-Petray	6.37	6.46	-1.41
Petray-North	5.87	5.69	3.13
Petray-South	5.45	5.19	4.77

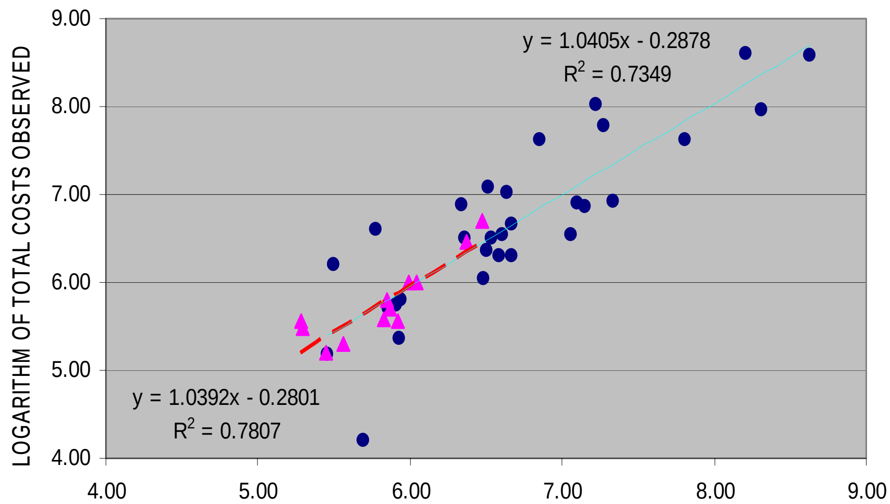

Figure 8. Comparison of USGS remediation-cost linear-regression model with engineering estimates by Tetra Tech, Inc. (2003). Dots, observed data used in developing regression model; triangles, Tetra Tech, Inc.'s cost estimates. Data points lie along a slope of 1.04, similar to slope in original cost model. Red dashed trendline, USGS model predictions with Tetra Tech, Inc. attribute data; blue trendline, regression-model predictions for same samples.

This type of regression model is a simple and consistent approach that can estimate an expected total cost for various Hg controls without spending large amounts of time and money. In addition, the analysis

[12] An explanation of relative percent difference (RPD) is provided in Table D2.

reflects the uncertainty in remediation-project costs, on the basis of the information that we currently have. A reduction in uncertainty could be achieved with site-specific and project-specific cost estimates made by a contractor, but accessing such information is difficult, and so the spread of the cost estimates cited reflects our current uncertainty. Research will continue to refine this cost-mitigation submodel.

Transaction Costs

Transaction costs are considered to be the additional costs of implementing an offset project beyond the direct remediation costs. Identifying potential offset locations/projects, negotiating a project with regulators and the public, monitoring water quality, and using government or private administration all contribute to transaction costs, which could negate the potential cost savings from making offsets between sources with different marginal costs.

Transaction costs include:

- **Search and information costs,** including the time, effort, and cost to gather environmental data in order to determine which offset sites will meet a point source's required loading reduction.
- **Bargaining, negotiation, and approval costs,** including costs to gain regulatory approval through bargaining and negotiating with a non-point source (if not abandoned) and the regulatory body, receiving credit for the offset, and future liability costs.
- **Contingent costs** that might or might not be incurred at some point in the future, including potential liability costs due to remediating unknown or future releases of pollutants and compensating for undiscovered or future damage to property or people.

Transaction costs are the additional costs (beyond the remediation costs) imposed on a point source when making an offset decision. Administrative and data gathering costs can vary, depending on the availability and accessibility of information. A data clearinghouse can help reduce these types of costs by providing information for a point source to distinguish which locations contain suitable offset projects. Bargaining and negotiation costs depend on whether certain negotiation mechanisms are in place. Establishing reconciliation periods, banking-offset credits, and credit agreements all incur a cost. Setting up an approach like the one described here could reduce such costs to help facilitate discussion between stakeholders. Assuming that a data clearinghouse and this approach are in place, both types of cost can be limited.

Contingent costs arise from potential liability lawsuits when unilateral remediation action at a particular site is committed for an offset and contamination resurfaces in the future. Under the current CWA, a "Good Samaritan," e.g., a wastewater-treatment plant that wants to clean up a site is not protected from liability if more discharges occur after the cleanup work is completed. Other legal issues include antibacksliding rules (CWA), the extent to which regulations authorize new or renewed permits, and potential liability post remediation (Wilson, 2001).

An offset program must do more than substitute one contributing source for another because Federal law prohibits new discharges from contributing to violations of water quality standards. The antibacksliding rule draws on this distinction between new and existing sources by forbidding, unless certain exceptions are met, permits to be renewed or modified "to contain effluent limitations which are less stringent than the comparable effluent limitations in the previous permit except in compliance with section 1313(d)(4) of this title" (CWA 33 U.S.C.   1342 (o)). The application of antibacksliding rules could have significant consequences in terms of permissibility of offsets because, in theory, offsets provide dischargers with flexibility in lieu of the application of an otherwise-stringent effluent limitation. Furthermore, provisions must be consistent with the CWA, such as developing baselines for offsets derived from TMDLs, not accepting pollutant-reduction credits that would cause a localized impairment, requiring that NPDES permits describe how baselines or limits for offsets will meet water-quality standards, etc. (U.S. Environmental Protection Agency, 2002). A more in depth look at contingent liabilities regarding offsets is documented in appendix I.

Framework for a Bayesian Network Decision Support System

These three submodels will be integrated into a DSS to evaluate various Hg-mitigation scenarios, using the same stream segment scheme proposed by the Cache Creek TMDL working group (Central Valley Regional Water Quality Control Board, 2004). The Bayesian network DSS (BN-DSS) user is expected to evaluate potential Hg-offset projects in terms of changes in HgT load, MeHg-production potential, project cost, and other suitability criteria. For this application, the primary user would be a wastewater-treatment plant evaluating various mitigation scenarios to see whether any projects meet their environmental and economic needs. Whereas the amount of HgT that is discharged from a wastewater-treatment plant may be well characterized, the predicted downstream impact of an Hg-offset program is highly uncertain in terms of response magnitude and timing. For this specific situation, the SRCSD has created no “harm” that requires mitigation (the Sacramento Regional Wastewater Treatment Plant has never exceeded its permit limit for Hg), however, if an offset does occur in the future, mitigation of Hg loadings would take place. The BN-DSS is structured around these various submodels, allowing predictions of the downstream impacts of HgT loading reductions from Hg-offset programs. This model takes a watershed- scale perspective for the purpose of project evaluations.

The BN-DSS integrates the available relevant water quality and streamflow data into the various submodels using the same stream segment scheme proposed by the Cache Creek TMDL working group (Central Valley Regional Water Quality Control Board, 2004). The model links HgT loadings by stream segment to within-segment and downstream MeHg contents in water and fish tissue on the basis of conditional probabilistic relation from stochastic empirical models of the available data. The data and the basis for many of the empirical relations used come from the Cache Creek TMDL report and its appendices (Central Valley Regional Water Quality Control Board, 2004). Watershed-data scarcity can be dealt with by using a Bayesian hierarchical model that incorporates relevant data from other watersheds. If watershed-specific data are too sparse to build an empirical model and a Bayesian hierarchical model is inappropriate, expert judgment can be used to elicit conditional-probabilistic relations between the needed variables. Well-studied practical methods for probability-distribution elicitations exist that have been used extensively in various fields (Howard and Matheson, 1984; Morgan and Henrion, 1990).

A BN-DSS is designed by first identifying the desired environmental *end points* (performance measures or decision values) of interest to stakeholders and decisionmakers. These end points reflect the values at stake in the offset decision. Examples of end points in an offset-implementation project include mitigation costs, annual Hg-load reduction, and Hg contents in fish. After end points are identified, the next step is to identify relevant *management options* (potential offset-mitigation decisions), such as percent reduction in Hg loading. The Bayesian network model is designed to reflect the significant relations between end points of interest and management options via *intermediate nodes*, which are the variables necessary for predicting the impacts of management options on the end points of interest (Labiosa 2003). These models incorporate the uncertain relations between Hg loading, MeHg formation, and MeHg bioaccumulation.

From a decision-analytical 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).

Influence diagrams allow determinations of optimal decisions, sensitivity of an optimal decision to key uncertainties and assumptions, and value of information on uncertainties, which may then be used to plan future information gathering activities. A simplified influence diagram for Hg-offset decisionmaking is shown in figure 9. Sensitivity analysis can be performed to explore the relations between key uncertainties and variables of interest, allowing the decisionmakers to explore “what-if” scenarios of interest.

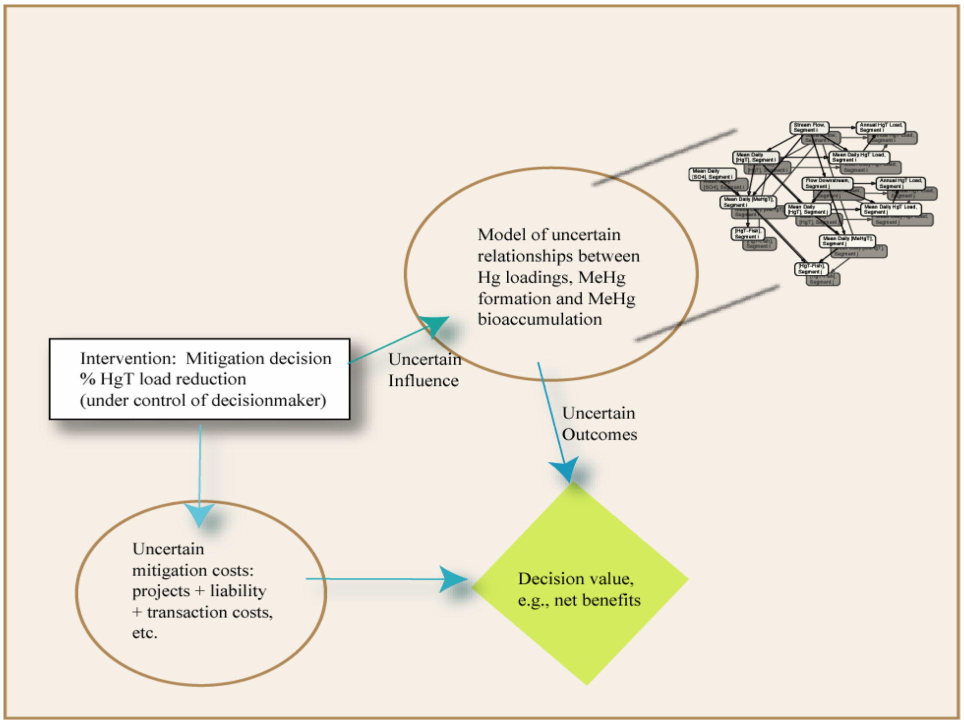

Figure 9. Example of an Hg-Offset Influence Diagram

Such an influence diagram can be used throughout the offset-mitigation decisionmaking process. The influence diagram is particularly important in determining information and modeling/forecasting needs because it helps decisionmakers and technical experts/scientists communicate about what information is important in terms of the decisions to be made. In addition to graphically representing important aspects of the decisionmaking 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 (Labiosa, 2003).

