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Estimating Willingness-To-Pay for Reduction in Uncertainty in Water Quality of Contaminated Aquifers

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Abstract

Management of contaminated aquifers is challenged by the limited resources available to monitor and remediate a large number of contaminated sites. Earlier research recognized the negative impacts of spatial data scarcity on the success of aquifer monitoring and remediation plans. Therefore, there exists an important question on how to allocate limited resources to collect additional information to better estimate the risks and remediation priorities versus the willingness to pay by the society. This work introduces one of the early applications of structural benefit transfer to quantify welfare impacts of improving aquifer monitoring in terms of willingness-to-pay (WTP). This work uses health risk assessment methodology and introduces a practical socio-economic framework to estimate individuals' WTP for a proposed improvement in data gathering. The proposed methodology develops scenarios of uncertainty reductions in subsurface heterogeneity by collecting additional spatial data to reduce health risk to target population and computed the health-economic impact to estimate the aggregate WTP. The variability of characteristics of the target population is represented through probabilistic distributions of income, health state, age, and risk exposure parameters. The proposed methodology produced predictions of WTP that are consistent with the patterns expected in the economic theory and literature.

Keywords: Groundwater, contamination, uncertainty reduction, additional data, Willingness-to-Pay

1. Introduction

1.1 Research Needs

The accurate monitoring of contaminated aquifers has been a difficult challenge because of the limited resources available, uncertainty arising from complexities of contaminants and media characteristics, and the presence of many large-scale polluted sites (Ward et al., 1986). Water quality problems affect many functions of society including environmental, economical, and ecological functions. Contaminated groundwater has effects on the population that ranges from direct health effects such as morbidity and mortality to indirect economic damages such as restrictions on recreational uses (Maxwell et al., 1998). Assessment of environmental and economic impacts of contaminated groundwater on a population is complicated and there is lack of quantitative research addressing the welfare impacts of the resulting health risks (Zhao and Kaluarachchi, 2002). Therefore, addressing water quality problems calls for a broad view that utilizes several types of data for various variables.

There are many contaminated sites on the National Priority List that requires millions of dollars in remediation costs. Stakeholders need a management tool to help guide allocation of limited resources to maximize socio-economic and health benefits.

In groundwater contamination, uncertainty translates to tangible outcomes such as under-estimation of health risks due to uncertain input variables. Logically, a decision that reduces uncertainty in aquifer contamination estimation has social benefits including reduction in exposure to unknown health risk and illnesses or even mortality. So, there is a need to evaluate the socio-economic benefits of decisions that reduce uncertainty in estimating groundwater contamination. The quantification of welfare impacts of such decisions in monetary terms is complicated task especially under the time constraints for decision making.

In essence, there is a need to fill this gap in groundwater research and to develop a practical methodology to evaluate the population willingness-to-pay (WTP) for improved data collection to reduce unknown health risks.

1.2 Assessment of Welfare Impacts of changes in Health Risk

Several studies investigated the valuation of health risk reduction in air and water quality applications. These studies adopt relevant measures of adverse health or environmental effects of expected exposure levels estimated using available information for a given contaminant. A potential decision is deemed feasible if it produces more accurate estimation of actual exposure levels which represents a positive welfare impact to the target population assuming that only identified risks are mitigated and unkown risks pose a threat to the population.

Typical valuation methods of welfare impacts are classified into revealed preference, where valuations are inferred from actual observations of choice behavior, and stated preference, where valuations are directly obtained from hypothetical statements of choice (Kolstad, 2000). The application of these methods is limited by budgetary and time constraints. Therefore, an alternative practical economic valuation method is needed. The Benefit Transfer Method (BTM) is a systematic framework that transfers an established welfare estimate from existing studies to derive welfare impacts at a new site in similar conditions (Johnston et al., 2005; and Florax et al., 2005; Pattanayak et al., 2004, Smith et al., 2006). Due to its high practicality and feasibility compared to typical methods; the BTM is increasingly used in environmental management studies (Rosenberger and Loomis, 2000; and Florax et al., 2005).

