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Multi-criteria decision analysis with probabilistic risk assessment for the management of contaminated ground water

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Abstract

Traditionally, environmental decision analysis in subsurface contamination scenarios is performed using cost–benefit analysis. In this paper, we discuss some of the limitations associated with cost–benefit analysis, especially its definition of risk, its definition of cost of risk, and its poor ability to communicate risk-related information. This paper presents an integrated approach for management of contaminated ground water resources using health risk assessment and economic analysis through a multi-criteria decision analysis framework. The methodology introduces several important concepts and definitions in decision analysis related to subsurface contamination. These are the trade-off between population risk and individual risk, the trade-off between the residual risk and the cost of risk reduction, and cost-effectiveness as a justification for remediation. The proposed decision analysis framework integrates probabilistic health risk assessment into a comprehensive, yet simple, cost-based multi-criteria decision analysis framework. The methodology focuses on developing decision criteria that provide insight into the common questions of the decision-maker that involve a number of remedial alternatives. The paper then explores three potential approaches for alternative ranking, a structured explicit decision analysis, a heuristic approach of importance of the order of criteria, and a fuzzy logic approach based on fuzzy dominance and similarity analysis. Using formal alternative ranking procedures, the methodology seeks to present a structured decision analysis framework that can be applied consistently across many different and complex remediation settings. A simple numerical example is presented to demonstrate the proposed methodology. The results showed the importance of using an integrated approach for

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decision-making considering both costs and risks. Future work should focus on the application of the methodology to a variety of complex field conditions to better evaluate the proposed methodology.
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1. Introduction

Contamination of ground water resources has been one of the major environmental concerns during the past few decades due to concerns on public health. Management of contaminated ground water resources has been a difficult challenge because of the limited resources that can be committed to remediate a large number of contaminated sites (National Research Council, 1994). In order to rationalize the allocation of these limited resources, health risk assessment was adopted as a management framework to screen and prioritize remediation of contaminated sites. Risk-based management of contaminated sites consists of two stages, risk assessment and decision analysis. Risk assessment includes quantification of the risk to human health, and the evaluation of the significance of this risk. When the risk is determined unacceptable, potential remedial alternatives are identified, and decision analysis is performed to choose the best corrective action.

Typical environmental decision analysis is performed using a cost benefit analysis framework. The comparison of different decision alternatives is measured by an economic index such as the total revenue, benefit/cost ratio, or rate of return. The best alternative is decided following a decision criterion such as the maximum, maximin, minimax regret, or robustness criteria. A common approach for a decision analysis problem is to maximize the total revenue objective function that incorporates the net present value of a stream of benefits and costs. The objective function may include uncertainty by incorporating the expected cost of failure. The uncertainty of each alternative can thus be included in the objective function using the risk of failure. This formulation of the risk–cost–benefit (RCB) objective function is widely used because of its simplicity, flexibility, capability of treating uncertainties, and above all due to the ease of interpreting the results in monetary terms (Massmann and Freeze, 1987a,b; Freeze et al., 1990; Massmann et al., 1991).

The risk in the RCB analysis, which is typically the probability of failure, should not be confused with the health risk, which is the probability of harm to human health. The definition of failure, through which the risk or failure probability is calculated, is based on the probability of exceeding the drinking water standard defined as the maximum contaminant level (MCL) of the contaminant of concern in ground water. In order to incorporate information from the health risk assessment into the RCB framework, risk-based cleanup levels are used instead of the MCL to define the failure probability. However, risk-based cleanup levels are estimated through back-calculation using the risk quantification model. Back-calculation of cleanup levels requires the use of point estimates in the risk calculations, which are often conservative estimates with unknown uncertainties (Finley and Paustenbach, 1993). Probabilistic risk assessment, which explicitly accounts for uncertainty and variability, is not carried out in the back-calculation mode because of the need to forwardly propagate the uncertainties (US EPA, 1999). Hence, crucial information on variability and uncertainty of risk estimates is not typically used in the RCB analysis.

Another shortcoming of the RCB analysis is the improper representation of the cost of failure, which accommodates the uncertainty. The failure cost term can never be guaranteed to be inclusive nor precise due to the nature of post-failure consequences that are inherently difficult to predict. Litigation costs, regulatory penalties, loss of opportunity or investment, and damage to public relations are difficult to quantify or predict. The magnitude of the failure cost affects directly the alternative that is chosen. Decisions made using a RCB analysis are regularly subject to high sensitivity of result to the failure cost (Wang and McTernan, 2002; Russell and Rabideau, 2000; Waldis et al., 1999; Rosen and LeGrand, 1997).

Public interest in health and environmental impacts of pollution has grown considerably in recent years due to improved public education. This interest has made it vital to include the public in the decision-making process. However, communication of risk information is inherently difficult due to the complexity of the technical information. Typically, a RCB analysis provides information on the current and future scenarios in monetary terms, which is easy to understand. However, it conceals the degree of uncertainty in the outcome, and does not provide important information about the actual risk, the significance of the risk, and the confidence of its estimates.

A recent study by Khadam and Kaluarachchi (2003) provided a detailed discussion on the limitations of the existing risk-based management of contaminated sites and provided evidence for the need to improve the current approach using the knowledge gathered from other fields such as dam safety management and the utility industry. The underlying motivation for this paper is to extend these ideas to attempt to establish an improved quantitative framework, in the context of environmental pollution and restoration, to address the trade-off between the acceptable health risk and the cost of risk reduction. Ideally, any health risk should be eliminated, but this desire is not practical due to resource constraints and sometimes the inherent complexity of the contamination event. Therefore, there exists a de minimis health risk, beyond which all risks are deemed trivial. This de minimis risk is often a function of the costs required to reduce a unit of risk, as well as the seriousness of threat to human health and life. This study is not concerned in resolving this trade-off due to some of these inherent issues and concerns, but only motivated by the challenge.

A rational public policy will consider a management plan only if its benefits exceed the costs. The benefits are typically difficult to quantify in the same metric as the costs, which is often in monetary terms, thus, an alternative approach should be found to compare the benefits and costs. In essence, the theme of this paper is to address the major issue of comparing the benefits with costs in decision-making at hazardous waste contaminated sites. In this work, an alternative approach for cost–benefit decision analysis is proposed and the potential applicability of the methodology is demonstrated through a numerical experiment involving a hypothetical field-scale scenario.

The proposed methodology aims at reformulating the decision problem of ground water remediation in a multi-criteria decision setting rather than the currently employed RCB analysis framework. We recognized that the trade-off between the residual risk and the cost of risk reduction should be the focus of the methodology. We also recognized the need to incorporate the uncertainty and variability of decision criteria in the methodology to ensure an informed decision-making process. In order to establish a broad and consistent definition of acceptable risk, we investigated the relationship between the individual risk and the population risk and the possible trade-off between these two parameters. The decision criteria were developed to describe the acceptable risk and cost-effectiveness as a measure of desirability of any given remediation alternative. Finally, the proposed methodology explores the use of three multi-criteria decision analysis methods to rank and select between remedial alternatives.

2. Proposed methodology

The proposed methodology integrates probabilistic risk assessment and multi-criteria decision analysis into a comprehensive framework for subsurface contamination management. The framework consists of two parts; i.e., the risk analysis and decision analysis as shown in Fig. 1. In a typical cleanup scenario, a set of remedial alternatives will be developed upon the detection of the contamination event. These remedial alternatives will be developed using the data gathered from the ongoing field monitoring and testing. The design of remedial alternatives is dependent on the available data, chemicals of concern, extent of contamination, and the exposed population. A risk assessment will then be conducted using the protocols suggested by the US Environmental Protection Agency (US EPA) (US EPA, 1989b, 1991) to determine the cancer risk for each proposed remedial alternative. The information needed for the risk assessment will be collected from a hydrogeologic model of flow and transport incorporating spatial variability and a population model incorporating variability of population characteristics. The information derived from the probabilistic risk assessment is then incorporated into the multi-criteria decision analysis model. Each remedial alternative is tested against the decision criteria, and then the alternatives are ranked to determine the best alternative.

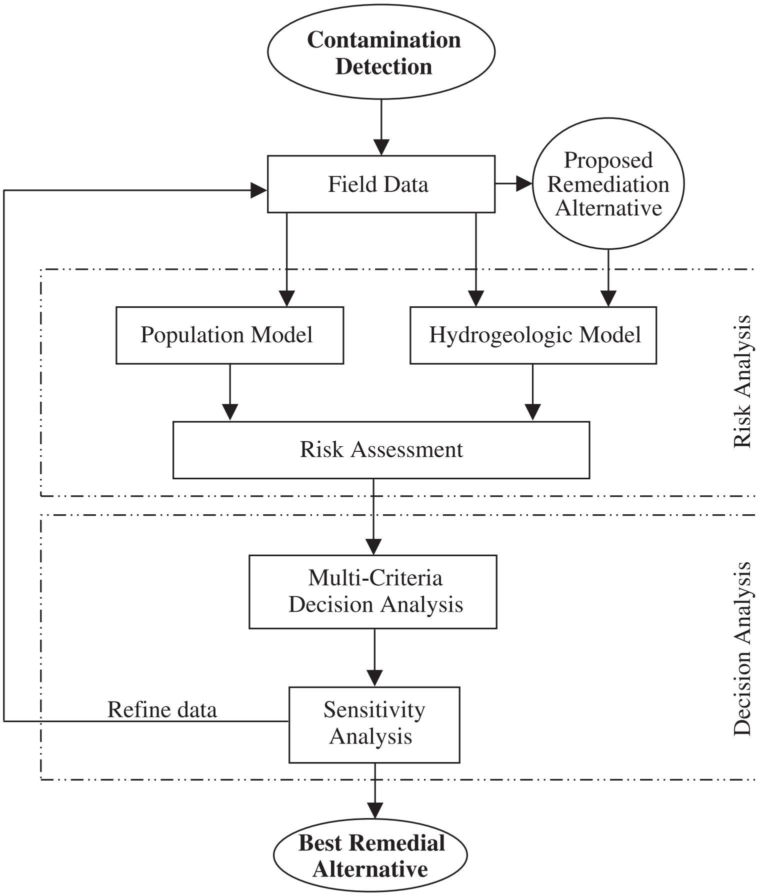

Fig. 1. A flow chart describing the proposed risk-based decision analysis methodology.