Decisionmaking related to offset scenarios requires making predictions relevant to evaluating strategies for mitigating Hg sources. The relevant predictions are, however, highly uncertain, whether owing to incomplete understanding of natural processes, analytical error, or the stochastic variation inherent in natural systems. Uncertainty is a reality that any water-quality-management decision framework must explicitly recognize, assess, and, when possible, reduce (National Research Council, 2001). Because a Bayesian network is built upon the conditional-probabilistic relations between random variables, uncertainty is explicitly represented in these models, and the propagation of uncertainty is straightforward. We emphasize that although an influence diagram is an imperfect representation of the natural system, it should faithfully represent how the decisionmaker *believes* the natural system will behave, given the available data and current scientific understanding.

IV. FUTURE RESEARCH

A Bayesian Network Decision-Support System for Evaluating Mercury-Offset Programs

The major focus of the second phase of this project will consist of finishing the HgT-loading model, integrating it with the empirical MeHg model described above, and implementing the BN-DSS for offset-project decisionmaking in the Cache Creek watershed (figs. 1, 2). With this extension, the Bayesian network model will be able to predict MeHg contents in water, invertebrates, and fish, on the basis of an empirical approach relating model relating HgT loads to MeHg contents, as described by Slotton et al. (2004). This model would propagate the substantial uncertainties in the relations between HgT loading and MeHg production and bioaccumulation, allowing probabilistic predictions about the impacts of HgT-load reductions on future MeHg contents in water and biota.

The ability of a Bayesian network to propagate uncertainty between variables allows the user to predict, for example, the degree of uncertainty in the downstream effects from local mitigation efforts. This uncertainty may include contributions from initial mass-load reduction uncertainty, rainfall/streamflow uncertainty, and the relations between local and downstream effects: local streamflow and HgT mass loads, HgT concentrations and MeHg concentrations, and between MeHg concentrations and ecological impacts, etc.

For illustration purposes, the results of what a mitigation scenario might look like in a BN-DSS are listed in table 3. Each project will have predicted local water quality and ecologic impacts, predicted downstream water quality and ecologic impacts, and many associated attributes relevant to project desirability, including cost effectiveness, technical feasibility, legal liability, etc. The BN-DSS will make predictions relevant to these selection criteria, including predictions relevant to local and downstream HgT mass load reductions, local and downstream MeHg concentration reductions, probabilities of meeting environmental targets locally and downstream (e.g., mass-load-reduction targets, median MeHg contents, and Hg content in fish tissue).

Table 3. Hypothetical example of a Cache Creek Hg-Offset Project Evaluation Using a BN DSS

Offset Mitigation Project	Project Location	% HgT Source Load Reduction[1]	HgT Load Downstream, g/day (Std Dev)[2]	Annual HgT Load, kg/yr (Std Dev)[3]	Cost, K$ (Std Dev)	Cost Effectiveness, $K/unit reduction (lower is more cost-effective)	Technical Feasibility Score[4] (1 (Best) – 5 (Worst)
1	Status quo	No reductions	32 (1,120)	85 (408)	0 (0)	NA	NA
2	Cache Creek settling basin	50%	30 (1,120)	83 (408)	350 (25)	117	2
3	Abbott-Turkey Run Mine	75%	32 (1,120)	85 (408)	200 (30)	1920	4

Notes: 1) Targeted % HgT load reduction from stream segment source (Std Dev)
2) Predicted median % HgT load reduction at Rumsey (Std Dev)
3) Predicted resulting annual HgT load reduction in kg/year at Rumsey (Std Dev)
4) Composite score from 1 (Best) – 5 (Worst), based on site access and "workability," state of science for chosen mitigation approach, state of experience with chosen mitigation approach, ease of project startup, and expected level of effort for operations and maintenance (O&M) and monitoring

From those various decision variables, a wastewater-treatment plant can decide which projects meet their permit requirements based on their risk preferences. Various methods exist for a wastewater treatment plant to organize their decisions for evaluating various offset scenarios and choices made to reflect the wishes of the decisionmaker. Implementation of an offset program may not even be realistic. Therefore, the question then becomes, is it cost effective for a wastewater-treatment plant to invest in more information for future offset decisions, or instead, resort to earlier regulatory approaches and update their own operations?

If the decisionmakers are willing to work with decision analysts in structuring the decisionmaking problem, eliciting probabilities for the various uncertainties faced by the decisionmakers, and eliciting preferences over possible outcomes/consequences, then decision analysis can be used to determine best decisions, decision robustness, and information value. A hypothetical decision diagram illustrates the relationships between decisions (possible future actions), key uncertainties faced by decisionmakers (conditional-probability distributions representing uncertain future states), and the value of the project (project construction and operation/maintenance costs, liabilities, project benefits from reduced Hg fish tissue burdens, etc.). This decision diagram is simplified for illustration purposes, and we make no claim that the wastewater-treatment plant would agree that it accurately represents their decision.

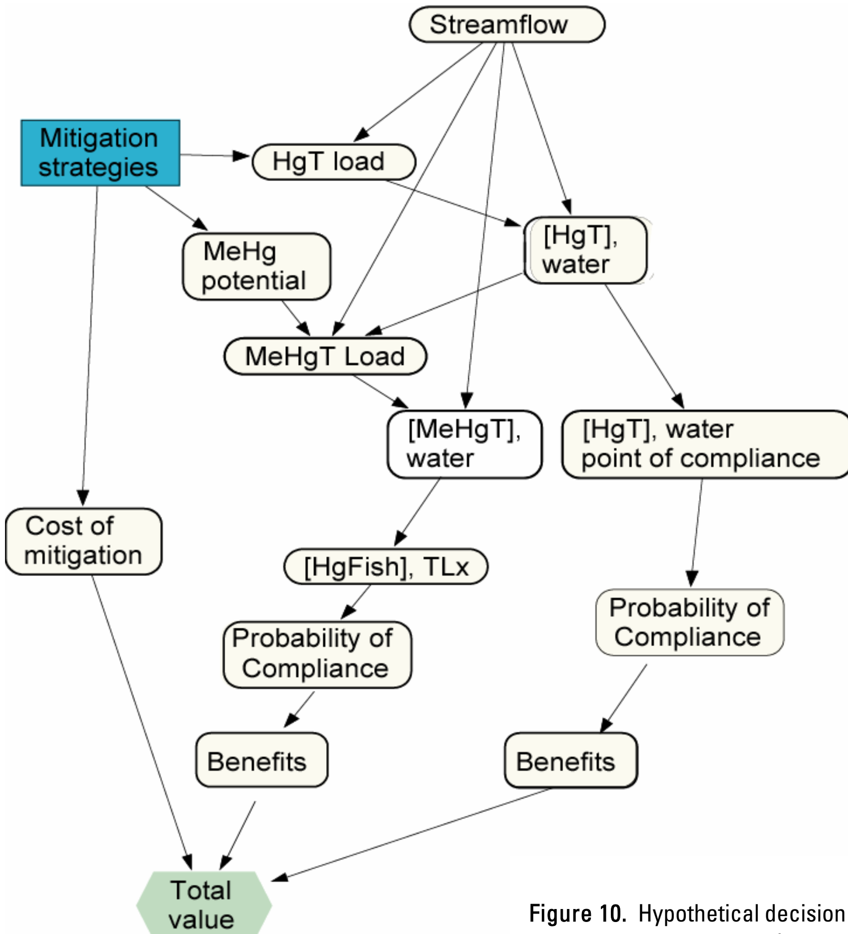

Figure 10. Hypothetical decision diagram for Hg-offset project by a wastewater treatment plant

However, if a collaborative process were set up with a wastewater treatment plant, a suitable decision diagram could be created and the necessary information could be elicited to create a working decision model. In figure 10, the selected offset program may influence local HgT loading (HgT load) and/or MeHg formation potential (MeHg potential), which would have an uncertain impact on local water quality ([HgT], water and [MeHgT], water). The uncertain downstream effects due to changes in upstream inputs are modeled as the HgT content at a point of compliance ([HgT, water, point of compliance) and the HgT content in fish of a particular trophic level ([HgFish], TLx); (further impacts on MeHg content, etc., could also be modeled) and has an uncertain associated total project cost (cost of mitigation). The total value of the project (Total Value) is modeled as the project's net benefits, but this is only one consideration; projects could be valued in any manner desired by the decisionmaker. Decision analysis is especially flexible in this regard.

An application of decision analysis for offset-program selection would be an extension of current practice in decision analysis, because Bayesian network models would be used to generate some of the needed probabilities that describe the behavior of the natural system. Such an integrated decision model should prove to be useful for project selection decisions of the sort faced by the wastewater treatment plants. A partly hypothetical decision model will be developed to illustrate and explore the approach from a research perspective.

Finally, an approach that could be developed in support of the BN-DSS that is also based on decision analysis is using decision trees to determine best strategies, to perform sensitivity analysis, and to rank uncertainties in terms of information value. The relevant uncertainties and value measures in the draft decision trees come from the wastewater treatment plant's working-group meeting process. For this approach to be directly useful to a wastewater treatment plant, it would have to be modified to reflect the decisionmakers' beliefs about uncertainties and values. We recognize that the wastewater treatment plant may be unable to collaborate to the needed degree, and so this tool will *at least* demonstrate how decision analysis could be performed for suggesting best decisions of this sort. Note that the first tool, the watershed Hg-loading model, can be used to estimate probabilities for Hg loading baselines and future environmental impacts of Hg-load reductions for use in the decision trees in this offset-project decision analysis. Note also that this approach is an extension of current decision-analytical applications, because it uses a Bayesian network to generate the "science-informed" probability distributions needed for performing decision analysis involving complex natural systems.

We conclude this section with a brief description of the concept of information values, which can be used to prioritize information gathering/modeling activities.