2. Methodology

In this study, we propose a phased interdisciplinary framework that cuts across fate and transport of contaminants, health risk assessment, social welfare analysis, and health economics. The proposed methodology represents a contribution to the risk-based decision analysis literature due to its unique capacity to elicit a monetary value of welfare benefit produced by a given decision.

The proposed framework is composed of three modules (phases) as shown in Figure 1 and these are (1) Decision of reducing uncertainty by acquiring additional data; (2) characterization of additional data impacts, and (3) economic and welfare analysis. The methodology and the application are for monitoring of a contaminated aquifer with a point-source of carcinogenic contaminant. The first and second modules adopt a similar approach to Maxwell et al. (1998) and Maxwell and Kastenberg (1999). The last module is developed specifically for contaminated aquifers and the economic analysis is inspired by the work of Pattanayak et al. (2004) to quantify incremental risk reductions.

2.1 Module 1: Decision of Additional Data Selection

This module simulates scenarios of different data availability levels in a related system variable which is the subsurface heterogeneity for contaminated groundwater. Data availability is expressed in the aquifer monitoring network design (MN) by varying level of assumed subsurface heterogeneity which determines the spatial distribution of hydraulic conductivity fields (K) and spatial correlation length (λ). The variables K and λ determine the optimal number of groundwater monitoring locations (Dagan and Fiori, 1997, Maxwell et al., 1998).

Typically, in groundwater contamination a range of subsurface heterogeneity levels are simulated by varying the K spatial correlation length (λ) which produces variable K spatial structures (K fields). The additional data scenarios are produced using Monte Carlo sampling method to produce different series of n equally likely, two-dimensional distributions of K fields using different correlation lengths (λ). For each λ , the set of generated K fields hereafter are referred to as ensemble which is used in the groundwater movement and contaminant fate and transport simulation to produce breakthrough concentration predicted at the receptor. Next, the maximum 30 yr-average concentration for each K field of an ensemble is used to construct a probabilistic distribution of expected concentration that is unique for a unique correlation length (λ) or data collection level.. Finally, the concentration distributions are used to calculate the expected concentration with 95% confidence level which produces contaminant concentration with 95% confidence as a function of correlation lengths (C_{λ}) or data collection level.

2.2 Module 2: Characterization of Additional Data Impacts

The purpose of the second module is to predict the distribution of exposure levels to health risk using the breakthrough concentrations calculated at the receptor for each data collection level. Health risk assessment is the process that estimates the individuals' exposure to contaminated drinking and urban water. The health risk assessment uses the approach suggested in Zhao and Kaluarachchi (2002) where cumulative carcinogenic health risk is calculated considering three off-site exposure pathways and linked to different age groups specific to the target population. The three exposure pathways considered are ingestion, inhalation, and dermal exposure. Typically, health risk of an individual is a function of the dose and individual characteristics. Therefore, variation in individuals characteristics produces different health risk levels for same one contaminant level (Bogen et al., 1997).

In this study, we integrate uncertainty in subsurface heterogeneity and individual variability in health risk exposure parameters. The total health risk (TR) for individual i is defined as the total off-site exposure to health risk as shown in Equation 1. Equation 1 integrates data collection level using expected contaminant concentration calculated in module 2 for each scenario with individual variability using age dependent distributions of health risk parameters.

$$TR_i = f(C_\lambda, X_i) = R_g + R_h + R_d \tag{1}$$

where C_λ is the contaminant concentration at 95% confidence estimated at given λ , X_i is a vector of age-dependent exposure parameters such as body weight, and skin surface area. R_g is health risk exposure due to ingestion, R_h is health risk exposure due to inhalation, and R_d is health risk exposure due to dermal contact of contaminated water source.

Population variability is represented by sampling recommended probabilistic distributions instead of fixed values for population exposure parameters such as water intake rate and skin surface area (EFH, 1997). In this work, specific age-dependent distributions of exposure parameters are employed in a Monte Carlo sampling process to simulate the characteristics of target population. Once these parameters are known, carcinogenic health risk (TR) can be computed per guidelines suggested by US EPA (2001).