2.1. Health risk assessment

Risk assessment is the process that estimates the likelihood of occurrence of adverse effects to humans and ecological receptors as a result of exposure to hazardous chemical, physical, and/or biological agents. Human health risk assessment is defined as the characterization of the potential adverse health effects of human exposures to environmental hazards. Risk assessment may be performed in short-term (acute) exposures or long-term (chronic) exposures, or a combination of these exposures. Risk assessment is composed of four steps; hazard identification, exposure assessment, toxicity assessment, and risk characterization (Asante-Duah, 1993; US EPA, 1989b).

The US EPA (1989a) proposed a linear relationship between the exposure and risk for both chronic (carcinogenic) and acute (non-carcinogenic) exposures. The equation used to predict the human lifetime excess cancer risk for a single-stage carcinogenic effect from exposure to organic contaminants is based on the Poisson model for individual cancer occurrence, with probability of at least one cancer occurrence of interest (Maxwell et al., 1998). The cancer risk, R, is given as

$$R = 1 - \exp[-\mathrm{DE} \times \mathrm{SF}] \tag{1}$$

where SF is the slope factor of the carcinogenic contaminant (kg day/mg) and DE is the average daily exposure of the carcinogenic chemical (mg/kg day).

Eq. (1) approaches a linear relationship for small values of risk (risk < 0.01), and therefore can be written as

$$R = \mathrm{DE} \times \mathrm{SF} \tag{2}$$

The slope factor represents the cancer developing potency. The average daily exposure of a carcinogenic chemical is approximated as the average concentration of the chemical of concern multiplied by the daily intake of contaminated media, e.g., water. The typical exposure pathways of cancer risk at an off-site receptor are due to ingestion of water, inhalation of volatiles, and dermal contact due to the use of water (US EPA, 1989a,b). The risk from each of these exposure pathways can be summarized as follows:

Risk due to ingestion of water (R_g)

$$R_g = \frac{\mathrm{SF}_g \times C \times I_g \times \mathrm{EF} \times \mathrm{ED}}{\mathrm{WB} \times \mathrm{AT} \times 365} \tag{3}$$

Risk due to inhalation of volatiles (R_h)

$$R_h = \frac{\mathrm{SF}_h \times C \times I_h \times K \times \mathrm{EF} \times \mathrm{ED}}{\mathrm{WB} \times \mathrm{AT} \times 365} \tag{4}$$

Risk due to dermal contact (R_d)

$$R_d = \frac{\mathrm{SF}_d \times C \times \mathrm{Sa} \times \mathrm{Pc} \times K_v \times \mathrm{ET} \times \mathrm{EF} \times \mathrm{ED}}{\mathrm{WB} \times \mathrm{AT} \times 365} \tag{5}$$

where C is the concentration of the chemical of concern in water at the receptor (mg/l); SF_g, SF_h, and SF_d are the slope factors of the chemical (kg day/mg) due to ingestion, inhalation, and dermal contact, respectively; I_g is the daily water ingestion rate (l/day); I_h is the daily indoor inhalation rate (m^3/day); K is the volatilization factor of the contaminant (l/m^3); Pc is the skin permeability constant (cm/h); Sa is the exposed skin surface area (cm^2); ET is the shower duration (h/day); EF is the exposure frequency (days/y); ED is the exposure duration (year); WB is the body weight (kg); AT is the average lifetime (year);

and K_v is the volumetric conversion factor (10^{-3} cm^3/l). The total cancer risk, R, is the sum of risks from all individual pathways given as

$$R = R_g + R_h + R_d \tag{6}$$

2.2. Probabilistic risk assessment

Many sources of uncertainty surrounding the existing risk assessment methodology are due to the incomplete exposure assessments, limited and questionable monitoring information, limitations of dose–response assessments, and/or the absence of complete toxicology profiles of some chemicals. The slope factor and the daily dose of chemical intake contribute to the uncertainty in the final risk value given in Eq. (1). The uncertainty in the slope factor is inherently high due to the extrapolation methods used to derive human cancer potency factors from laboratory test results on animals. Unfortunately, it is difficult to characterize such uncertainty in the slope factor. The average daily intake of a chemical typically shows considerable variability and uncertainty. Sources of the uncertainty and variability are attributed to the concentration of the chemical and the population characteristics. The uncertainty in the concentration is due to the high uncertainty generally associated with the hydrogeologic parameters of the subsurface. The variability of the population characteristics, for example ingestion rate, is associated with a large variability in physical and behavioral characteristics of individuals in any population (Zhao and Kaluarachchi, 2002). A population model can account for the variability of population characteristics by means of age-independent statistical distributions of some important characteristics, e.g., inhalation rate, ingestion rate, and body surface skin (McKone and Bogen, 1991).

Probabilistic risk assessment incorporates the variability and uncertainty of the risk parameters in the risk estimate. The input parameters are described through probability distributions, and the solution provides the statistical distribution of the risk estimate. The risk model used here is given as (Bogen and Spear, 1987):

$$R = \mathrm{Prob}(\boldsymbol{U}, \boldsymbol{V}) \tag{7}$$

where $\boldsymbol{U}=\{u_1, u_2, \ldots u_n\}$ is a vector of n uncertain parameters, and $\boldsymbol{V}=\{v_1, v_2, \ldots v_m\}$ is a vector of m variable parameters. In the context of human health risk, $\boldsymbol{U}$ and $\boldsymbol{V}$ are defined as: $\boldsymbol{U}=\{C\}$ and $\boldsymbol{V}=\{I_g, I_h, \mathrm{Sa}, \mathrm{ET}, \mathrm{EF}, \mathrm{ED}, \mathrm{WB}, \mathrm{AT}\}$. The vectors $\boldsymbol{U}$ and $\boldsymbol{V}$ are represented through statistically independent probability distribution functions, and the output provides the statistical distribution of the risk. In this work, we propose to use the Monte Carlo method to compute the risk due to the joint uncertainty and variability of the input parameters.

The modified two-stage simulation using the Monte Carlo method (Cohen et al., 1996) has an "inner loop" which accounts for the variability, and an "outer loop" that accounts for uncertainty (see Fig. 2). The computational effort can be reduced substantially, especially in handling large amounts of data by storing only

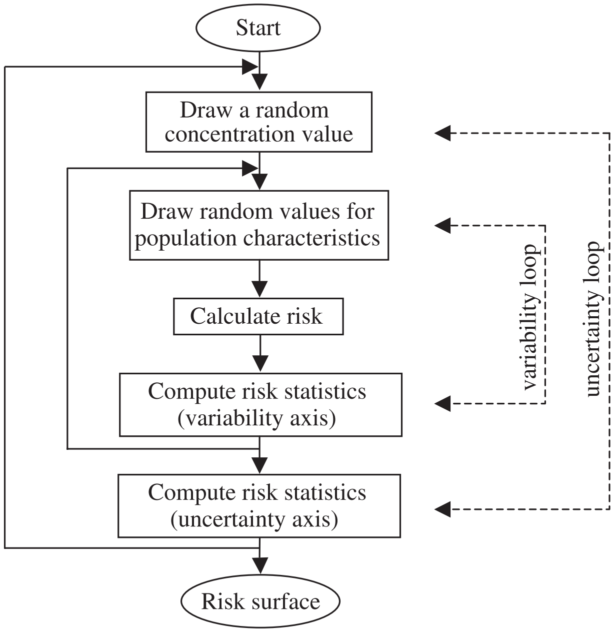

Fig. 2. A flow chart describing the modified two-stage Monte Carlo simulation.

the summary statistics such as the 50th and 95th percentiles of the results of the inner loop.

2.3. Hydrogeologic analysis

Ground water flow is described using the Darcy's law and the mass conservation equation. The governing equation, describing transient ground water flow in a two-dimensional flow domain, is given as

$$\frac{\partial}{\partial x}\left(K_x B\frac{\partial h}{\partial x}\right)+\frac{\partial}{\partial y}\left(K_y B\frac{\partial h}{\partial y}\right)=s\frac{\partial h}{\partial t}+W \tag{8}$$

where x and y are spatial coordinates; t is time; K_i is the hydraulic conductivity (L/T) where $i=x$ or y; h is the hydraulic head (L); B is the aquifer thickness (L); s is the storage coefficient (L^0); and W is the sink or source term (L/T). The pore water velocity, v_x (L/T) along the x-direction, is estimated from Darcy's law as

$$v_x=-\frac{K_x}{n}\frac{\mathrm{d}h}{\mathrm{d}x} \tag{9}$$

where n is the effective porosity. Note v_y can be computed in a similar manner to Eq. (9).