Information Value

New information may change a decisionmaker's beliefs about the uncertainties relevant to the decisionmaking problem. Information value refers to the fact that improvements in the state of information could lead to a change in the prescribed optimal policy under relevant scenarios (Labiosa, 2003). It is precisely the potential for changing the optimal policy that generates economic value (see Howard, 1968; Lawrence, 1999). Thus, new information may or may not have value within the context of the decisionmaking process.

The benefits of additional watershed information are computed by comparing the economic impacts of decisions that would be made by using the new watershed information relative to decisions based on existing watershed data.

This analysis may conclude that a particular uncertainty has a high associated information value and that it may be in the decisionmaker's best interest to collect further information or to make better use of existing information through modeling, analysis, or consultation with experts (Arrow and Fisher, 1974). For instance, real option theory (ROT), relating to investment decisions under uncertainty, explains that when facing irreversibility and uncertainty, delaying the investment and waiting for information may be advisable to avoid the downside risk (Kolstad, 1996). Information value analysis may also demonstrate that, even though a particular variable is highly uncertain, reduction of that uncertainty will not have much (or any) decision value. Insights of this sort should prove particularly useful in Hg-offset programs. The concept of information value is related to the concept of "decision robustness." If a best decision strategy is highly robust, then additional information would be predicted not to change that strategy (Morgan and Henrion, 1990).

V. SUMMARY

This interim report describes the development of a decision analytical approach to decision support for Hg-offset programs. The proposed empirical model makes use of a Bayesian network, which treats uncertainty as a probability and allows the decisionmaker to combine various types of information with the best available scientific models, data, and expert judgments into a unified probabilistic framework. In practice, empirical models and expert judgment are a straightforward means of creating the needed probabilistic relations. Although the uncertainty analyses of mechanistic models can be used for this purpose, the computation burden is excessive. Therefore, given the lack of detailed understanding of Hg environmental behavior, empirical models are justifiable.

The key hypothesis is whether a probabilistic approach explicitly incorporating scientific uncertainty, cost information, and value judgments is applicable. Future research directions will focus on the application of this approach through a BN-DSS to support Hg-offset decisionmaking by a wastewater treatment plant in evaluating potential Hg-mitigation projects in terms of changes in HgT load, MeHg-production potential, project cost, and other suitability criteria. Subsequently, scenarios can be analyzed through decision-analytical models by performing sensitivity analyses and ranking environmental and economic uncertainties in terms of the decisionmakers' preferences and risk choices. A wastewater treatment plant may decide that the offset-mitigation scenarios proposed will not meet their environmental and economic needs. If scenarios lead to such a decision, then a study will be conducted analyzing the level of environmental and economic information needed to encourage an Hg-offset program.

This research seeks to innovatively analyze available science, data, and statistics in a manner maximally applicable within a stakeholder framework. In addition, the research might provide alternative statistical methods for TMDL and water-quality analyses, providing a more accurate and better representation of environmental water-quality conditions.

APPENDIX A

Environmental Concerns for Mercury Offsets

The EPA published a Water Quality Trading Policy on January 13, 2003. Four environmental-advocacy organizations (American Rivers, the National Wildlife Federation, the Natural Resources Defense Council, and the Sierra Club) provided comments to that policy document on March 14, 2003. Members of the national environmental community strongly opposed the inclusion of toxics trading in the policy, even in such relatively limited circumstances. Environmentalists argued that trades are likely to lead to the creation of hotspots, areas of aquatic toxicity, that severely threaten human health and aquatic life. Such localized concentrations of pollutants could result in fish kills, contamination, and adverse human exposure. Participation from local environmental-advocacy groups at various local and regional stakeholder meetings has been limited.

Although these concerns are valid from environmentalists, the environmental conditions in the Sacramento River watershed reduce the potential of hotspots occurring from offset projects. The Hg contents in SRCSD's effluent and in the Sacramento River are far below levels at which aquatic toxicity from Hg has been observed. All wastewater dischargers in the watershed combined add up to less than 2% of the annual HgT load to the San Francisco Bay-Delta. As a result of low point-source discharge levels, offsets would not cause an exceedance of criteria.

Offsets are a potentially useful mechanism for trying a remediation option in the short term and improving the environment in the long term. As a result of Hg's serious threat as well as the severe limitation of remediation funds, offsets may serve as a suitable tool to meet water-quality objectives cost effectively. The "pilot" nature of this effort provides a mechanism for attempting remediation even though results cannot be assured (until someone attempts remediation and monitors its effectiveness). Although local and regional responses from environmental-advocacy groups have been absent, the offset working-group meetings conducted by the SRCSD have been essential in identifying most of the stakeholders' interests for assessing the feasibility of offsets for meeting Hg-discharge-permit requirements and ancillary concerns.

APPENDIX B

Background on Bayesian Probabilistic Networks

Bayesian network models are probabilistic representations of a system of related variables of interest (Shachter, 1986, 1988; Pearl et al., 1990; Jensen, 2001), e.g., variables representing a water-quality-management problem (Varis, 1995; Reckhow, 1999; Borsuk et al., 2002). Although non causal models are common, the Bayesian network models described in this report are assumed to be structured in terms of causal relations between the random variables that describe environmental end points of interest. These relations are identified and quantified by using historical data, physical process-based models, other conceptual models, and expert judgment. Bayesian network models are probabilistic and are based on a coherent set of beliefs about the relations between system variables, in contrast to deterministic approaches that model system behavior on the basis of mathematical representations of underlying mechanisms and on empirical deterministic approaches that ignore uncertainty. Bayesian network models do not ignore scientific knowledge about system mechanisms and behavior, but instead, represent this knowledge in terms of causal relations between random variables and conditional probabilities that describe these cause and effect relationships.

In the Bayesian network model of the Cache Creek Hg-offset project, causal relations and conditional probabilities are based on what is currently known about the relations between HgT loading, MeHg loading, Hg fish-tissue burdens, and other natural-system variables. The model is a probabilistic representation of what is currently known about how mitigation efforts may impact the natural system.

This approach takes advantage of the specific modularity of a problem domain, greatly simplifying the computational requirements for making predictions and inferences based on the conditional probabilistic relations between the system's variables (Chen, 2001, p. 215). These relations can be quantified in a modular fashion suitable to the type and amount of information available, allowing various types of probabilistic information (from data, models, and expert judgment) to be integrated into a single model that can be used for various purposes useful to decisionmaking.

A Bayesian network consists of a graph and probabilistic data associated with the nodes in the graph. The graph consists of nodes (ovals) connected by arrows, where the ovals represent chance (uncertain) nodes, each of which is associated with a random variable. The random variables in the Bayesian network represent the attributes of interest to decisionmakers. Arrows represent potential conditional-probabilistic dependence between the various random variables and can be drawn in a causal direction. Graphically, an arrow from a parent node to an uncertain variable (child) means that the probability distribution in the uncertain variable (child) is conditioned by the state of the parent node. The absence of an arrow between two variables in a network indicates that these variables are conditionally independent given their parents (Labiosa, 2003).

The variables included in a Bayesian network may be included for various reasons, including the decisionmaker's direct interest in the state of a variable or the variable's usefulness in interpreting or predicting variables of direct interest. Importantly, 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 decisionmakers or stakeholders, etc. (Shachter, 1988; Pearl et al., 1990). One way to understand the difference between "technical variables" needed for modeling purposes only and "variables of interest" at the decisionmaking level is to think in terms of a "submodel level" and "model level." At the submodel level, one or more variables in the submodel are of interest at the model level, but the remaining technical variables are needed only for modeling purposes. These technical variables are explicitly included at the submodel level for determining the conditional-probability distributions for the variables of interest at the model level. Once the conditional-probability distributions for the variables of interest at the model level have been determined, the technical variables are probabilistically *absorbed* (i.e., their uncertainty is transferred to the remaining model-level variables). After the technical variables have been probabilistically absorbed, only the variables of interest at the decisionmaking model level remain.

APPENDIX C

Statistical Analyses for Water-Quality Management

The objective of statistical analysis is to predict some response, such as in Hg content, given a set of variables. A common procedure, multiple linear regression, is used to model the relation among variables. The method requires a dataset that includes the independent variables and associated values of the dependent variable. Multiple linear regression requires on assumption of normally distributed errors and a linear relation among the variables, or one that can be linearized such transformations as logarithms. Thus, the functional form is assumed to be linear and is imposed on the data—the outcome is assumed to be related to a linear combination of the independent variables. An advantage of linear regression is that it allows the testing of individual coefficients for statistical significance. Large deviations from normality, nonlinearity, or multimodal distributions, however, cause this and related methods to fail.

Artificial neural networks, which have been used for various applications that are commonly thought of as statistical, compose a group of methods, originally motivated by models of the human brain, that can be used for classification (binary or multiple class), auto association (noise reduction), and function approximation (prediction) (Warner and Misra, 1996). Neural networks can typically handle highly complex distributions and can approximate any continuous function. The network stores the weights of the inter-neuronal connections that are acquired from the training data. Neural networks do not allow the testing of individual coefficients for statistical significance, and the functional form is not known. Neural networks are most useful where the functional form of the relations is unknown and deeply hidden, where interactions occur among the variables, and where the data are subject to large errors. Neural networks determine the relations among variables from the data with which they are trained, and so they typically require considerable amounts of data (Masters, 1993, 1995).

On the basis of this research, statistical analysis was undertaken to investigate whether neural networks were appropriate for predicting MeHg contents in water. Although the analysis provided interesting results, the data were insufficient to train a credible neural network, and the available data tended to have inconsistent numbers of variables and missing fields. However, additional studies (not presented here) showed that neural networks are credible predictors of empirical functions when the data requirement is met. As more data become available, neural networks can be tested once again with chemical variables.

Another statistical method is useful when data are sparse and yet expert information is available to help in making predictions. Classical inferential models do not permit the introduction of previous knowledge into the estimation. At times, the use of previous knowledge would be a useful contribution to the evaluation process. Bayesian networks can be used to integrate information from experts and observations to construct a simple model and represent uncertainty in our knowledge. The uncertainty comes from the experts themselves concerning their own knowledge, inherent uncertainty in the subject being modeled, uncertainty in translation of the knowledge, and uncertainty about the accuracy and availability of knowledge. Relations can be defined by using data and expert judgment. Bayesian networks use probability theory to manage uncertainty by explicitly representing the conditional dependencies, enabling an intuitive graphical visualization of the knowledge including the interactions among the various sources of uncertainty. Bayesian networks provide an integrated approach to uncertainty analysis and allow easy updating of prediction and inference when observations of model variables are made. This approach allows new information to be integrated as it becomes available and the graphical representation of a Bayesian network shows the relations among variables in a manner that eases the communication, as well as providing a means to update initial probabilities and beliefs as more data are gathered.