2.3 Module 3: Welfare and Socio-Economic Analysis

Health is viewed as a human capital and individuals tend to invest assets to reduce uncertainty in health risk or to achieve more accurate estimation of actual exposure level. This work considers the welfare and WTP of the members of a working population exposed to health risk (mortality) due to contamination of drinking water.

2.3.1 Willingness-to-Pay Analysis

The WTP is defined as the cost of averting behavior needed to alleviate the harmful impacts of health risk holding the initial health state constant (Krupnick et al., 2002). In general, WTP is the monetary equivalent of the welfare impact of change in expected exposure to health risk.

This analysis uses the Structural Benefit Transfer approach (SBT) which imposes a theoretical behavioral structure on established welfare estimates to calibrate the behavioral model and estimates its parameters. In environmental risk literature, SBT models are often constructed in the context of labor markets using labor/risk models based on the compensation workers are willing to accept to assume increased risks of job related mortality. The use of labor/risk models is emerging in various air and water quality studies (Smith et al., 2003).

We suggest a semi-log labor supply model to assess the WTP. For an individual i with w annual labor supply (hours worked/year), r hourly wage rate ($/hr), and S annual non-wage income ($/yr), the labor supply model is defined for individual i as follows

$$\ln(w_i) = \alpha_i + \beta_i r_i + \mu_i S_i \tag{2}$$

where α_i, β_i, and μ_i are empirical parameters describing the behavior of individual i.

In this work, the expected mortality risk (m) due to a selected data collection level in MN design is linked to WTP estimates to reduce risk of uncertainty in contaminated groundwater monitoring and seamlessly connects the work of modules 1 and 2 to the welfare analysis in module 3.

The WTP formulation for contaminated groundwater monitoring is provided as

$$WTP_i = \frac{1}{\mu_i} \ln\left[1 + \frac{\mu_i}{\beta_i}(m_0 - m_1)\exp(\alpha_i + \beta_i r_i + \mu_i S_i)\right] \tag{3}$$

where m_0 and m_1 are expected mortality risk due to contaminated groundwater at two MN designs with different spatial data collection levels. Technically, Equation 3 estimates the compensating variation between two mortality risk levels determined by different spatial data collection levels. The compensating variation estimate is defined as the amount of income that makes an individual indifferent between two different risk levels.

2.3.2 Stochastic Simulation of Willingness-to-Pay Model

In this analysis, there are several stochastic elements in the uncertainty and variability assessment. The labor/risk model (Equation 2) is estimated for individual i of the population using Monte Carlo sampling of probabilistic distributions for related population variables. The Monte Carlo approach (depicted in Figure 1) is composed of two loops: 1) an outer structured uncertainty loop and 2) inner variability loop. The outer loop represents subsurface heterogeneity. A range of subsurface heterogeneity levels is assumed and the matching field correlation lengths (λ) are used to generate the ensembles of equally likely realizations of K fields. The inner loop calculates the expected exposure to health risk using the procedure described in (Maxwell and Kastenberg, 1999). The maximum 30 year average contaminant concentration at the receptor well is calculated for each K field realization in a given K field ensemble. The maximum 30-year average contaminant concentration values for one K field scenario are used to produce a probabilistic distribution of contaminant concentrations with 95% probability (C_λ) which is used to estimate the mortality risk. The mortality risk values are used as inputs to the WTP equation.

3. Case Study Application

A carcinogen is leaking underground at an upstream location from a water well supplying a community located downstream. A two-dimension regional aquifer composed of unconfined sandy fluvial material with 4 km in length and 2 km in width, and 100 m thick was used in the analysis. A population is assumed to be located downstream of the municipal well that provides drinking water to the community as shown in Figure 2. A constant leaking source of trichloroethylene (TCE) is introduced 3 km upstream of the well at an estimated concentration of 100 ppm for ten years. TCE is a common carcinogen used as an industrial solvent and found at many hazardous waste sites. TCE has a low maximum contaminant level of 5 ppb established by the US EPA.