The transport of a reactive organic contaminant in ground water can be described by the advection–dispersion–reaction equation with the inclusion of a reaction term to account for biodegradation. The two-dimensional form of the equation is given as

$$R^* \frac{\partial C}{\partial t} = D_{\mathrm{L}} \frac{\partial^2 C}{\partial x^2} + D_{\mathrm{T}} \frac{\partial^2 C}{\partial y^2} - v_x \frac{\partial C}{\partial x} - v_y \frac{\partial C}{\partial y} - \frac{C_{\mathrm{O}} W}{nb} + \Sigma m \tag{10}$$

where C is the water phase concentration of the contaminant (M/L^3); $(C_{\mathrm{O}}W)/(nb)$ is the source or sink term (M/L^3-T); Σm is the rate of removal or addition of contaminant (M/L^3-T); R^* is the retardation coefficient (L^0); and D_{L} and D_{T} are longitudinal and transverse dispersion coefficients, respectively. The dispersion coefficients can be estimated from

$$D_{\mathrm{L}} = D^* + v_x \alpha_{\mathrm{L}}, \text{ and } D_{\mathrm{T}} = D^* + v_y \alpha_{\mathrm{T}} \tag{11}$$

where D^* is the effective diffusion coefficient (L^2/T), and α_x and α_y are longitudinal and transverse dispersivities, respectively. Longitudinal dispersivity can be estimated from (Xu and Eckstein, 1995):

$$\alpha_x = 0.83(\log x)^{2.414} \tag{12}$$

where x is the length of a typical flow path for the specific problem. The longitudinal to transverse dispersivity ratio $((\alpha_x)/(\alpha_y))$ is generally within the range of 6–20 (Fetter, 1999). The retardation coefficient due to linear adsorption is calculated as

$$R^* = 1 + \rho_{\mathrm{b}} \frac{K_{\mathrm{d}}}{n} \tag{13}$$

where ρ_{b} is the bulk density of the soil (M/L^3); and K_{d} is the distribution coefficient of the contaminant which is soil-dependent (L^3/M).

2.3.1. Biodegradation

Organic contaminants dissolved in ground water typically undergo intrinsic biodegradation, also known as natural attenuation, subject to the availability of one or more electron acceptors, nutrients such as N and P, and favorable environmental conditions such as pH, microbial population, and non-toxic conditions. Common aromatic hydrocarbon species, such as benzene or toluene, can be easily biodegraded under aerobic conditions followed by other electron acceptors under anaerobic conditions. Aerobic biodegradation is typically fast but accounts for less than 15% to 20% of the long-term biodegradation under natural conditions (Newell et al., 1995). The reason for this small attenuation is the limited supply of oxygen to the contaminated zone by natural ground water flow, which typically contains less than 6 mg/l of dissolved oxygen. However, when enhanced biodegradation is promoted through the injection of oxygen to the contaminated zone via ground water, the rate of biodegradation can accelerate substantially. Anaerobic biodegradation is also possible in the presence of electron acceptors such as nitrate, iron, and sulfates. However, it is a slow process, but the long-term biodegradation potential is higher than with oxygen alone as the electron acceptor (Newell et al., 1995).

In this paper, we propose to consider remedial alternatives requiring both natural and enhanced biodegradation. There are many biodegradation reaction models present in the literature that includes models using complex Monod-type reaction kinetics (Bordon et al., 1986; Semprini and McCarty, 1991; Clement et al., 1998) to simple instantaneous reaction models (Rifai et al., 1988). The use of a given model is dependent on the availability of site-specific data to model the appropriate reaction kinetics. Although Monod-type reaction models are broad, flexible, and accurate, these models also require substantial data, especially data that depends on aqueous phase chemistry and microbiology. Due to the large variability of soil biota and the uncertainty in accurately measuring or estimating such parameters, the use of complex Monod-type models may not be appropriate for many sites. On the other hand, simple instantaneous reaction models have been successfully used in many field sites (Rifai et al., 1988).

The purpose of this work is to demonstrate the need for health risk-based decision analysis for aquifer remediation and to introduce a candidate framework for such a decision analysis. In keeping with this focus while not being too specific in the hydrogeologic modeling, we propose to use the instantaneous reaction model to describe both intrinsic and enhanced biodegradation. The proposed framework is independent of the biodegradation model, and future work may include sophisticated models that require more data.

The instantaneous reaction model of biodegradation can be simply demonstrated as follows:

$$\Delta C = -\frac{O}{F} \tag{14}$$

where ΔC is the change in the organic contaminant concentration (M/L^3); O is the oxygen or the electron acceptor concentration (M/L^3); and F is the stochiometric ratio (L^0) between the electron acceptor and the contaminant. When the oxygen concentration in ground water is small compared to the demand exerted by the organic contaminant, then the oxygen is depleted from the system causing oxygen-limited biodegradation. This is the common scenario with natural attenuation and thereafter, long-term anaerobic degradation can help reduce the dissolved phase plume unless aerobic degradation is promoted through the injection of oxygen to the contaminated area.

In this study, the ground water flow model, MODFLOW (McDonald and Harbaugh, 1988; Harbaugh and McDonald, 1996), is used. The fate and transport model that includes instantaneous biodegradation, RT3D, is used in this work (Clement et al., 1998). RT3D has the advantage of simulating instantaneous biodegradation of fuel hydrocarbons under both aerobic and anaerobic conditions.

2.3.2. Spatial variability

Hydraulic conductivity is the most important spatially variable hydrogeologic property in a heterogeneous aquifer. Hydraulic conductivity is considered a spatially correlated random field, and there are many models available to describe this random stochastic field using a lognormal distribution (Gelhar, 1993; Dagan, 1979). The spatial variability of hydraulic conductivity can be represented as a statistically stationary, two-dimensional random field. The natural logarithm of hydraulic conductivity is assumed to be second-order stationary with an exponential semi-variogram, γ, given as (Gelhar, 1993),

$$\gamma(z) = \sigma^2\left[1 - \exp\left(-\frac{\delta}{\lambda}\right)\right] \text{ and } \sigma^2 = \mathrm{Var}[\ln(K)] \tag{15}$$

where λ is the correlation length (L); σ^2 is the variance of $\ln K$; and δ is the distance.

The semi-variogram of hydraulic conductivity is used to generate multiple realizations of the random hydraulic conductivity field. The turning band method of Thompson et al. (1989) was used in this work to generate the random fields of hydraulic conductivity through unconditional simulations.

The simulation of flow and transport using a large number of random fields can be time-consuming. In order to reduce this effort, the minimum number of simulations needed to achieve statistical convergence was estimated prior to the simulation using the approach described by Lahkim and Garcia (1999). In this approach, the cumulative mean and variance at each node were evaluated and assessed for convergence based on the number of random fields included in the simulation.

2.4. Decision analysis

2.4.1. Decision criteria

Decision-making to select the best remedial alternative requires the identification of the decision objective, which is crucial to the outcome. The immediate objectives of a decision-maker, faced with a subsurface contamination situation, typically include (a) reducing the cancer risk to the exposed population to the extent feasible; (b) minimizing legal liability by complying with the acceptable risk established by the regulators; and (c) minimizing the cost of the corrective measures. This set of objectives is not inclusive and may include a variety of other objectives based on the breadth of the decision field, and the interests and attitudes of the decision-maker. The abovementioned decision objectives, however, are sufficient to describe the desire of many decision-makers involved in a contamination issue.

The proposed methodology introduces five decision criteria that measure the desirability of each remedial alternative in accordance with the decision objectives. These decision criteria are (a) maximum individual risk, (b) expected individual risk, (c) population risk, (d) risk index, and (e) cost per cancer case avoided or cost per life saved. These criteria describe the basic features of each alternative in terms of performance, compliance with environmental regulations, and cost-effectiveness. The decision analysis framework described next will use these decision criteria in the decision-making process.

The joint uncertainty–variability risk analysis generates a three-dimensional risk surface, R,

$$R = f(u, v)$$

where u is degree of uncertainty, and v is degree of variability. The 3-D risk surface can be reduced to a two-dimensional risk profile describing the uncertainty at a given variability, or to a profile describing population variability at a given uncertainty. A risk profile resulting from a cut parallel to the variability axis, $R(v=a,u)$, provides information about the uncertainty of risk estimate for a given population variability. Similarly, a risk profile resulting from a cut parallel to the uncertainty axis, $R(u=b,v)$, indicates the variation of risk with population variability for a given hydrogeologic uncertainty.

Maximum individual risk (MIR) measures the lifetime risk at an upper limit of the uncertainty and variability; hence, MIR gives a conservative estimate of any individual developing cancer. In other words, the maximum individual risk is the risk posed on the maximum exposed individual in the population. This definition of individual risk is such that it satisfies the regulatory requirement to consider the risk at a high percentile (US EPA, 1999). The MIR here will be defined as the risk estimated at the 95th percentile of variability and 95th percentile of uncertainty, or

$$\mathrm{MIR} = R(v = 0.95,\ u = 0.95) \tag{16}$$

The use of the 95th percentile is to avoid the effect of the extreme points at the tail of the risk distribution.

Expected individual risk (EIR) is an expression of the average maximum risk. In contrast to the MIR, EIR estimates the average risk posed on the maximum exposed individual in the population. EIR is calculated as the average of the risk profile at the 95th percentile of the population variability:

$$\mathrm{EIR} = \int_0^1 R(v = 0.95, u)\mathrm{d}u \tag{17}$$

Population risk (PR) is the number of expected cancer cases in the exposed population per year. PR is estimated by averaging the risk profile using the formulation of Zhao and Kaluarachchi (2002),

$$\mathrm{PR} = \frac{N}{\mathrm{ED}} \int_0^1 R(v, u = 0.95)\mathrm{d}v \tag{18}$$

where N is the size of the exposed population, and ED is the exposure duration (years).