Problems exist, however, when developing a Bayesian network. The first problem is the computational difficulty of exploring a previously unknown network. To calculate the probability of any branch of the network, all branches must be calculated. Although the resulting ability to describe the network can be performed in linear time, this process of network discovery is difficult and possibly costly to perform, or even impossible given the number and combination of variables. The second problem is the quality and extent of previous beliefs used in Bayesian inference processing. A Bayesian network is only as useful as this previous knowledge is reliable. Either an excessively optimistic or pessimistic expectation of the quality of these previous beliefs will distort the entire network and invalidate the results. Related to this concern is the selection of the statistical distribution induced in modeling the data. Selecting the proper distribution model to describe the data has a notable effect on the quality of the resulting network.

If the research situation involves a great deal of data representing all the variables of interest, then multiple linear regression or neural networks are good candidates as methods of analysis and prediction. If the functional form of the relation is known to be linear, or can be linearized, then multiple regression is preferred over neural networks because it is more parsimonious and easier to understand. Multiple linear regression performs well when theory or experience suggests an underlying linear relation among the variables, and it can deal with small datasets. A Bayesian network would be appropriate when data are sparse for some of the variables and experts have knowledge about the relations and likelihoods of events.

Uncertainty is a reality that any water-quality-management decision framework must explicitly recognize, assess, and, when possible, reduce (National Research Council, 2001). Although various deterministic and empirical models have been developed for Hg, the uncertainty of Hg scientific processes may produce large uncertainties in the decisionmaking process. As a result, the USGS' Western Geographic Science Center decided to focus its research efforts on the statistical models mentioned above. Uncertainty is explicitly represented in these models and is better incorporated in policy decisionmaking, in contrast to deterministic models that calculate Hg loads without explicitly quantifying the uncertainty at each segment of the watershed and that propagate the uncertainty in loading by combining or subtracting Hg loads for various watershed segments. When dealing with such skewed frequency distributions as Hg loads, the expected amount (and higher values) can be a fairly unlikely outcome. Being able to estimate the probabilities of different outcomes allows the decisionmaker to take appropriate actions. (For further information, contact Donald Singer at *singer@usgs.gov*).

APPENDIX D

Verification of the Methylmercury Submodel

Table D1. Summary of Predicted MeHg Contents of Sampling Site in the Cache Creek Watershed, north-central California [All values in nanograms per liter. NA, not available]

Study Site		*Mean*	*25% Percentile*	*Median*	*75% Percentile*	*Standard Error*	*No. of Samples*
1	Cache Creek at Lower Lake	0.11	0.08	0.11	0.14	0.01	22
2	North Fork Cache Creek at Hwy 20	0.13	0.07	0.11	0.15	0.02	27
3	South Fork Confluence	0.14	0.11	0.11	0.16	0.03	3
4	North Fork Confluence	0.14	0.08	0.17	0.18	0.03	6
5	Petrified Canyon	0.07	0.05	0.07	0.09	0.04	2
6	Rocky Creek	0.17	0.15	0.17	0.20	0.05	2
7	Harley Gulch	0.62	0.37	0.48	0.07	0.10	14
8	Stemple Creek	0.16	0.13	0.16	0.19	0.05	2
9	West Harley Gulch	2.10	0.64	0.88	1.72	0.91	10
10	Judge Davis Creek at Cache Creek	0.08	0.06	0.08	0.09	0.03	2
11	Brushy Creek at Cache Creek	0.05	NA	0.05	NA	0.00	1
12	East Harley Gulch	0.34	0.21	0.24	0.43	0.14	3
13	Sulphur Creek tributary	0.75	0.61	0.86	0.95	0.20	3
14	Sulphur Creek at Cache Creek	1.23	0.72	1.03	1.64	0.13	23
15	Upper Bear Creek	0.07	0.05	0.08	0.10	0.01	10
16	Trout Creek at Bear Creek	0.14	0.10	0.17	0.19	0.05	3
17	Jack Canyon at Cache Creek	0.13	NA	0.13	NA	0.00	1
18	Crack Canyon	0.12	0.08	0.11	0.16	0.05	3
19	Davis Creek at Cache Creek	0.28	0.12	0.21	0.31	0.08	9
20	Lower Bear Creek	0.36	0.32	0.38	0.43	0.03	13
21	Cache Creek before Bear Creek	0.28	0.15	0.24	0.27	0.06	14
22	Cache Creek and Bear Creek Confluence	0.36	0.23	0.37	0.46	0.03	18
23	Cache Creek at Rumsey	0.21	0.12	0.17	0.24	0.02	74
24	Capay	0.48	0.28	0.37	0.62	0.20	3
25	Cache Creek below Hwy 505	0.21	0.10	0.17	0.29	0.04	11
26	Road 102 at Cache Creek	0.46	0.29	0.48	0.62	0.05	24
27	Cache Creek into settling basin	0.38	0.18	0.33	0.43	0.10	9
28	Cache Creek out of settling basin	0.43	0.25	0.38	0.63	0.06	17

APPENDIX D cont.

Table D2. Logarithms (base 10) of observed and predicted MeHg contents at sampling sites in the Cache Creek Watershed, north central California, with relative percent difference and residual MeHg Predictions, L10 Observed MeHg Concentrations, RPD, and Residuals

[Relative percent difference (RPD) measures the precision between two values. Thus, an RPD of 5 or less between observed and predicted value indicated good precision. RPD is calculated by subtracting the observed from the predicted value, dividing the difference by the average of the two values, and multiplying the result by 100]

Sampling Site (number)	***MeHg content (ng/L)***		***Relative Percent Difference***	***Residual***
	Observed	***Predicted***		
Clear Lake outflow (1)	-0.89	-1.114	-22.8	0.23
Clear Lake outflow (1)	-1.30	-1.022	24.0	-0.28
Clear Lake outflow (1)	-0.92	-0.928	-0.8	0.01
Clear Lake outflow (1)	-0.96	-1.071	-11.0	0.11
Clear Lake outflow (1)	-0.82	-1.201	-37.2	0.38
Clear Lake outflow (1)	-0.33	-0.815	-85.3	0.49
Clear Lake outflow (1)	-0.74	-0.775	-3.9	0.03
Clear Lake outflow (1)	-1.52	-0.854	56.3	-0.67
Clear Lake outflow (1)	-1.70	-1.678	1.3	-0.02
Clear Lake outflow (1)	-1.70	-1.620	4.8	-0.08
Clear Lake outflow (1)	-1.30	-1.102	16.5	-0.20
Clear Lake outflow (1)	-1.05	-1.237	-16.7	0.19
Clear Lake outflow (1)	-0.85	-1.066	-22.1	0.21
Clear Lake outflow (1)	-0.59	-0.860	-38.1	0.28
Clear Lake Outflow (1)	-0.89	-0.943	-6.2	0.06
North Fork at Highway 20 (2)	-1.10	-1.046	4.8	-0.05
North Fork at Highway 20 (2)	-1.70	-1.284	27.8	-0.41
North Fork at Highway 20 (2)	-0.77	-0.622	21.3	-0.15
North Fork at Highway 20 (2)	-1.15	-1.114	3.6	-0.04
North Fork at Highway 20 (2)	-1.30	-1.310	-0.7	0.01
North Fork at Highway 20 (2)	-1.70	-0.790	73.0	-0.91
North Fork at Highway 20 (2)	-1.10	-0.943	15.1	-0.15
North Fork at Highway 20 (2)	-0.72	-0.870	-18.7	0.15
North Fork at Highway 20 (2)	-1.40	-0.830	51.0	-0.57
North Fork at Highway 20 (2)	-1.70	-1.409	18.7	-0.29
North Fork at Highway 20 (2)	-1.52	-1.357	11.6	-0.17
North Fork at Highway 20 (2)	-1.22	-1.046	15.5	-0.18
North Fork at Highway 20 (2)	-1.05	-1.328	-23.8	0.28
North Fork at Highway 20 (2)	-1.15	-0.848	30.7	-0.31
North Fork confluence (4)	-1.52	-1.337	13.0	-0.19
North Fork confluence (4)	-1.70	-1.347	23.1	-0.35
Harley Gulch (7)	-1.15	-0.432	91.1	-0.72
Harley Gulch (7)	-1.05	-0.452	79.2	-0.59
Harley Gulch (7)	-0.01	-0.183	-181.7	0.17

Harley Gulch (7)	-0.46	-0.310	38.2	-0.15
Harley Gulch (7)	-0.92	-0.538	52.6	-0.38
Harley Gulch (7)	-0.35	-0.034	164.4	-0.31
Harley Gulch (7)	0.89	0.118	153.2	0.77
Harley Gulch (7)	0.04	-0.328	-251.5	0.37
Harley Gulch (7)	-0.18	-0.446	-84.8	0.27
Harley Gulch (7)	0.93	0.173	137.4	0.76
Sulphur Creek (14)	-0.32	-0.200	45.8	-0.12
Sulphur Creek (14)	0.61	0.123	132.6	0.48
Sulphur Creek (14)	1.26	0.413	101.3	0.85
Sulphur Creek (14)	1.31	0.391	108.3	0.92
Sulphur Creek (14)	-0.66	-0.309	72.1	-0.35
Sulphur Creek (14)	-0.18	0.158	3023.1	-0.34
Sulphur Creek (14)	0.39	-0.082	306.1	0.47
Sulphur Creek (14)	0.20	0.281	-35.7	-0.09
Sulphur Creek (14)	-0.82	0.294	422.0	-1.12
Sulphur Creek (14)	-0.04	0.034	5869.6	-0.07
Sulphur Creek (14)	-0.12	0.281	-494.6	-0.40
Sulphur Creek (14)	-0.39	-0.149	89.0	-0.24
Sulphur Creek (14)	0.11	0.005	182.6	0.11
Sulphur Creek (14)	0.39	-0.139	420.8	0.53
Sulphur Creek (14)	-0.48	-0.346	32.8	-0.14
Sulphur Creek (14)	-1.22	-0.298	121.7	-0.92
Sulphur Creek (14)	-0.12	0.209	-730.9	-0.33
Upper Bear Creek (15)	-0.74	-1.229	-49.1	0.48
Upper Bear Creek (15)	-0.68	-1.081	-45.8	0.40
Upper Bear Creek (15)	-1.30	-1.357	-4.2	0.06
Upper Bear Creek (15)	-1.05	-1.032	1.4	-0.01
Upper Bear Creek (15)	-1.05	-1.081	-3.3	0.04
Upper Bear Creek (15)	-1.15	-1.509	-26.6	0.35
Upper Bear Creek (15)	-1.22	-0.991	20.8	-0.23
Upper Bear Creek (15)	-0.64	-0.947	-38.9	0.31
Upper Bear Creek (15)	-0.52	-0.991	-61.9	0.47
Upper Bear Creek (15)	-1.30	-1.469	-12.1	0.17
Davis Creek at Cache Creek (19)	-0.57	-0.860	-40.8	0.29
Davis Creek at Cache Creek (19)	-0.44	-0.176	86.5	-0.27
Davis Creek at Cache Creek (19)	-0.96	-0.551	54.0	-0.41
Davis Creek at Cache Creek (19)	-0.62	-0.190	106.2	-0.43
Davis Creek at Cache Creek (19)	-0.13	-0.509	-118.2	0.38
Davis Creek at Cache Creek (19)	-1.70	-0.936	58.0	-0.76
Lower Bear Creek (20)	-0.59	-0.845	-36.3	0.26
Lower Bear Creek (20)	-0.33	-0.433	-27.6	0.11
Lower Bear Creek (20)	-0.24	-0.496	-70.9	0.26
Lower Bear Creek (20)	0.04	-0.417	-239.5	0.45
Lower Bear Creek (20)	-0.77	-0.371	70.0	-0.40
Lower Bear Creek (20)	0.45	-0.408	4517.8	0.85
Lower Bear Creek (20)	-0.89	-0.386	78.6	-0.50
Lower Bear Creek (20)	-0.46	-0.282	47.0	-0.17