For demonstration purposes, a target population of 5,000 individuals is selected to describe the community affected by the contaminated aquifer. For simplicity, the simulated population characteristics are for population of the State of Utah for the year 2000. The collected data include probabilistic distributions of 1) health risk exposure parameters such as age and body weight, 2) labor/risk model variables such as wage rate and working hours, and 3) related population properties namely the health state.

3.1 Additional Data Scenarios Simulation

A set of realizations of K fields are produced based on variable spatial K correlation lengths (λ). In this example, we consider an aquifer with an area of 6 km^2. For base case, we assume field with a correlation scale of 112 m which corresponds to 120 monitoring wells. For additional data scenario, we assume a field with a correlation scale of 22 m which corresponds to 3,000 monitoring wells. Therefore, reducing uncertainty in subsurface heterogeneity is directly linked to number of monitoring locations needed.

For each K correlation length (λ), an ensemble of 500 equally likely random realizations of K fields is generated using a mean K of 10 m/day and a variance of ln K of 1. We follow the recommendations of Tompson and Gelhar (1990) to select the spatial discretization to simulate flow and transport. The K fields are generated using the Turning Bands method (Tompson et al., 1989) and they are used in the groundwater flow model MODFLOW (Harbaugh and McDonald, 1996) to simulate the flow field. Then, fate and transport of TCE is simulated using MT3D (Zheng and Wang, 1999). The flow domain consists of a single layer aquifer with flow occurring in areal two-dimensional flow field. Fate and transport consists of advective-dispersive mass transport with linear sorption and first-order decay. The values of flow and transport properties used include longitudinal and transverse dispersivity values of 5 and 0.5 m, respectively, and the well discharge was assumed to be 1,000 m^3/day. These values are similar to the values used by Maxwell et al. (1998) and Maxwell and Kastenberg (1999).

3.2 Health Risk Assessment

The TCE concentration at 95 % probability computed in the previous step is used to estimate the population cumulative health risk. The exposure-related population characteristics are presented as age-dependent probabilistic distributions following Zhao and Kaluarachchi (2002). Then, probabilistic distribution of age classes for Utah population and the corresponding characteristics are estimated using surveys and empirical studies conducted by various state and federal agencies. In this work, we use the published data from the Utah

Department of Health (UDOH, 2006).

The representative population of the state of Utah is simulated using Monte Carlo sampling approach. For the exposure parameters, age-dependent distributions of ingestion, inhalation, and dermal exposure parameters (except slope factors) were developed from published data as shown in Table 1.

Figure 3 shows the uncertainty effect on TCE concentration. The results of this analysis show that the receptor concentration increases as more monitoring wells are considered compared to less monitoring wells and this observation is consistent with the results of Maxwell et al. (1998).

3.3 Welfare and Socio-Economic Analysis

The WTP assessment employs labor/risk model that requires calibration using various population data to calibrate Equation 2 and produce individual-specific constants to be used in the benefit transfer formulation (Equation 3).

The calculation approach represents variability among individuals and sets the calibration process at the individual level. To produce individual specific WTP estimates, the parameters of Equation 2 are estimated for each individual (i) using the vector of inputs sampled by the Monte Carlo method. The sampled inputs are labor supply, (wi) wage rates, (r_i) and non-wage income, (S_i). Once the calibrated parameters for individuals are obtained, the individual WTP for data collection improvement is computed using Equation 3.

3.4 Application to Management Question

Given the high uncertainty of subsurface heterogeneity, stakeholders are challenged by the question of how many spatial data points (monitoring wells) should be present in the optimal monitoring network design. The base case assumes a MN design with K correlation length of 502 m (minimal data collection requirement). Assume that decision maker likes to improve data collection to reduce uncertainty in estimating TCE levels. We simulate incrementally increasing data collection levels (scenarios). The data collection improvement scenarios are as follows, one with λ=112 m and the other with λ=22 m.

The labor /risk model is calibrated for Utah population at the individual level. The average estimates of parameters α, β, and μ for Utah population are 92.56, $2.92\text{x}10^{-4}$, and $-3.24\text{x}10^{-2}$ respectively. For each improvement scenario; TCE concentration and health risk profile are estimated.