Risk index (RI) describes the trade-off between the individual and population risks. Travis and Richter (1987), through the review of cancer risk data used to support regulatory decisions concerning carcinogenic substances, found that the key to understanding regulatory practices is in the relationship between the individual lifetime risk and the population risk. The analysis of data from several regulatory agencies suggests that for small population risks (fewer than 0.1 cancer deaths per year in the exposed population), regulatory action is seldom taken on an individual lifetime risk less than about 10^{-4}. As the population risk approaches 250 cancer deaths per year (which could occur only in a population similar to the US), the tolerable individual risk decreases to 10^{-6}. The formulation of these findings is presented in Fig. 3. The upper left side of the graph corresponds to a high individual risk experienced in a small group of people, e.g., risk in the workplace. The lower right side corresponds to the individual risk experienced in a large population, e.g., risk in large metropolitan centers. The relationship between the individual and population risks can be described using the following relationship:

$$\mathrm{RI} = -\log_{10}(\mathrm{PR} \times \mathrm{MIR}) \tag{19}$$

Eq. (19) indicates that an acceptable risk can be described with a RI of 5 (see Fig. 3).

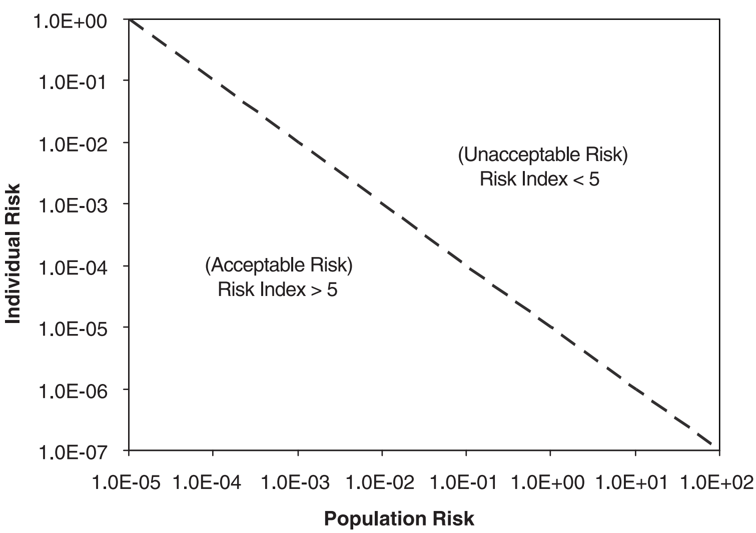

Fig. 3. Definition of acceptable risk using the risk index.

Cost per-life saved is a measure of the cost-effectiveness of a remedial alternative. CPLS is expressed as the cost per cancer case avoided or saved. CPLS is defined as follows,

$$\mathrm{CPLS} = \frac{\mathrm{Cost}^i - \mathrm{Cost}^0}{(\mathrm{PR}^0 - \mathrm{PR}^i) \times \mathrm{ED}} \tag{20}$$

where (^{0}) refers to the basecase scenario which is the *no-action* scenario and (^{i}) refers to the *i*th alternative. Cost is the present discounted cost of the remedial alternative defined as

$$\mathrm{Cost} = \sum_{t=1}^{t} \frac{1}{(1+r)^t} [\text{Capital Cost} + \text{Operation Cost}] \tag{21}$$

where r is the discount rate and t is the time horizon of the remedial alternative.

2.4.2. Methodology

The choice of an alternative from a set of alternatives is inherently difficult if no one option is dominant for the given decision criteria. The dominance is established if an alternative is the best or worst considering all the decision criteria. The challenge of a decision-making process is to identify the best alternative when none of the alternatives are dominating. In such circumstances, there is a necessity to have a scientific, reliable, and consistent framework to identify the best alternative given the decision criteria. The purpose of this proposed decision analysis framework is to identify the best alternative in the presence of a set of non-dominant alternatives. In this work, the general expectation is that any additional cost should provide additional risk reduction and better compliance of environmental regulatory requirements. The degree of desirability of an alternative increases with the increase in the RI and risk reduction while the desirability decreases with the increase in total cost and CPLS. Therefore, remedial alternative ranking requires a multi-criteria decision analysis that provides a reliable tool for non-dominant alternative analysis.

Two approaches for decision analysis will be presented here. The first is an explicit analysis of the proposed alternatives based on the decision objectives stated previously. The second approach is an implicit analysis of the alternatives based on a standard multi-criteria decision analysis tool developed in operations research. Both approaches use the decision criteria developed in the previous section to analyze the desirability of each alternative.

2.4.3. Explicit decision analysis

Explicit decision analysis is a two-stage approach that has a filtering stage followed by a selection stage as shown in Fig. 4. The filtering stage rejects the alternatives that do not match the decision criteria, and the decision-maker has the option of re-evaluating these alternatives for modifications. The selection stage ranks the filtered alternatives in a detailed manner for the final selection.

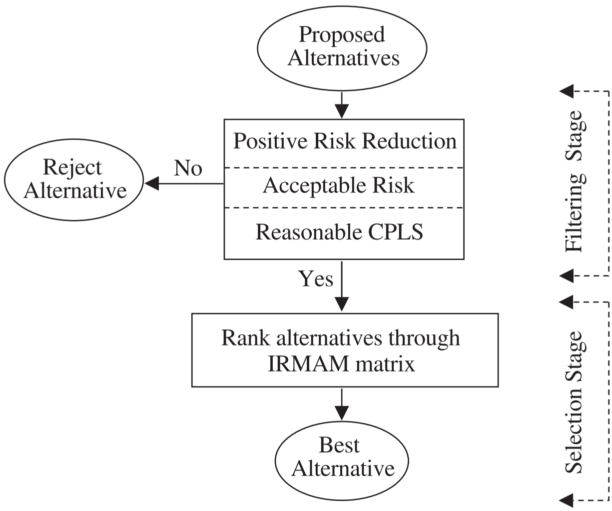

Fig. 4. A flow chart describing the proposed explicit decision analysis.

2.4.3.1. Filtering stage. The proposed methodology requires that all alternatives pass three conditions of the filtering stage given as (a) positive risk reduction, (b) acceptable risk, and (c) reasonable CPLS. The positive risk reduction condition requires that each alternative should not lead to an increase in the risk to the exposed population. In some occasions, the proposed remedial alternative may cause a reduction of risk to certain segments of the population while increasing the risk to other segments of the population. In such cases, the accurate prediction of the overall impact of the remedial alternative is important.

Risk reduction alone is not a sufficient justification for implementing a remedial alternative; the alternative should also lead to a risk below the acceptable risk. The acceptable risk is typically not clearly defined and depends on various other considerations. In order to satisfy the regulatory requirement of acceptable risk, we will examine the acceptable risk criteria developed in the previous section. The RI of a proposed alternative should fall within the acceptable risk range as indicated in Fig. 3. In addition, the maximum and expected individual risk should fall within the range of the acceptable risk of 10^{-4} to 10^{-6}. These criteria, when viewed jointly, give a good judgment about the acceptability of the final risk.

The CPLS is a measure of the efficiency of a proposed alternative. A high CPLS indicates inefficient management of the contamination event. Thus, alternatives with low CPLS are more preferable than those with high CPLS while achieving similar cleanup targets and risk reduction. The decision about how high or low a certain CPLS is a subjective judgment that relies on the comparability to CPLS and other expenditures in similar events. In summary, this criterion will depend on the subjective judgment of the decision-maker and data from the US EPA in similar events (Khadam and Kaluarachchi, 2003; also see Table 1).

Table 1
Values of CPLS established by US EPA in various environmental regulations (from US Office of Management and Budget, Fiscal year 1992)

Regulation	CPLS (US$*m*)
Trihalomethane drinking water standards	0.2
Standards for radionuclide in uranium mines	3.4
Benzene NESHAP (Original: Fugitive Emissions)	3.4
Ethylene dibromide drinking water standard	5.7
Benzene NESHAP (Revised: Coke byproducts)	6.1
Arsenic emission standards for glass plants	13.5
Arsenic/copper NESHAP	23
Hazardous waste listing for petroleum refining sludge	27.6
Cover/move uranium mill tailings (Inactive sites)	31.7
Benzene NESHAP (Revised: Transfer operations)	32.9
Cover/move uranium mill tailings (Active sites)	45
Benzene NESHAP (Revised: Waste operations)	168
Dichloropropane drinking water standard	653
Hazardous waste land disposal ban (1st and 3rd)	4190
Municipal solid waste landfill standards (proposed)	19,107
Trazine/alachlor drinking water standard	92,069
Hazardous waste listing for wood preserving chemicals	5,700,000

2.4.3.2. Ranking stage. The selection of the best alternative from a set of alternatives, which satisfies the conditions of the filtering stage, requires the ranking of the alternatives. To develop a consistent and logical ranking procedure, a matrix known as the **M** matrix is proposed. The **M** matrix is a simple analytical tool that computes the amount of risk reduction achieved when moving from alternative i to alternative k, and the corresponding change in the cost. In general, the difference in the increased cost due to the reduction in risk from alternative $\boldsymbol{i}$ to alternative j, Cost_{ik} is given as

$$\mathrm{Cost}_{ik} = \frac{\mathrm{Cost}^i - \mathrm{Cost}^k}{(\mathrm{PR}^k - \mathrm{PR}^i) \times \mathrm{ED}} \tag{22}$$

where the terms with i and j refer to the corresponding values of alternatives i and j, respectively. The **M** matrix is an upper triangular matrix with $n-1$ rows and n columns, where n is the number of alternatives (see Fig. 5). Since the order of the alternatives in the matrix is crucial in the analysis, the alternatives should be in an ascending order of their total cost; column i has a lower total cost that column $(i+1)$ for the same row. The value of each cell of the upper triangle is the additional cost that may incur due to the additional safety, Cost_{ik}. The last column of the **M** matrix holds the best alternative of each row, which corresponds to that of the column with the lowest entry in any row that is greater than 0.