Lower Bear Creek (20)	0.06	-0.421	-262.5	0.48
Lower Bear Creek (20)	-0.72	-0.321	76.9	-0.40
Lower Bear Creek (20)	-0.09	-0.311	-109.0	0.22
Lower Bear Creek (20)	-0.49	-0.712	-36.0	0.22
Lower Bear Creek (20)	-0.66	-0.721	-9.2	0.06
Bear Creek confluence (21)	-0.09	-0.388	-127.3	0.30
Rumsey (23)	-0.66	-0.893	-30.3	0.24
Rumsey (23)	-0.52	-0.627	-18.1	0.10
Rumsey (23)	-0.64	-0.747	-15.7	0.11
Rumsey (23)	-1.00	-1.155	-14.4	0.15
Rumsey (23)	-0.77	-0.767	0.3	0.00
Rumsey (23)	-0.70	-0.772	-9.9	0.07
Rumsey (23)	-0.39	-0.405	-4.4	0.02
Rumsey (23)	-1.40	-0.936	39.6	-0.46
Rumsey (23)	-0.11	-0.440	-121.2	0.33
Rumsey (23)	-0.96	-0.728	27.3	-0.23
Rumsey (23)	-1.00	-1.174	-16.0	0.17
Rumsey (23)	-0.55	-0.848	-42.1	0.29
Rumsey (23)	-1.30	-1.252	3.9	-0.05
Rumsey (23)	-1.40	-0.824	51.7	-0.57
Rumsey (23)	-1.15	-1.114	3.6	-0.04
Rumsey (23)	-0.89	-0.870	1.9	-0.02
Rumsey (23)	-0.70	-0.772	-9.9	0.07
Cache Creek below Highway 505 (25)	-0.64	-0.839	-27.1	0.20
Cache Creek below Highway 505 (25)	0.03	-0.299	-250.3	0.33
Cache Creek below Highway 505 (25)	-0.82	-0.936	-12.7	0.11
Cache Creek below Highway 505 (25)	-0.72	-0.757	-4.8	0.04
Cache Creek below Highway 505 (25)	-1.05	-1.046	0.0	0.00
Cache Creek below Highway 505 (25)	-0.72	-0.738	-2.2	0.02
Cache Creek below Highway 505 (25)	-0.57	-0.429	27.9	-0.14
Cache Creek below Highway 505 (25)	-0.85	-0.684	22.1	-0.17
Cache Creek below Highway 505 (25)	-1.05	-1.276	-19.8	0.23
Cache Creek below Highway 505 (25)	-1.15	-1.292	-11.2	0.14
Cache Creek below Highway 505 (25)	-0.57	-0.429	27.9	-0.14
Cache Creek into Settling Basin (27)	-0.32	-0.366	-13.7	0.05
Cache Creek into Settling Basin (27)	-0.74	-0.519	35.8	-0.23
Cache Creek into Settling Basin (27)	-0.46	-0.478	-4.6	0.02
Cache Creek into Settling Basin (27)	-0.29	0.033	250.9	-0.33
Cache Creek into Settling Basin (27)	-1.05	-1.149	-9.4	0.10
Cache Creek into Settling Basin (27)	-1.05	-0.745	33.6	-0.30
Cache Creek into Settling Basin (27)	-0.74	-0.971	-26.3	0.23
Cache Creek into Settling Basin (27)	-0.59	-0.268	74.5	-0.32
Cache Creek into Settling Basin (27)	-0.24	-0.398	-50.9	0.16
Cache Creek out of Settling Basin (28)	-0.70	-0.857	-20.3	0.16
Cache Creek out of Settling Basin (28)	-0.36	-0.412	-14.5	0.06
			Variance of residuals	0.13
			Mean of residuals	0.00

APPENDIX D cont.

The USGS' analyzed the data in terms of the meeting the following requirements to verify the necessary assumptions inherent in regression modeling in order to use the regression analyses properly for prediction purposes (Stuart and Ord (1991)): (1) The residuals should be independent; (2) The residuals have a mean of zero; (3) The residuals have a constant variance; and (4) The residuals have a normal distribution.

Residuals, which represent the unexplained variation in the regression model, and are calculated as the differences between observed and predicted values. Examination of the residuals confirms whether the fitted model is correct. To confirm the residual behavior, most commonly graphical analyses are performed and examined its adequacy.

The purpose of the MeHg submodel is to predict MeHg contents in Cache Creek at the watershed scale. Our model builds on the observation by Slotten et al. (2004) that, at the watershed scale in Cache Creek, aqueous raw HgT "explains" about 52% of the variation in aqueous raw MeHg. Our model improves upon this predictive power (explaining 63% of the variation) by the inclusion of other relevant variables, as explained above. The linear- regression model was developed by transforming both the response variables and relevant predictor variables into log arithmetic space. To address concerns, we provide the following analysis, using the appropriate data which show that the relevant regression assumptions stated above are met.

(1) The residuals are independent: Graphical plots for residual error analysis (fig. D1) suggest that the residuals are independent and trendless.

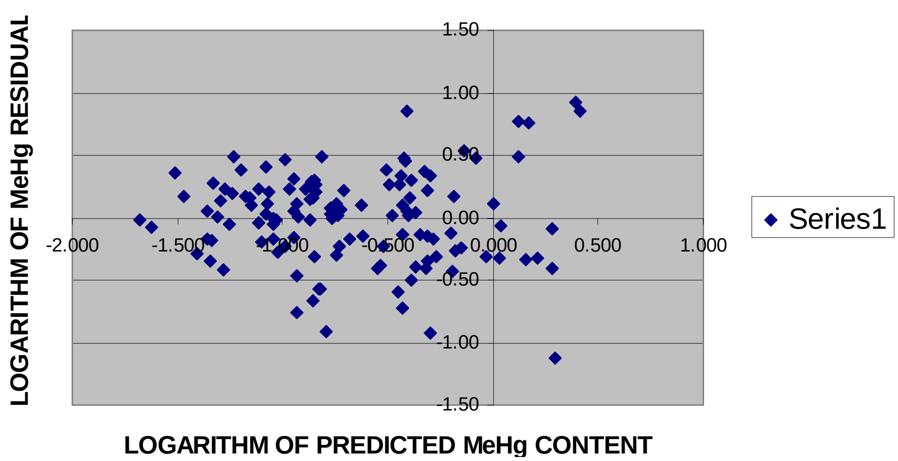

Figure D1. Logarithmic plot of MeHg residuals versus predicted MeHg contents in the Cache Creek Watershed, north-central California

(2) The residuals have a mean of zero. (See table D1).

(3) The residuals have a constant variance: We do acknowledge that the predictions vary site-to-site. We attempted to deal with these differences when incorporating fixed- effect variables, such as a local source effect (whether n immediate source was nearby, such as the Abbott-Turkey Run Mine) and a sulfate effect (see table D1).

(4) The residuals have a normal distribution: The following plot shows that the residuals do have a normal distribution, as tested by either the "Shapiro Wilks W test" and/or the "Lilliefors test." Both of which demonstrate normality for this equation.

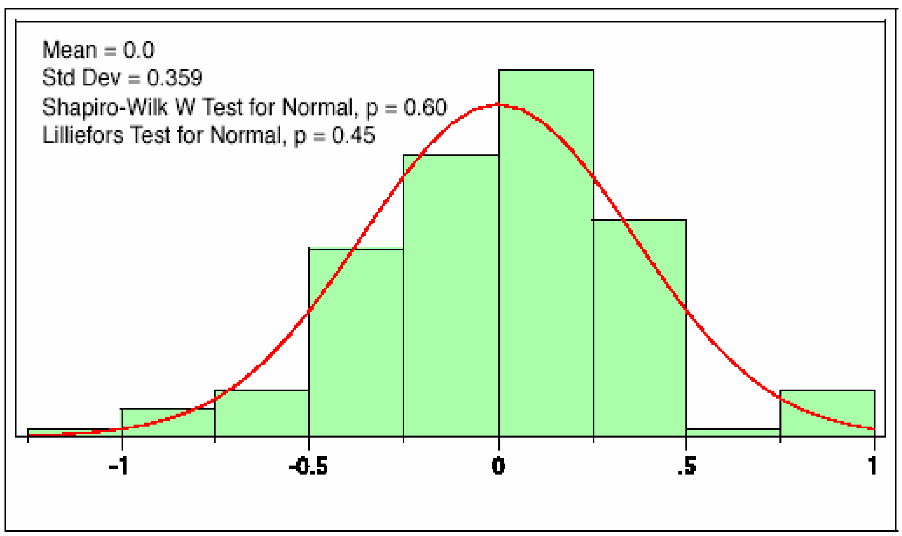

Figure D2. Logarithm of Residuals from MeHg Regression

The MeHg regression model's predictive value is adequately described by the statistics shown in this report.