Table 2 summarizes the various outputs for the two data collection scenarios and demonstrates the practical use of the new health and economic metrics for decision making process. It is seen that the estimated contaminant concentration is higher as the number of monitoring locations is increased. The increase in identified concentration with more data collection indicates that low number of data points under-estimates actual concentration.

In Table 2, the change in health risk causes a change in the welfare of individuals. An identified higher risk level with additional information produces higher welfare by reducing unknown risk to the population. The aggregate WTP for a proposed improvement in MN design from scenario of λ=502 m to scenario of λ=112 m represents an increase in population welfare by $\$1.21\text{x}10^6$ per year. Similarly, addition of monitoring locations from scenario of λ=502 m to scenario of λ=22 m increases population welfare by $\$1.26\text{x}10^6$ per year. Therefore, by comparison one can estimate the increase in population welfare due to addition of monitoring wells (from a MN design of λ=112 m to λ=22 m) by $55,000 per year for a population of 5000 individuals in Utah or by a median of $11/year-Household.

4. Summary and Conclusions

This work introduces an interdisciplinary framework that integrates rigorous socio-economic concepts with traditional Benefit cost analysis used in groundwater contamination monitoring.

The proposed framework quantifies the impacts of decisions of acquiring additional data on the change in contaminant level, exposure to health risk, and socio-economic value. The developed framework estimates the impact of uncertainty in subsurface heterogeneity on the health risk exposure considering population variability.

The proposed methodology is attractive because the needed data are typically available in the public domain such as census and health databases which allows estimating WTP for reducing uncertainty in new setting. The methodology has the advantage of allowing stakeholder to allocate risk-reduction expenditures based on explicit monetary estimates of gain in welfare due to decisions of uncertainty reduction.

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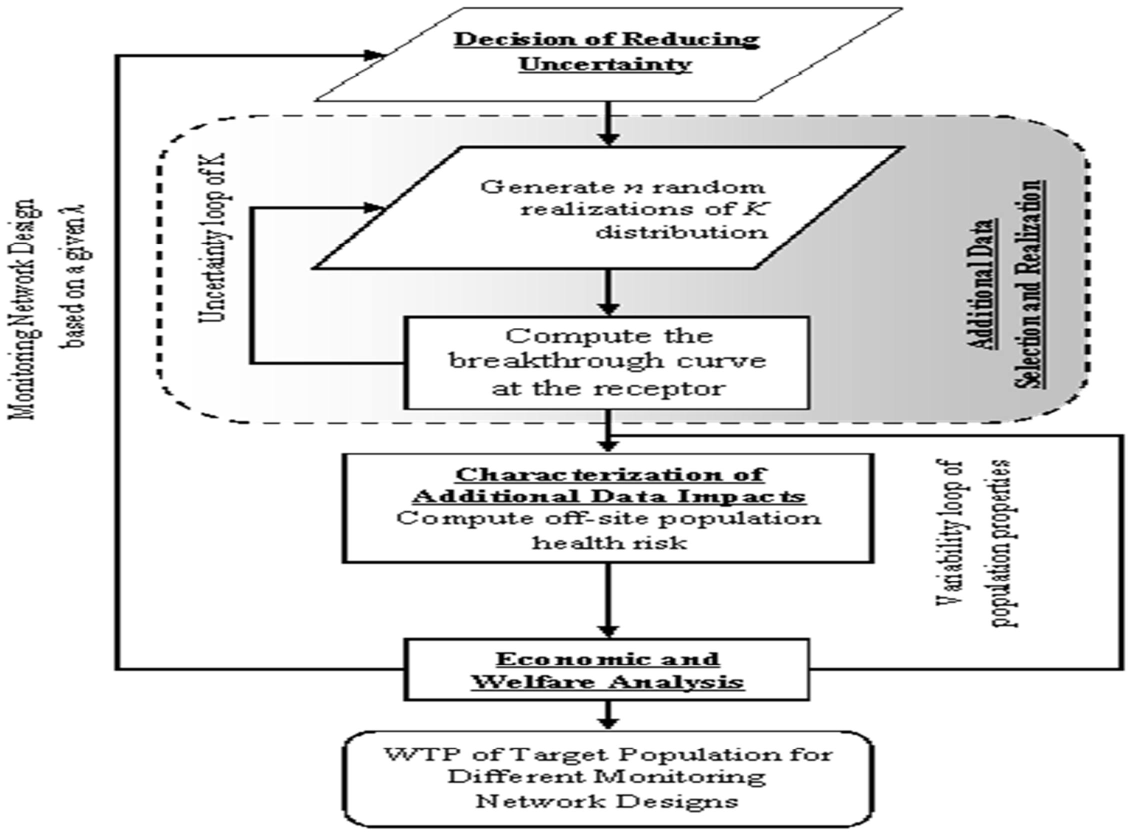