Once the **M** matrix is prepared, the frequency of appearance of a given alternative in the last column across all alternatives provides the highest rank among all alternatives. This ranking is an expression of the relative preference of

	A_1	A_2		A_{n-1}	A_n	Best A
A_1	0	$C^1{}_2$		$C^1{}_{n-1}$	$C^1{}_n$	$A_?$
A_2		0		$C^2{}_{n-1}$	$C^2{}_n$	$A_?$
A_{n-1}				0	$C^{n-1}{}_n$	$A_?$

A_1, ..., An are n alternatives in ascending order of their total cost.

$$C^i{}_k = \frac{\mathrm{Cost}^i - \mathrm{Cost}^k}{(PR^k - PR^i) \times ED}$$

Best A:A with the least non-negative $C^i{}_k$

Fig. 5. The **M** matrix of the explicit decision analysis.

the proposed alternatives. The ranked alternatives then undergo the final step to select the best remedial alternative. In this step, other criteria, mainly non-technical considerations and decision-maker preferences, play an important role in the decision for the best alternative.

2.4.4. Implicit decision analysis

The first task of this technique is the definition of decision criteria that are applicable to all alternatives. Unlike the explicit method, the implicit method does not attempt to study each alternative separately to measure its compliance with the decision objectives. Instead, the method performs a one-step process to rank all the alternatives based on the decision criteria. Two mathematical methods for ranking alternatives are used, and these are the importance order of criteria (IOC) method and the fuzzy dominance and resemblance (FDR) method.

2.4.5. Importance order of criteria method

When faced with a set of non-dominant alternatives, a common practice is to assume an additive utility function by assigning weights to the decision attributes (Clemen, 1996). The total utility of an alternative is the simple arithmetic sum of weighted attributes. The different options are then ranked based on their total utility. However, the assignment of numerical scores and weights is highly subjective and reflects the risk-aversion, preferences, and policies of the decision-maker that may change with time. In order to overcome some of the bias associated with the weight assignment, Yakowitz et al. (1993) proposed a method of ranking of alternatives based on the order of importance of decision criteria. The method calculates the best and the worst total utility for each alternative using the importance order without requiring the decision-maker to set a prior weight. The ranking of alternatives is then carried out based on the best and worst utilities. If the resultant two rankings are not similar, then the final ranking is carried out using the average utility.

Imposing the importance order implies that the m decision criteria, $q_1, q_2 \ldots q_{\mathrm{m}}$, can be ordered so that the weights satisfy $w_1 \geq w_2 \geq \ldots \geq w_m$. The total utility function, U, of an alternative is given as

$$U = \sum \sum_{i=1}^{m} w_i q_i \tag{23}$$

subject to the following set of constraints:

$$\begin{aligned} & w_1 \geq w_2 \geq \ldots \geq w_m \\ & \sum_{i=1}^{m} w_i = 1 \\ & w_i \geq 0 \end{aligned} \tag{24}$$

The solution to the maximum and minimum utilities can be expressed in a closed form (Yakowitz et al., 1993). The best total utility, BU, and the worst total utility, WU, are given as

$$\mathrm{BU} = \max\{s_k\}$$

$$\mathrm{WU} = \min\{s_k\},$$

where

$$s_k = \frac{1}{k} \sum_{i=1}^{m} q_i (k = 1 \ldots m) \tag{25}$$

The solution to the above equation provides the maximum and minimum total utility possible for any combination of weights that do not violate the given importance order of the criteria. It should be noted that this closed-form solution does not solve explicitly for the weights, instead the maximum and minimum utility values are computed directly. For details about the mathematical derivation of the solution, refer to Yakowitz et al. (1993).

When the utility of each alternative is calculated, these alternatives can be ranked based on maximum, minimum, or average utilities. The spread between the minimum and maximum utility values expresses the sensitivity of each alternative to a choice of weights where the higher difference reflects greater sensitivity (Yakowitz, 1996; Yakowitz et al., 1993).

2.4.6. Fuzzy dominance and resemblance method

Wenger and Rong (1987) used a method based on the fuzzy set theory to rank alternatives. In this approach, a pair-wise comparison of alternatives is performed, and this task is called the Level 1 analysis. The second task is called the Level 2 analysis, and it identifies the degree of similarity between alternatives. Level 1 and 2 analyses are based on the fuzzy dominance and fuzzy resemblance relationships described by Kaufman (1975). Level 1 analysis ranks alternatives, but those with adjacent positions in the ranking list may or may not be similar. Level 2 analysis provides insights into the similarity between alternatives.

For a given set of n alternatives and m criteria, there exists a data matrix that contains the decision matrix, **X**, with elements x_{ik} where i represents the row containing the remedial alternative, and k represents the column containing the decision criterion. The data matrix should be set up such that $x_{ik}>0$. The data matrix **X** can also be transformed by assigning weights to the decision criteria. A matrix **Y** is then set up by normalizing each column in **X** between 0 and 1. Hence, for each criterion, the attributes are scaled separately between 0 and 1.

2.4.6.1. Fuzzy dominance analysis. The alternatives can now be ranked based on the dominance relationships between pairs of alternatives using matrix **Y**. For a pair of alternatives i and j, the dominance index, $D_k(i,j)$, is defined as

$$D_k(i,j) = \begin{cases} 1, \ \text{if}(y_{ik} - y_{jk}) > 0 \\ 0, \text{if } (y_{ik} - y_{jk}) < 0 \quad (k = 1 \ldots m) \\ 0.5, \text{if } (y_{ik} - y_{jk}) = 0 \end{cases} \tag{26}$$

A new matrix $\mathbf{Z}^1$ is now constructed as

$$z_{ij}^1 = \begin{cases} \sum_{k=1}^{n} D_k(i,j), & \text{if } i \neq j \\ 0, & \text{if } i = j \end{cases} \quad (i,j = 1 \ldots m) \tag{27}$$

The degree of dominance of one alternative over another to achieve remedial goals and objectives is measured by first calculating the sum of each row. The alternatives can then be ranked.

2.4.6.2. Fuzzy resemblance analysis. The purpose of this additional layer of analysis is to identify the degree of similarity among remedial alternatives based on the information in the **Y** matrix. Since two alternatives with adjacent positions in the ranking list may or may not be similar, Level 2 analysis can be applied to determine whether the alternatives are truly distinct or essentially slight variations of the same theme. Wenger and Rong (1987) provide a full discussion of the theory behind this level of analysis. A matrix $\mathbf{Z}^2$ with elements $z_{ij}{}^2$ is defined as

$$z_{ij}^2 = 1 - c\left|\sum_{k=1}^{n} y_{ik} - y_{jk}\right| \tag{28}$$

where c is a constant chosen so that $0 \leq z_{ij}{}^2 \leq 1$. The particular value of c is not important, as long as the chosen value satisfies $0 \leq z_{ij}{}^2 \leq 1$ for all i and j. A power matrix, $\mathbf{Z}^{\mathrm{P}}$, is now constructed to perform the clustering analysis, which is based on the concept of similarity. $\mathbf{Z}^{\mathrm{P}}$ is constructed as the product of ($\mathbf{Z}^2 \otimes \mathbf{Z}^2$), with the "$\otimes$" operator indicating a row-column operation similar to that of ordinary matrix multiplication that can be described by,

$$z_{ij}^p = (z_{i1}^* \wedge z_{1j}^*) \vee (z_{i2}^* \wedge z_{2j}^*) \vee \ldots (z_{im}^* \wedge z_{mj}^*) \tag{29}$$

where ($a \wedge b = \max(a,b)$, and $(a \vee b) = \min(a,b)$. The $\mathbf{Z}^{\mathrm{P}}$ power matrix can be used to identify clusters of similar alternatives by defining

$$\mathbf{Z}^{\mathrm{P}} = [z_{ij}^P(a)] \text{ and } z_{ij}^P = \begin{cases} 1, & \text{if } z_{ij}^p \geq a \\ 0, & \text{if } z_{ij}^p < a \end{cases} \tag{30}$$

where z_{ij} is the ijth entry of $\mathbf{Z}^{\mathrm{P}}$. The variable a provides a "similarity measure." By varying a from 0 to 1, it is possible to determine how clusters are formed and to identify similar alternatives. A value of a close to 1 indicates that a rigid measure is being used; therefore, few, if any, alternatives are likely to be clustered into a single group. On the other hand, a value of a close to 0 is indicative of a lax measure under which most of the alternatives are likely to be clustered into a single group (Hope, 1996).