APPENDIX E

Observed MeHg Contents

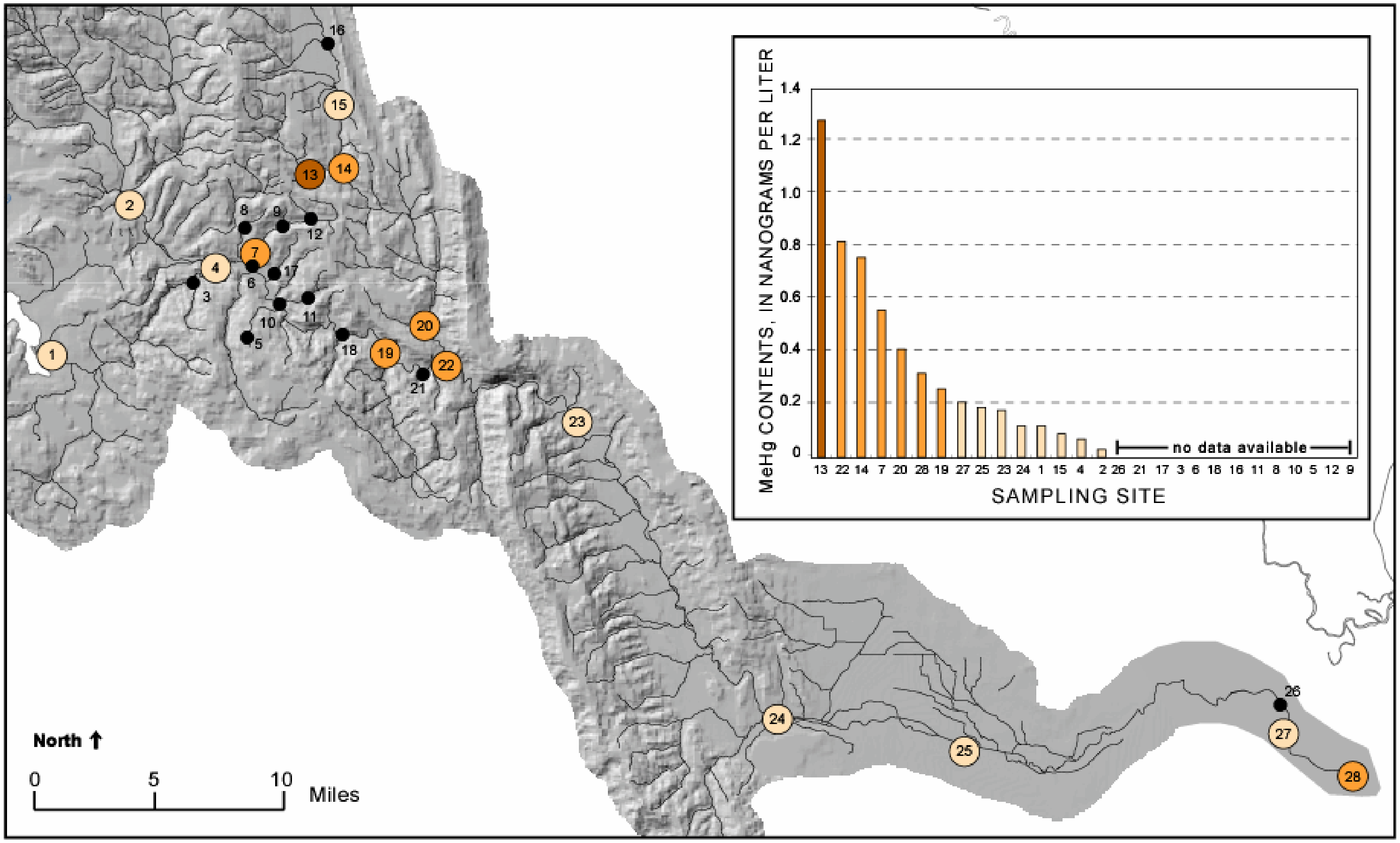

Figure E1. Cache Creek watershed, north-central California, showing locations of sampling sites (numbered circles and dots) and observed MeHg contents

APPENDIX E cont.

Table E1. Summary of observed MeHg Contents in the Cache Creek watershed, north-central California [All values in nanograms per liter]

Sampling Site		*Mean*	*Standard Error*	*Median*	*Standard Deviation*	*95% Confidence*	*No. of Samples*
1	Cache Creek at Lower Lake	0.13	0.03	0.12	0.11	0.06	16
2	North Fork Cache Creek at Hwy 20	0.08	0.01	0.07	0.05	0.03	16
4	North Fork confluence	0.03	0.00	0.03	0.00	0.04	2
7	Harley Gulch	2.01	1.03	0.56	3.26	2.33	10
13	Sulphur Creek tributary	4.13	2.75	1.28	7.27	6.72	7
14	Sulphur Creek at Cache Creek	3.26	1.50	0.76	6.18	3.18	17
15	Upper Bear Creek	0.12	0.02	0.09	0.08	0.05	12
19	Davis Creek at Cache Creek	0.29	0.10	0.26	0.25	0.26	6
20	Middle Bear Creek	0.63	0.16	0.41	0.65	0.35	16
22	Cache Creek and Bear Creek Confluence	0.82	NA	0.82	NA	NA	1
23	Cache Creek at Rumsey	0.23	0.05	0.18	0.22	0.11	18
24	Capay	0.17	0.05	0.12	0.11	0.17	4
25	Cache Creek below Hwy 505	0.25	0.09	0.19	0.28	0.19	11
27	Cache Creek into settling basin	0.26	0.03	0.21	0.15	0.06	23
28	Cache Creek out of settling basin	0.32	0.12	0.32	0.17	1.52	2

Table E2. Summary of observed versus predicted MeHg Contents in the Cache Creek watershed, north-central California

Sampling Site	***Name***	***No. of Samples***	***Median observed MeHg content (ng/L)***	***Median Predicted MeHg content (ng/L)***	***Relative percent Difference***
1	Clear Lake	15	0.12	0.09	33.3
2	N. Fork Cache Creek at Highway 20	14	0.07	0.09	-31.4
4	North Fork confluence	2	0.03	0.05	-54.2
7	Harley Gulch	10	0.56	0.48	15.0
14	Sulphur Creek	17	0.76	1.08	-34.3
15	Upper Bear Creek	10	0.09	0.08	6.3
19	Davis Creek at Cache Creek	6	0.26	0.30	-13.6
20	Lower Bear Creek	13	0.35	0.38	-8.4
22	Bear Creek confluence	1	0.82	0.41	66.6
23	Rumsey	17	0.17	0.15	12.3
25	Cache Creek below Highway 505	11	0.19	0.18	5.4
27	Cache Creek into settling basin	9	0.26	0.33	-23.7
28	Cache Creek out of settling basin	2	0.32	0.26	20.6

APPENDIX F

Economic Cost Data Sample Sites

California Sample Sites for Economic Linear Regression Model

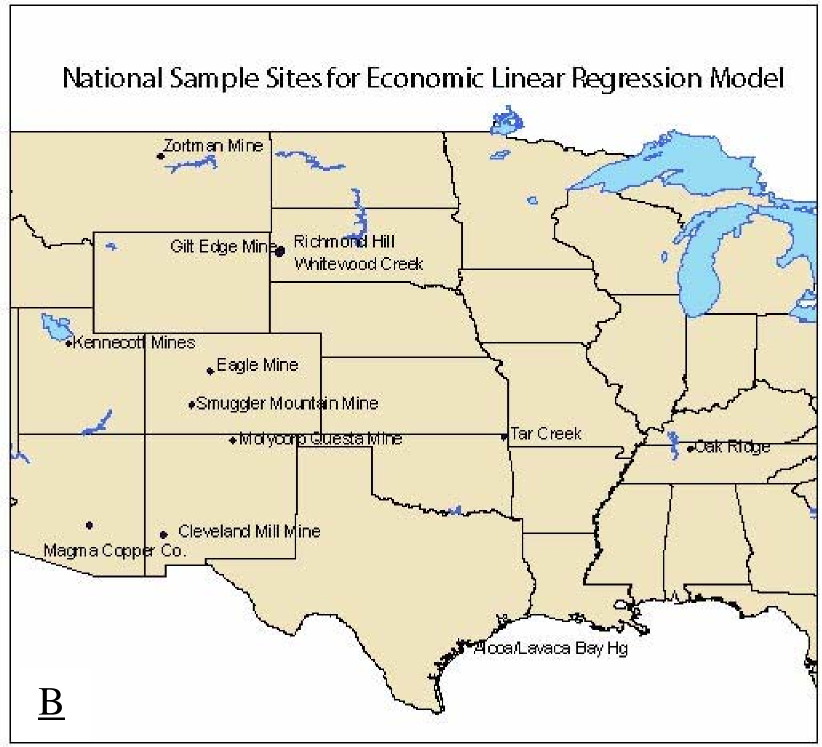

Figure F1. California (A) and Central United States (B), showing locations of data for economic linear regression model

APPENDIX G

Economic Cost Database

For comparison purposes, a Gross Domestic Price (GDP) deflator was used to adjust costs from one year to another using a GDP deflator inflation index (***http://www.jsc.nasa.gov/bu2/inflateGDP.html***). All of the costs in this table report 2003 deflator costs. Variables used in developing linear regression-cost model: (1) a dependent variable, the total costs (*TC*); and (2) several independent variables:

- Volume moved, removed, or capped (in cubic yards) (*VolCy*);
- Elevation of remediation site (*EleFT)*;
- Ownership of project site (*OWN)*;
- Whether the area contains acid mine drainage (*AMD*);
- Location of the site [location is in California (1)] (*CA*);
- Slope is relatively high (1) or low (0) at the site (*Slo*);
- Deposit type or type of site of proposed remediation site: Epithermal gold (*EpiAu*), Gold (*Au*), Industrial (*Ind*), Poly metallic (*Poly*), Porphyry Copper (*PoCu*), Silica Carbonate Hg (*SiCaHg*), Sulfur (*Su*). Deposit types for the various remediation project sites were identified using expert judgment from a USGS geologist (James Rytuba) and a USGS mineralogist (Don Singer)

Table G1. Economic-cost database used for developing linear regression model.