Figure 1. A flow chart illustrating the proposed methodology to compute WTP for a given health risk reduction by additional data collection.

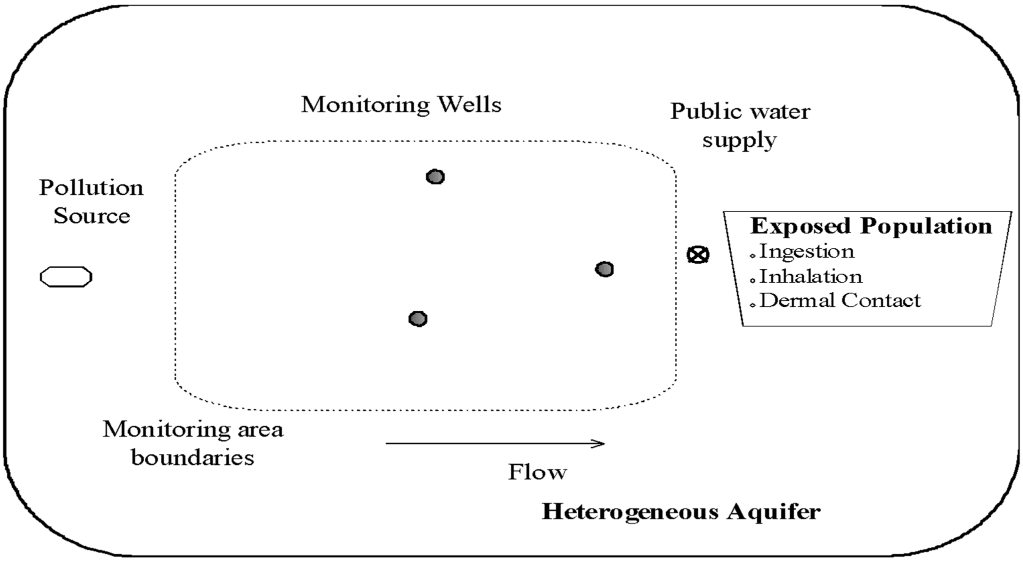

Figure 2. The areal layout of the aquifer used in the numerical experiment. The length and width of the aquifer are 4 and 3 km, respectively. The public water supply well is located 3 km down-gradient of the pollution source.