3. Demonstration example

3.1. Problem description

The purpose of this section is to evaluate the applicability of the proposed decision analysis methodology. In this work, we propose to use a numerical experiment developed for the purpose of demonstration and has key features representing field-scale scenarios. Consider a high yielding regional aquifer used for a municipal water supply that has been recently detected with serious ground water quality concerns due to a high dissolved organic content. Preliminary field investigations concluded that the source of the contamination is a leaking underground storage tank (LUST) from a nearby gasoline station. A municipal well is located downgradient of the LUST (see Fig. 6). The municipal well supplies drinking water to a population of 4000 with 2000 m^3 daily. The contamination history is unknown; the leaking could have started anytime during the working life of the tank which is 30 years. The major chemical of concern is benzene, which is present in high concentrations and is known to pose a serious carcinogenic risk. In a typical field site, detailed field investigations and monitoring would be conducted to assess the extent of soil and ground water contamination and this information is used to determine the future remedial alternatives. Since this example was developed as a numerical experiment for the purpose of demonstration, there are no measured or observed data to develop the current status of the dissolved plume. This difficulty is overcome by recreating the problem by simulating the historical event of the leakage for a known period of time. In an actual field site, the field-measured concentration distribution can be used to develop the dissolved plume and carry out the remaining analysis. The

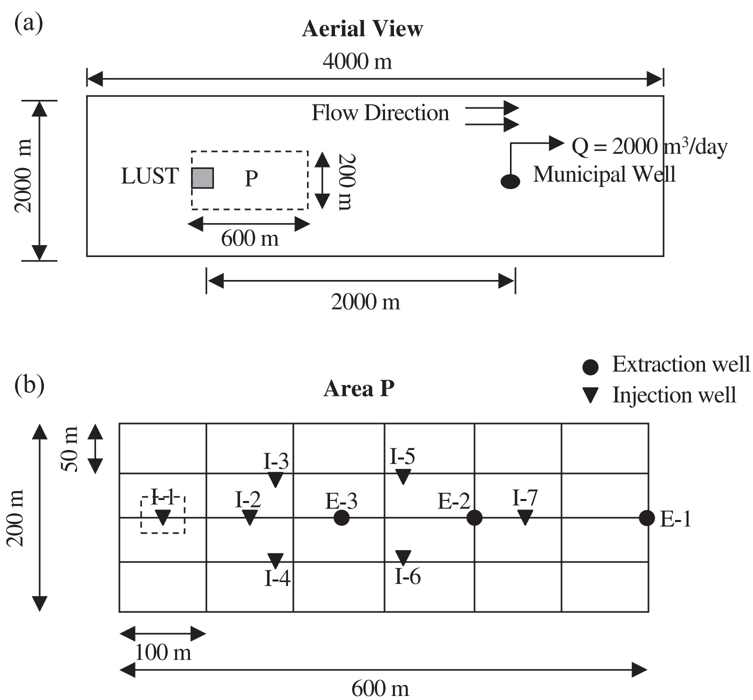

Fig. 6. A schematic showing the areal views of the aquifer used in the demonstration example. (a) Location of the source and the municipal wells. (b) Locations of injection and extraction wells for different remedial alternatives described in Table 3. Alternative 1 uses E-1. Alternative 2 uses E-1 and E-2. Alternative 3 uses E-1 and E-3. Alternative 4 uses E-1 and E-2 for extraction and I-1 and I-2 for injection. Alternative 5 uses E-1 for extraction and I-1, I-3, I-4, I-5, I-6, and I-7 for injection.

demonstration example described here uses an aromatic hydrocarbon constituent, benzene, which is a carcinogen. However, the methodology can be easily applied to sites with dissolved plumes of industrial solvents, such as trichloroethylene (TCE) or similar carcinogens, through proper representation in the risk assessment and hydrogeologic analysis.

3.2. Hydrogeologic analysis

The idealized aquifer considered in this study is a sandy gravel confined aquifer with a uniform thickness of 100 m, length of 4 km, and a width of 2 km. A background gradient of 0.002 m/m is causing the ambient steady ground water flow from west to east, while the north and south sides of the aquifer are assumed no-flow boundaries. The geologic formation of the aquifer has an effective porosity of 0.2, a bulk density of 1.75 g/cm^3, and a soil carbon fraction, f_{oc}, of 0.01 similar to the values described by Bedient et al. (1984). The longitudinal dispersivity, α_L, is estimated from Eq. (12) for a flow path of 2000 m and found to be 15 m. Assuming a dispersivity ratio of 10, the transverse dispersivity, α_T, is about 1.5 m. The retardation factor, R^*, of 2.3 was estimated using a partition coefficient, K_{oc}, of 1.5 for benzene (Fetter, 1999). The instantaneous biodegradation model considered O^{2-}, Fe^{2+}, SO_4^{2-}, and CO_2 as electron acceptors (Bedient et al., 1984) and further details are given in Table 2. Nitrification was not considered here because biodegradation of benzene by nitrification is found to be insignificant (Barker and Wilson, 1997).

The heterogeneous hydraulic conductivity field for the study area is described by a lognormal distribution with a geometric mean of ln(K) of 2, and a variance of 1. The correlation lengths were 200 m ($\lambda_h = 200$) horizontally and 10 m vertically ($\lambda_z = 10$), yielding a domain of 20 λ_h in length, 10λ_h in width, and 10λ_z in depth. This hydraulic conductivity field is similar to the values published in the literature (Smalley et al., 2000; Lahkim and Garcia, 1999; Maxwell et al., 1999). The above-described aquifer was not intended to represent a particular site, but to provide a convenient demonstration of the methodology presented in this paper.

The dissolved ground water plume of benzene was recreated modeling the LUST as a point source for 20 years under steady flow conditions. The resulting plume, which is a depth-averaged concentration distribution, is used to represent the observed plume.

Table 2
Data of electron acceptors used in the simulation

Electron acceptor	Stoichiometric ratio	Background concentration (mg/l)	Concentration in plume (mg/l)
O_2	3.08	3.0	0.5
Fe^{3+}	21.48	3.5	100
SO_4^{2-}	4.62	10	1
CO_2	2.12	0.001	0.1

3.3. Remedial alternatives

In order to demonstrate the proposed decision analysis methodology, five remedial alternatives are proposed and the details are given in Table 3. The alternatives include simple configurations of pump-and-treat (PAT) with injecting wells as shown in Fig. 6. The simplest alternative is the no-action alternative which allows the plume to be destroyed through natural attenuation. Other alternatives include different combinations of PAT and two involving enhanced biodegradation using oxygen injected into the plume. Air stripping is used to clean the contaminated ground water extracted from the PAT operations. This simple configuration facilitates the optimization of the well locations using a trial and correction process without the use of a sophisticated optimization analysis.

To explore the applicability of the proposed remedial alternatives, the breakthrough curve (BTC) at the municipal well for each alternative is compared to the no-action alternative. Fig. 7 shows an example of BTCs obtained for different alternatives when a uniform K of 30 m/day is used. These BTCs are presented here for demonstration purposes only using a uniform hydraulic conductivity field. The results provide an indication on how the level of contamination is reduced by each alternative, while the actual impact of such a reduction on the risk to the exposed population should be explored separately. The risk-based decision analysis of each alternative will later use the spatially variable random hydraulic conductivity field described earlier.

The cost of remediation for each alternative was estimated using Tank RACER software (Talisman Partners, 1999), which was developed for the US Department

Table 3
Details of different remedial alternatives considered in the demonstration example (also refer to Fig. 6)

Item	Alternative					
	No-action	1	2	3	4	5
Remediation technology	IB	PAT	PAT	PAT	PAT + EB	PAT + EB
No. of pumping wells	0	1	2	2	2	1
Pumping rate (gpm)	–	35	15, 10	35, 20	15, 10	35
Pumping duration (years)	–	7	6, 5	6, 5	4, 3	2.5
Treatment of extracted ground water	–	AS	AS	AS	AS	AS
Discharge of treated ground water	–	POTW	POTW	POTW	POTW	POTW
No. of injection wells	0	0	0	0	2	6
Oxygen in injected water (mg/l)	–	–	–	–	10	10
Injection duration (years)	–	–	–	–	3	2.5

PAT is pump-and-treat, IB is intrinsic biodegradation, EB is enhanced biodegradation, AS is air stripping, and POWT is a publicly owned water treatment plant.

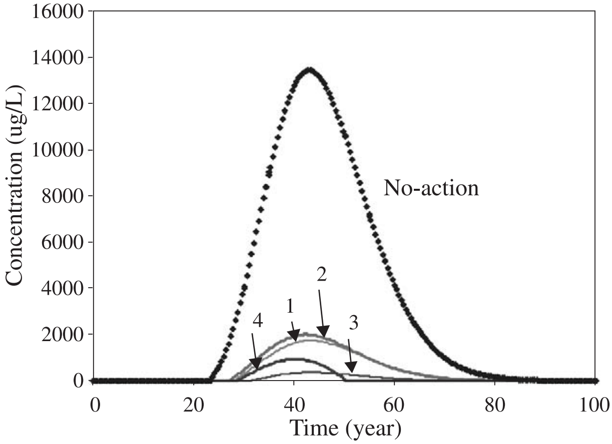

Fig. 7. Breakthrough curve at the municipal well for different remedial alternatives using a uniform K of 30 m/day. Breakthrough curve for alternative 5 does not show on graph because of scale (magnitude of concentration is small).

of Defense and later used by state and local agencies to determine the costs of cleanup on a site-specific basis. Tank RACER is a parametric cost modeling system for estimating environmental costs. The details of cost estimation for each alternative are presented in Table 4. The costs include the capital, operation and maintenance, and sampling costs. This cost model represents a simple description of essential cost components, and this model can be further modified to include additional cost components. The results show that the no-action alternative has the least cost, which essentially is the monitoring costs, whereas the PAT alternatives with enhanced biodegradation (alternatives 4 and 5) have higher costs due to water injection with dissolved oxygen.

Table 4
Cost of remediation for different alternatives

Cost	Alternative					
	No-action	1	2	3	4	5
Capital cost	0	\$311,017	\$325,898	\$354,933	\$512,049	\$646,961
O & M Cost	0	\$249,091	\$297,668	\$325,139	\$433,130	\$449,995
Monitoring duration (year)	10	10	10	10	10	10
No. of samplings (per year)	3	3	3	3	3	3
No. of parameters sampled	8	8	8	8	8	8
Monitoring cost	\$602,956	\$602,956	\$602,956	\$602,956	\$602,956	\$602,956
Total cost	\$602,956	\$1,163,064	\$1,226,522	\$1,283,028	\$1,548,135	\$1,699,912

3.4. Probabilistic risk assessment

The uncertainty in the concentration of the BTC was modeled using a spatially variable random hydraulic conductivity field developed using the turning band algorithm (Thompson et al., 1989) with the correlation length and semi-variogram described previously. The number of random realizations needed to characterize the uncertainty of K was determined using the procedure described by Lahkim and Garcia (1999). In this approach, cumulative mean and variance maps were generated. The N cumulative mean maps have values at each cell corresponding to the mean from N simulations. The same procedure is followed for the cumulative variance maps. Two parameters were used to quantify the stability of the mean and variance for all the cells, and these are (a) the arithmetic average of the cumulative mean of all nodes up to the simulation N and (b) the arithmetic average of the cumulative variance of all nodes up to the simulation N. The results, although not shown here, indicated that the average cumulative mean decreases to an asymptotic value after about 60 simulations. The same observation is true for the cumulative variance. Hence, 100 simulations were used to describe the uncertainty of the K field in the joint uncertainty–variability analysis.