Project site	***TC***	***VolCY***	***EleFT***	***OWN***	***SiCaHg***	***EpiAu***	***Au***	***PoCu***	***Su***	***Poly***	***Ind***	***AMD***	***CA***	***Slo***
Buena Vista	4,718,507	474,100	880	1	1	0	0	0	0	0	0	1	1	1
Klau	2,300,804	192,400	1250	1	1	0	0	0	0	0	0	1	1	1
Gambonini	3,060,000	218,000	600	0	1	0	0	0	0	0	0	0	1	1
Polar Star	1,623,024	500	420	1	0	0	1	0	0	0	0	0	1	1
Sulphur Bank	12,000,000	193,600	1400	1	1	0	0	0	0	0	0	1	1	0
Gibraltar Mill	550,612	5,555	1600	0	1	0	0	0	0	0	0	0	1	1
Aurora	344,890	8,000	3900	0	1	0	0	0	0	0	0	0	1	1
Alpine	132,650	5,000	3600	0	1	0	0	0	0	0	0	0	1	1
Carson River	3,350,214	9,087	5200	1	0	1	0	0	0	0	0	0	0	0
Oak Ridge Site	2,026,902	8,300	875	0	0	0	0	0	0	0	1	0	0	0
Alcoa/Lavaca Bay	59,573,205	467,773	50	1	0	0	0	0	0	0	1	0	0	0
Lava Cap	3,162,000	80,000	2850	1	0	0	1	0	1	0	0	0	1	1
Leviathan	7,843,918	69,373	7000	0	0	0	0	0	1	0	0	1	1	0
Penn	10,757,736	408,000	380	1	0	0	0	0	1	1	0	1	1	1
Walker	3,500,000	4,800,000	6000	1	0	0	0	0	0	1	0	1	1	0
Cleveland Mill	7,897,560	164,960	7100	0	0	0	0	0	0	1	0	0	0	1
Kennecott (South)	38,6327,000	14,600,000	4347	0	0	0	0	1	0	0	0	1	0	0
Kennecott (North)	91,870,000	2,200,000	4347	0	0	0	0	1	0	0	0	1	0	0
Smuggler Mountain	7,200,000	217,800	8000	1	0	0	0	0	0	1	0	0	0	0
Sailor Flat	247,000	4,033	3200	0	0	0	1	0	0	0	0	0	1	0
Almaden Park	3,996,000	2500	2800	0	1	0	0	0	0	0	0	0	1	1
Red Top	627,382	180	1700	0	1	0	0	0	0	0	0	0	0	1
Grey Eagle	2,016,279	475,000	1360	1	0	0	0	0	1	0	0	1	1	1
Gilt Edge	42,175,069	10,500,000	4600	1	0	1	0	0	0	0	0	1	0	1
Richmond Hill	8,500,000	645,333	5750	1	0	0	1	0	0	0	0	1	0	1
Zortman	41,580,600	40,000	4018	0	0	1	0	0	0	0	0	1	0	1
Molycorp Questa	405,361,110	1,210,000	8300	1	0	0	0	1	0	0	0	1	0	1
Tar Creek	107,000,000	350,000	700	0	0	0	0	0	0	1	0	1	0	0
Whitewood Creek	1,108,549	4,500	2700	1	0	0	1	0	0	0	0	0	0	0
Deer Trail	150,000	400	540	0	1	0	0	0	0	0	0	0	1	1

Table G2. Economic-cost results for developing a linear regression model

Final Regression Equation: L10TC ~ PoCu + CA + L10VolCY

	Value	Std. Error	t value	Pr(>|t|)
(Intercept)	5.0510	0.3940	12.8184	0.0000
PoCu	0.7661	0.3363	2.2780	0.0312
CA	-0.6161	0.1874	-3.2869	0.0029
L10VolCY	0.3934	0.0762	5.1637	0.0000

Residual standard error: 0.4759 on 26 degrees of freedom
Multiple R-Squared: 0.7614
F-statistic: 27.65 on 3 and 26 degrees of freedom, the p-value is 3.007e-008

L10 TC = 5.05 + 0.77PoCu – 0.62CA + 0.39Log10VolCY

Project site	*TC*	*PoCu*	*CA*	*L10VolCY*	*L10Costs*	*L10Predicted Costs*	*TC Prediction*
Buena Vista	4,718,507	0	1	5.68	6.67	6.66724	4,647,720
Klau Mercury Mine	2,300,804	0	1	5.28	6.36	6.51004	3,236,235
Gambonini Hg Mine	3,060,000	0	1	5.34	6.49	6.53362	3,416,803
Polar Star Au Mine	1,623,024	0	1	2.7	6.21	5.4961	313,401
Sulphur Bank Hg Mine	12,000,000	0	1	5.29	7.08	6.51397	3,265,653
Gibraltar Mine Mill	550,612	0	1	3.74	5.74	5.90482	803,193
Aurora Mine	344,890	0	1	3.21	4.19	5.69653	497,199
Alpine Mine	132,650	0	1	3.81	5.37	5.93233	855,717
Carson River	3,350,214	0	0	3.96	6.53	6.60728	4,048,368
Oak Ridge	2,026,902	0	0	3.92	6.31	6.59156	3,904,451
Alcoa/Lavaca Bay	59,573,205	0	0	5.67	7.78	7.27931	19,024,358
Lava Cap Mine	3,162,000	0	1	4.9	6.5	6.3607	2,294,563
Leviathan Mine	7,843,918	0	1	4.84	6.89	6.33712	2,173,302
Penn Mine	10,757,736	0	1	5.61	7.03	6.63973	4,362,445
Walker Mine	3,500,000	0	1	6.68	6.54	7.06024	11,487,883
Cleveland Mill Mine	7,897,560	0	0	5.22	6.9	7.10246	126,607,667
Kennecott (South) Mine	386,327,000	1	0	7.16	8.59	8.63088	427,444,762
Kennecott (North) Mine	91,870,000	1	0	6.34	7.96	8.30862	203,526,048
Smuggler Mountain Mine	7,200,000	0	0	5.34	6.86	7.14962	14,113,021
Sailor Flat Mine	247,000	0	1	3.61	5.7	5.85373	714,052
Almaden Park	3,996,000	0	1	3.4	6.6	5.7712	590,473
Red Top Mine	627,382	0	0	2.26	5.8	5.93918	869,321
Grey Eagle Mine	2,016,279	0	1	5.68	6.3	6.66724	4,647,720
Gilt Edge Mine	42,175,069	0	0	7.02	7.63	7.80986	64,544,613
Richmond Hill	8,500,000	0	0	5.81	6.93	7.33433	21,593,846
Zortman	41,580,600	0	0	4.6	7.62	6.8588	7,224,370
Molycorp Questa Mine	405,361,110	1	0	6.08	8.61	8.20644	16,0857,013
Tar Creek	6,096,290	0	0	5.54	8.03	7.22822	16,912,975
Whitewood Creek	1,108,549	0	0	3.65	6.04	6.48545	3,058,088
Deer Trail	150,000	0	1	2.6	5.18	5.4568	286,286

APPENDIX H

Verification of Cost-Mitigation Submodel

The USGS' Western Geographic Science Center analyzed the data in terms of meeting the following requirements to verify the necessary assumptions inherent in the regression modeling in order to use the regression analyses properly for prediction purposes (Stuart and Ord (1991)): (1) The residuals should be independent; (2) The residuals have a mean of zero; (3) The residuals have a constant variance; and (4) The residuals have a normal distribution.

Residuals, which are the unexplained variation of the regression model, are calculated as the differences between the observed and predicted values. Examination of the residuals confirms whether the fitted model is correct. To confirm the residual behavior, most commonly graphical analyses are performed and examined for their adequacy. The cost-mitigation submodel predicts HgT mitigation costs. The residuals were analyzed to verify the assumptions of regression modeling. Below are the results:

(1) The residuals appear to be independent: The following graph shows that there is no trend in the residuals.

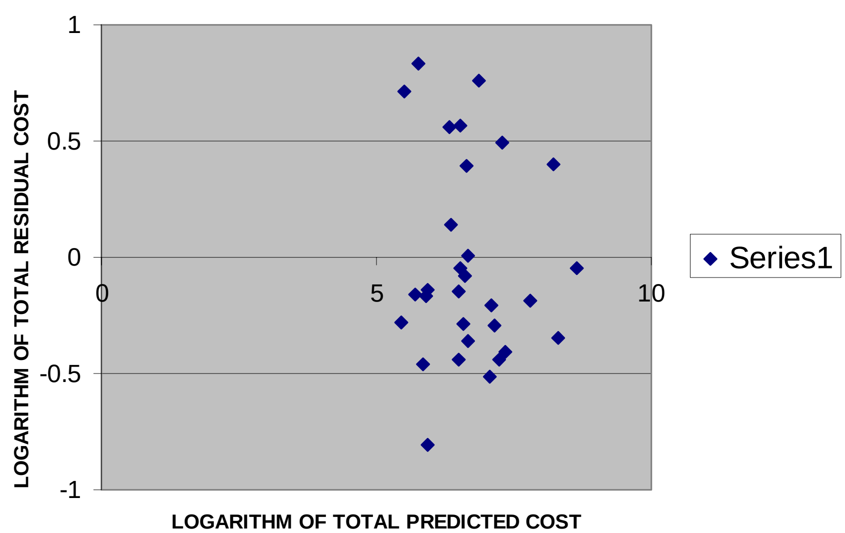

Figure H1. Logarithmic plot of total cost residuals versus predicted

(2) The residuals have a mean close to zero (~0.03): Excel generally provides an approximation in its calculations.

(3) The residuals have a constant variance: (0.18) Again, Excel provides an approximation in its calculations.

(4) The residuals have a normal distribution.

This analysis reflects the uncertainty in remediation-project costs, based on the information that we currently have. A reduction in uncertainty could be achieved with site-specific project-specific cost estimates made by a contractor, but we have no access to this information, and so the spread cited reflects our current uncertainty. We acknowledge that the cost model was developed on a national scale and contains variables that are irrelevant on a regional scale, such as copper deposits and whether the project is in California or not. This is one reason why we tested the model using Tetra Tech figures, Inc. data--cost estimates in the Sulphur Creek area.

APPENDIX I

Liability Issues for Offsets

The agency undertaking Hg cleanup can be liable for postremediation contamination in several ways. Most commonly, the agency paying for remediation is also the owner. Whether a public agency—which now owns property polluted by a previous owner—or a private party—who may or may not have been the polluting party —liability for contamination runs through ownership and/or previous actions. Estimating future liability costs for offset projects are difficult because, for each remediation site, no obvious owner or responsible polluter exists. The main issue is whether entering and cleaning up properties, with which the point source has no connection, can result in potential liability for postremediation contamination. Answering this question requires evaluating several contingent scenarios that may confront the point source during remediation. The following section lays out the contingent scenarios and proposes solutions—where possible—for addressing liability issues. The scenarios presented are for point sources to use when evaluating a remediation site.