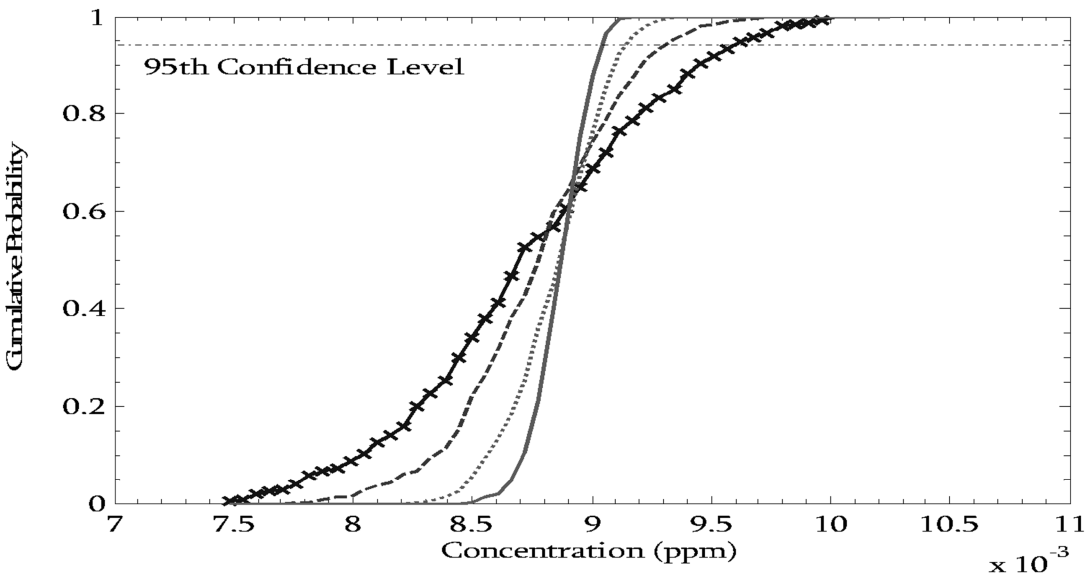

Figure 3. A plot of the cumulative distribution function of maximum 30-year average TCE concentration at the receptor for different correlation scales. A larger correlation scale reflects a more homogeneous structure compared to a small value of correlation scale.

Table 1. A summary of the sources and types of data used in the individual exposure to health risk.

Variable	Typical Values	Unit	Value used in this Study
Age	Variable	yrs	US Census Bureau International Data Base, 2006 using data from year 2006
Body weight	Variable	kg	Age dependent distributions recommended in EFH (1997)[a]
Exposure duration	30	yr	Constant
Exposure frequency	350	day/yr	Constant
Ingestion			
Ingestion rate	Variable	L/day	Uniform distribution with a range of 1.4 to 2.3 L/day; EFH, (1997)[a]
Ingestion slope factor	0.011	1/[mg/Kg-day]	Constant
Inhalation			
Inhalation rate	Variable	m^3/day	Fitted distribution to data using age as the variable; EFH (1997)[a]
Inhalation slope factor	0.011	1/[mg/Kg-day]	Constant
Dermal Contact			
Dermal contact slope factor	2.67	1/[mg/Kg-day]	Constant
Exposed skin surface area	Variable	cm^2	Function of age and body weight using surface area/body weight ratio; EFH (1997)[a]
Shower duration	Variable	hr/day	Fitted to distribution in the range of 0.016 to 2 hr/day; EFH (1997)[a]

*EHF is the US EPA Exposure Factors Handbook (1997).

Table 2. Data and results of the management example corresponding to two additional data scenarios with correlation scales of 22 and 112 m.

Variable	Scenario 1	Scenario 2	Comments
Additional Data Realization			
Information Level	λ=112 m	λ=22 m	2,979 additional locations needed finer resolution monitoring network to better represent subsurface heterogeneity
Number of monitoring locations	120	3,099	
Characterization of Additional Data Impacts			
95^{th} percentile concentration at the receptor	11.8 ppb	20.3 ppb	High resolution monitoring network produces a higher concentration and therefore higher health risk
Change in individual carcinogenic health risk from base case (λ= 502 m)	$2.9x10^{-4}$	$3.1x10^{-4}$	
Socio-Economic Estimates			
Calibrated Parameters Statistics			
Benchmark VSL	\$5 million (US EPA, 2004)		
Mean	α=92.56, β=$2.92x10^{-4}$, μ=$-3.24x10^{-2}$		
Standard deviation	α=12.45, β=$7.03x10^{-5}$, μ=-0.0076		
Household Heads' WTP (\$/yr)			
Median	238	249	A higher risk detected produces higher WTP statistics for additional data.
25^{th} percentile	156	188	
75^{th} percentile	360	386	
SID*	102	99	
Σ Household Heads' WTP for a 5,000 population size			
Total	\$$1.21x10^6$	\$$1.26x10^6$	An increase in population WTP of \$55,000

*SID is the Semi Interquartile Deviation. SID= (75^{th} percentile -25^{th} percentile)/2=inter quartile range/2 and accounts for 50% of the data (median and 1 standard deviation around the median).