In each simulation, the BTC at the municipal well was generated, and the corresponding 30-year average concentration curve was calculated. The resulting maximum 30-year average concentration for each alternative was used to generate the cumulative density function, CDF. The CDF of concentration was then used to model the uncertainty in the contaminant concentration in the risk assessment.

The population characteristics were described using the average characteristics of the US population as shown in Table 5. The variability in the population was described using three parameters; water ingestion rate per unit body weight, air inhalation rate per unit body weight, and skin surface area per unit body weight.

The three-dimensional risk surfaces were generated using the two-stage Monte Carlo method to analyze the joint uncertainty–variability of each

Table 5
Population characteristics used in the demonstration example

Parameter	Distribution	Values	Unit
Average lifetime	Constant	70	years
Shower duration	Constant	0.2	h/day
Exposure frequency	Constant	350	day/year
Exposure duration	Constant	30	years
Skin Permeability constant	Constant	0.1	cm/h
Water ingestion rate per unit body weight	Lognormal	(0.033,0.013)	l/day/kg
Air inhalation rate per unit body weight	Lognormal	(0.39,0.5)	m^3/day/kg
Skin surface area per unit body weight	Lognormal	(270,25)	cm^2/kg

Sources: US EPA (1989a) and McKone and Bogen (1991).

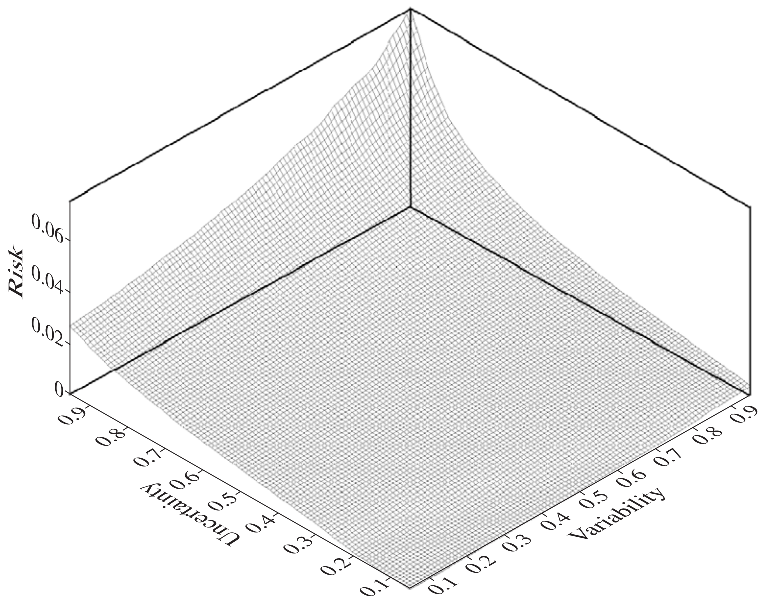

Fig. 8. Computed risk surface from the joint uncertainty–variability analysis for the no-action alternative.

remedial alternative. Fig. 8 shows the risk surface for the no-action alternative. Fig. 9 shows cuts through the surface parallel to the uncertainty axis at the 5th, 50th, and 95th percentile variability. The results show a modest change in the estimated cancer risk across the complete range of the uncertainty of K for the 5th and 50th percentile variability of the population characteristics. However, as

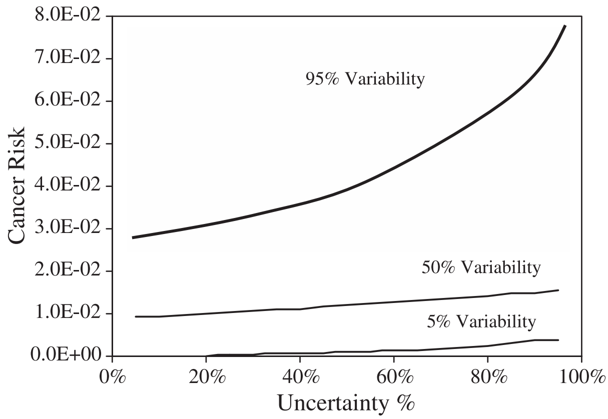

Fig. 9. Variation of risk with uncertainty of K for different population variability values for the no-action alternative.

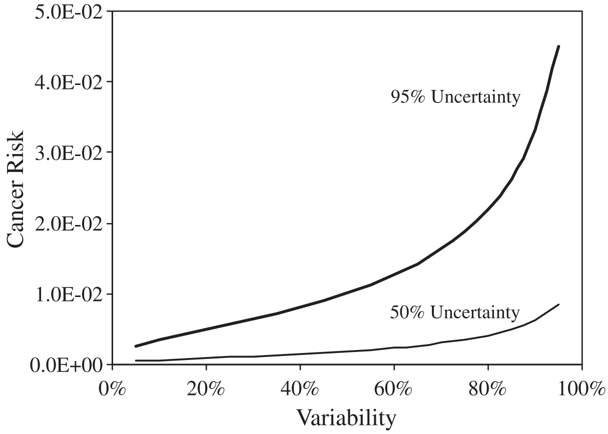

Fig. 10. Variation of risk with variability of population characteristics for different uncertainty values of K for the no-action alternative.

the population variability is high, say at the 95th percentile, the estimated cancer risk varies substantially with the uncertainty of K. Similarly, Fig. 10 shows cuts through the surface parallel to the population variability axis at the 50th and 95th percentiles of uncertainty of K. In this case too, the changes in the estimated cancer risk with population variability remain relatively small for low to medium values of uncertainty of K. As the uncertainty of K is high at the 95th percentile, the estimated cancer risk is highly sensitive to the population variability.

Table 6 provides the summary statistics of the decision criteria for all remedial alternatives. As expected, the least total cost of remediation is with the no-action case. The cost of remediation and CPLS both increase from alternatives 1 to 5. However, there are other decision criteria such as the IR, PR, and RI that provide different insight to the problem and need to be considered in the decision-making.

Table 6
Computed risk statistics for different remedial alternatives

Alternative	IR	EIR	PR	RI	Cost (US$)	CPLS (US$)
No-action	7.61e – 02	4.15e – 02	2.765	0.940	602,956	–
1	2.21e – 02	7.95e – 03	0.490	2.410	1,163,064	8204
2	1.18e – 02	4.70e – 03	0.288	2.868	1,226,522	8391
3	8.41e – 03	2.48e – 03	0.134	3.480	1,283,028	8613
4	7.13e – 03	1.90e – 03	0.106	3.693	1,548,135	11,849
5	3.00e – 04	2.77e – 05	0.002	7.255	1,699,912	13,232

3.5. Explicit decision analysis

3.5.1. Filtering stage

All remedial alternatives should satisfy the three criteria of the filter; positive risk reduction, acceptable risk, and acceptable CPLS. The results in Table 6 show that all remedial alternatives reduce the risk on the exposed population. However, the acceptable risk criterion is not satisfied by all alternatives as indicated in Table 7. The acceptable risk is decided by three criteria, and these are the MIR, EIR, and RI. For an alternative to satisfy the acceptable risk condition, it should at least satisfy either the MIR, or RI and EIR. MIR is a formulation of the acceptable risk suggested by the US EPA and is between 10^{-4} and 10^{-6}. The RI and EIR are alternative acceptable risk criteria developed in this study. Table 7 indicates that only alternative 5 satisfies the MIR criterion, while the other alternatives violate this criterion for acceptable risk. MIR reflects the maximum risk posed on any individual in the population. To assess the uncertainty in the MIR, the EIR, which is an average estimate of the risk posed on the maximum exposed individual, is calculated and shown in Fig. 11.

The analysis of the alternatives for acceptable risk criterion and RI confirms that only alternative 5 satisfies the acceptable risk requirement (see Table 7). In addition, it is noted that alternatives 3 and 4, which do not satisfy the MIR criterion, do satisfy both the RI and EIR criteria. This observation suggests that alternatives 3 and 4 can be considered plausible for the selection stage.

The final criterion to be satisfied is the CPLS. All alternatives have a CPLS that falls within the range of US$8000–14,000 (see Table 6). This range of CPLS is considered reasonable when compared to the data in Table 1. However, there is

Table 7
Details of the filtering stage of the explicit decision analysis; ✓ and x refer to satisfactory and unsatisfactory decision criteria

Parameter		No-action	1	2	3	4	5
Positive risk reduction		x	✓	✓	✓	✓	✓
Acceptable risk criteria	MIR	x	x	x	x	x	✓
	EIR	x	x	x	✓	✓	✓
	RI	x	x	x	✓	✓	✓
CPLS		✓	✓	✓	✓	✓	✓

M matrix

	No-action	1	2	3	4	5	Desired alternative
No-action		$28,349	$33,018	$30,850	$43,804	$47,590	1
1			− $72,796	$52,458	$211,583	$163,034	3
2				$17,890	$119,484	$113,671	3
3					− $567,793	$414,400	5
4						$103,046	5

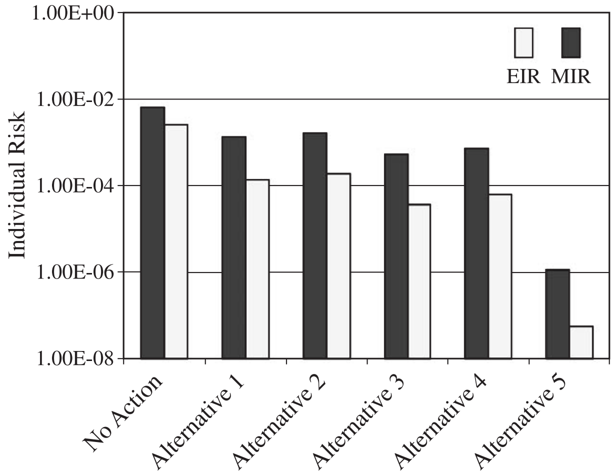

Fig. 11. Computed maximum individual risk (MIR) and expected individual risk (EIR) for different remedial alternatives.

a strong need to further study the definition of "reasonable CPLS" based on legal, social, and political constraints.