The first question is whether a potential remediation offset project site currently belongs to an existing entity (person, corporation, limited liability company, limited liability partnership, etc)? The polluting party has abandoned many of the sites, but nevertheless, the current titleholder can be held liable for existing contamination. If an existing entity can be found that holds title to the land, several options are available for the potential offset participant.

Ownership Established

The first option is to work with the EPA under the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA) to require the owner to perform the necessary remediation. The EPA has the authority to require a polluting property to remediate and/or can require reimbursement from the owner for remediation efforts. This option would essentially place the point source in the form of a third party, who would merely work with the EPA and the owner in case the EPA requires the owner to remediate the site. Alternatively, the point source can pay for the remediation, and the EPA can require the owner to reimburse the point source. In either case, the costs of remediation and future liability will stay with the current owner. The current owner would have several options:

1. They may have comprehensive general liability, which would cover an EPA-mandated cleanup. (Courts have looked at these controversies on a case-by- case basis.) AIU INS. Co. v. Superior Court, 51 Cal. 3d 807, (1990); (Julian and Schlumberger, 1996).

2. If they do not have an applicable insurance policy, they will have to assume the remediation costs. In paying for remediation, they can purchase Cleanup Cost Cap (CCC) Insurance (which will cover remediation-cost overruns) and postremediation or pollution liability insurance to ensure against future torts for property and bodily harm due to remaining contamination.

In the event that EPA will not mandate cleanup under CERCLA, then the point source will likely have to bear the costs of remediation (this is a general assumption of the project), which case the point source will be entering land owned by an existing entity and performing cleanup on private property. This situation presents several different issues. The current owner may challenge the point source's authority to enter the land. There are several reasons for taking such a stance.

a. Privacy and Property

First, the owner may simply be against government interference on his/her/its property. The owner will cite right to privacy and property in trying to keep the point source out. In this case, the government may be forced into a regulatory takings or nuisance action. The best course of action would be to sue the owner on the grounds of a current *nuisance* (in the form of pollution) and potentially collect damages and/or an injunction allowing entry and remediation. For the point source, such an action may provide the potential for remediation-cost reimbursement, but it would be a risky lawsuit entailing time and money in litigation (Bailey and Gulledge, 1997).

The owner may argue in that the point source's plans will result in a *takings*, or eminent domain, of their property (either temporarily or permanently). If the court finds that a *temporary* taking occurs, the point source may not only have to pay for the time it inhabited a section of land for remediation (in terms of lost use of that part of land), but may also have to pay for the consequences of their actions while on the land—such as negligent cleanup leading to post-remediation contamination. If an owner were to win a *permanent* takings issue, the point source would have to buy the remediation site from the owner for full market value and then would be responsible for the land as an owner in full title. However, since the land in question is contaminated, the market value may be determined as very low or potentially negative and so "buying" the land may not be an issue. Postremediation liability would rest on the point source.

Generally, none of these contests will make it to court, but to plan for settlement of such questions ahead of time (i.e. before deciding which sites to pay for full-scale remediation-cost estimates) the point source should know all potential contingencies. The worst-case scenario for confronting a privacy/property rights owner would be buying the land and assuming post remediation liability. Thus, the highest-cost solution would be buying remediation and post remediation/pollution liability insurance.

b. Reputation and Liability

Second, the owner may not necessarily be against government action but may be wary of the potential liability or reputation damage that may occur if it becomes common knowledge that they own contaminated land. An owner in this case is looking for reassurances that they will not be harmed—in any way—by the impending point source's remediation efforts, while still wanting to control/own their land. To avoid costly legal battles described in the privacy/property-rights scenario, the point source would be wise to negotiate with the reputation/liability owner. Both the point source and the owner will be in awkward positions. Without a nuisance claim or an EPA mandate, the point source will basically be paying for the remediation; still, the owner will not want to assume the high-profile reputation as an owner of polluted land, or the long-term liability. Even if the owner has commercial general liability (CGL) insurance that may cover postremediation costs, the owner would be unlikely to want to risk higher premiums by contacting or relying upon their insurance company to cover postremediation liability.

Both parties may want the same goal—the cleanup of contamination—but to get to that stage, the point source may have to arrange a deal on sharing or explicitly determining who will have postremediation liability and how to keep the confidentiality of the owner. Such a scenario brings up important issues of freedom of information, unconscionable contracts, and insurance fraud. The point source should be ready, in a worst-case scenario, to assume full postremediation liability for the site. We note, however, that short of negligently performing on remediation (i.e., hiring an incompetent contractor), no real precedent exists for making a nonowner of property pay for postremediation liability. Thus, in cases where the point source does not have to assume ownership of land, there is no guarantee that they should pay for postremediation liability. However, to accomplish smooth transactions and avoid legal battles, it may be worth assuming the costs (the costs may be reimbursable—as discussed below)

c. Holdout

Third, the owner may no longer use the land and may want to hold out for government purchase rather than allow entry. In this case, the owner is holding out for the point source to purchase the land and thus assume responsibility for any contamination issues. Two issues may arise. First, if the owner is responsible for the contamination, they may still be held liable—even if they sell to the point source—for postremediation property and bodily damage. Second, if the current owner was not responsible and did not know about the contamination, they may still be held liable after selling the property to the point source. This would be a complex legal issue on which the point source would be wise to avoid trying to pursue a decision. In either case, the owner may want the point source to buy the land, potentially adding to the cost of remediation because contamination should be factored into the market value and may make the purchase price below zero. Also, the point source could bargain the purchase down to only the land necessary for remediation by arguing eminent domain. This would be a negotiation threat; actual litigation would be cost prohibitive.

The worst-case scenario would be the point source having to pay for some costs of title transfer (including purchase price), postremediation liability and the costs of cleanup. The options would be to purchase CCC insurance and postremediation/pollution liability insurance (Steneri, 2002). Another scenario is that the current owner may be the responsible party. In this case, even without an EPA mandate, the point source may be able to require the owner cleanup the site at the owner's expense. Fortunately, this will not be the point source's responsibility.

Lack of Ownership

A scenario of no current owner and no remaining responsible party represents probably the most likely case for potential offset remediation sites. In such cases, there is no transfer of liability issues exist because there is no current liable party. However, the question becomes, does the point source assume all liability for undertaking remediation on the site? This seems to be a question of first impression. States and municipalities commonly remediate abandoned property—and assume ownership—under CERCLA

Brownfield suits (Fletcher, 2002). However, in such cases, the public agency assumes ownership knowing that Superfund will reimburse remediation costs and cover postremediation liability. Even municipalities responsible for polluted sites are generally immune to Superfund liability (Steinway, 2001).

Offset projects will most likely be dealing with postremediation liability for non Superfund sites as well as third-person/citizen suits. The first issue is whether the point source will be liable under CERCLA for any remaining contamination issues. Considering the EPA involvement, it would not make sense for the point source to enter into a remediation program without an agreement that the EPA will not hold the point source liable for postremediation Superfund purposes. Even without Superfund liability, the potential remains for postremediation liability for third-party suits against the point source (Mink et al, 1997).

Another question is whether the point source is liable for contamination that occurs after the cleanup. Generally, ownership creates strict liability where the owner is liable regardless of whether they act negligently or recklessly. Here, however, it is unclear whether the point source will be the owner of the abandoned site. If the point source becomes the owner, the point source will likely be strictly liable (regardless of whether a mistake is made during remediation) for post-cleanup contamination. If the PS is not considered the owner postremediation, then the PS will likely be held liable only for negligent or reckless or intentional flaws in remediation.

Thus, the liability and ownership issue is vital but rather uncertain. On a case-by-case basis, the point source will have to evaluate the ownership issue. These property issues will be complex, leading to a transaction cost that we have not looked at*: property acquisition and management*. The best solution may be for the point source to create a nonprofit organization to hold title to the land as a buffer for tax and liability issues. In any case, assuming the worst—i.e., responsibility for the most legal transaction costs—the point source should consider the following insurance packages:

1. During remediation, hire only a contractor who has contractor insurance—holding the contractor responsible for any potential liability resulting from mistakes during remediation. In this report, contractor insurance is assumed to be reflected within the direct-cost model.

2. The point source should consider purchasing CCC insurance, which will provide (Bressler, 2001):

a. Cover against cost overruns during performance of remediation plan, such as known conditions that exceed costs + a buffer 10-20%, unknown conditions that contribute to exceeding predicted remediation costs +10-20% buffer or changes in regulations during remediation
b. Typically, coverage of costs up to 100% of expected remediation costs, with the option to purchase more coverage.
c. Deductible of usually 10-20% of expected remediation costs.
d. Duration the length of project plus a few months
e. Pricing 8-12% of the limit of liability purchased.

3. The point source should consider purchasing postremediation or pollution liability (PR/PL) insurance which generally covers onsite and offsite cleanup of known and unknown contamination, as well as torts by third parties against the site for property and bodily damage. Limits of liability can range from $1 million to more than $100 million. The deductible is variable and can be tailored to the purchaser's level of risk aversions (i.e., from $10,000 to $1 million). The variables for determining premiums are type of contaminant found and remediated, surrounding properties, slope and location to adjacent properties, depth to ground water, and composition of the soil. The pricing varies, depending on the choice of deductible, length of policy term, and site conditions, but generally, premiums will range from 0.5 to 3% of transaction costs (for a new purchaser of remediated property) and determination of purchasing postremediation liability premiums will be more difficult for the remediating agency. Generally, a 10-year policy with a $1 million limit will have a $10,000 annual premium, leading to an estimate of 10% of the desired limit as the cost of insurance. The insurance length runs approximately 1 to 10 years, with option for renewal.

Finally, we note that in many States, including California, insurance premium tax refunds are available from the State. Eligibility is not guaranteed, however, for non-Superfund sites. Regardless of whether the point source purchases insurance, any postremediation claim could be linked to orphan shares of liability—nonexistent parties who caused the pollution. By California law, as much as 75% of liability can be attributed to orphan shares and paid by a State fund (New California Superfund Law, Regulatory Alert). Again, it is uncertain whether orphan shares liability applies to non-Superfund sites. The best estimate may be that annual premiums for a 10-year policy will be 1% of the desired limit. Thus, total insurance costs are equal to 10% of the desired limit.[13]

[13] See Robb Kapla for further information (*kapla2005@student.law.ucla.edu);(rkapla@usgs.gov*).

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