Although the no-action alternative and alternative 1 do not satisfy the filter criteria, they will be considered in the selection stage of this example. This action, although, is in contradiction to the proposed outline of the method, elimination of these two alternatives will reduce the number of alternatives to three and make the problem less interesting. This limitation is present because the demonstration example is relatively simple and has a much smaller number of alternatives than in a typical large-scale field setting such as the example of Russell and Rabideau (2000). It is therefore important in future work to explore this method with field examples with more complex settings and remedial alternatives.

3.5.2. Selection stage

The selection of the best alternative from the set of alternatives, which satisfies the decision criteria of the filter, requires the ranking of these alternatives to indicate the desirability order. This is accomplished by means of the **M** matrix, which studies the incremental cost per additional life saved when moving from the less costly alternative to a more costly alternative, assuming the additional cost provides additional risk reduction.

The **M** matrix is presented in Table 7 and calculated as follows: the first row contains the incremental costs per unit population risk reduction for all designs with respect to the no-action alternative. The best option to be chosen for this row is the one with the least CPLS, i.e., alternative 1. For row 2, the incremental CPLS for alternatives 2 through 5 is calculated with respect to alternative 1. The best option for this row is alternative 3, which has the least non-negative incremental CPLS. Alternative 2, which has a negative value in this row, is rejected because the negative value indicates that additional costs resulted in increased risk. The same procedure is applied for rows 3 to 5, which correspond to alternatives 2 to 4.

The **M** matrix indicates that alternatives 3 and 5 have good economical justification to be implemented. Alternative 1 is also recommended economically, but to a lesser degree than alternatives 3 and 5. It is also noted that the implementation of alternative 4 is not economically justified compared to both alternatives 3 and 5. In addition to alternative 4, alternative 2 is also not economically justified compared to alternatives 1 and 3. Compiling the information obtained from the filtering stage and the **M** matrix, the proposed alternatives can then be ranked as shown in Table 8. Alternative 5 is at the top because it has the best compliance with the acceptable risk criteria and has a high recommendation from the **M** matrix. Alternative 3 is the next best alternative in compliance with the acceptable risk criteria, and has equivalent recommendation in the **M** matrix. Thus, it is logical that alternative 3 holds the second position in the ranking of the alternatives. Alternative 4, which is not recommended by the **M** matrix as alternative 1, has a higher compliance with the acceptable risk criterion than alternative 1. For this reason, alternative 4 was offered a position higher than alternative 1 in the alternative ranking. Finally, alternative 2 and the no-action alternative are the least favorable with alternative 2 preferred over the no-action alternative.

3.6. Implicit decision analysis

3.6.1. Importance order of criteria method

The first step in this method is to normalize the decision criteria between zero and one. The second step in the IOC method is to specify the importance order of the decision criteria as shown in Table 9. The ranking of the criteria was such that the compliance with the acceptable risk requirement was given more importance than the economic considerations.

Following the normalization of the decision criteria and the specification of their order of importance, Eq. (25) was used to calculate the best and worst utility scores for each decision alternative that satisfy the specified criteria ordering. The best and worst utility scores refer to the maximum and minimum total scores

Table 8
Ranking of alternatives from the explicit decision analysis

Ranking	Alternative
1	5
2	3
3	4
4	1
5	2
6	No action

Table 9
Details of the IOC method

Normalized decision criteria and the order

Importance order	Criteria	Alternative					
		Base case	1	2	3	4	5
1	MIR	0.000	0.793	0.745	0.916	0.888	1.000
2	RI	0.000	0.291	0.260	0.439	0.386	1.000
3	Cost	1.000	0.489	0.432	0.380	0.138	0.000
4	CPLS	1.000	0.404	0.306	0.352	0.080	0.000

Ranking of decision alternatives

Ranking	Best score	Worst score	Average
1	5	3	5
2	3	5	3
3	4	1	1
4	1	2	4
5	2	4	2
6	No action	No-action	No-action

possible for any combination of the actual weights that one could choose, given that the weights are consistent with the order of the importance of the decision criteria. Thus, the spread of the best and worst utility scores shown in Fig. 12 describes the sensitivity of each alternative to its weights.

Table 9 summarizes the ranking of the decision alternatives obtained from the best, worst and average utility scores. The ranking shows that alternatives 3 and 5 exchanged the first and second positions with each other in the best and worst utility, indicating that the best alternative is one of them. On the other end, the no-

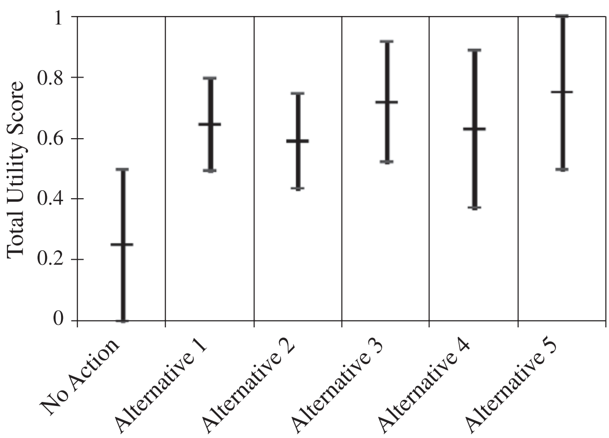

Fig. 12. Computed best, worst, and average utility scores for different remedial alternatives in the implicit decision analysis.

action alternative is the last ranking for the best and worst utility cases, indicating that it is the least favorable alternative. On the other hand, alternatives 1, 2, and 4 exchanged positions with each other in the best and worst utility cases, indicating that no clear distinction exists between these decision alternatives.

It is worth noting that the ranking from the best utility matches the ranking obtained from the explicit decision analysis. The ranking obtained from using the average utility is also close to that of the explicit decision analysis. However, the ranking corresponding to the worst utility has little in common with the explicit decision analysis except the no-action alternative.

3.6.2. Fuzzy dominance and resemblance method

Level 1 analysis ranks alternatives, but those with adjacent positions in the ranking list may or may not be similar. Level 2 provides an insight into the issue of similarity. Level 1 analysis is commenced by constructing the dominance matrix shown in Table 10. The first row in the matrix corresponds to the degree by which the first alternative, i.e., no-action alternative, dominates over the other alternatives. For example, the no-action alternative dominates alternative 1 by two degrees; this means that there are two criteria for which alternative 1 scores are better than those of no-action. These criteria, as noted in Table 10, are the total cost and CPLS. The sum column in the dominance matrix contains the sum of scores in each row. The sum indicates the degree by which each alternative dominates the other alternatives. Hence, using the sum columns, the decision alternatives can be ranked and are given in Table 10.

Level 2 analysis has two steps; the first is the calculation of the $\mathbf{Z}^2$ matrix, and the second step is the generation of the power matrix $\mathbf{Z}^{\mathrm{P}}$. The $\mathbf{Z}^2$ given in Table 11

Table 10
Details of the Level 1 analysis of the fuzzy dominance method

$\mathbf{Z}^1$ matrix

	No-action	1	2	3	4	5	Sum
No-action	0	2	2	2	2	2	10
1	2	0	4	2	2	2	12
2	2	0	0	1	2	2	7
3	2	2	3	0	4	2	13
4	2	2	2	0	0	2	8
5	2	2	2	2	2	0	10

Ranking of decision alternatives

Ranking	Alternative
1	3
2	1
3	5
4	No-action
5	4

Table 11
Details of the Level 2 analysis of the fuzzy dominance method

	No-action	1	2	3	4	5
Scaled $\mathbf{Z}^2$ *data matrix (c = 0.4)*						
No-action	1.00	0.67	0.60	0.67	0.44	0.60
1		1.00	0.92	0.99	0.77	0.93
2			1.00	0.93	0.84	1.00
3				1.00	0.77	0.93
4					1.00	0.84
5						1.00
Power matrix, $\mathbf{Z}^{\mathrm{P}}$						
No-action	1	0.674	0.674	0.674	0.674	0.674
1		1	0.931	0.994	0.843	0.932
2			1	0.932	0.843	0.999
3				1	0.843	0.932
4					1	0.843
5						1
Cluster analysis with power matrix, $\mathbf{Z}^{\mathrm{P}}$*(0.8)*						
No-action	1	0	0	0	0	0
1		1	1	1	0	1
2			1	1	0	1
3				1	0	1
4					1	0
5						1
Cluster analysis with power matrix, $\mathbf{Z}^{\mathrm{P}}$*(0.9)*						
No-action	1	0	0	0	0	0
1		1	1	1	1	1
2			1	1	1	1
3				1	1	1
4					1	1
5						1
Cluster analysis with power matrix, $\mathbf{Z}^{\mathrm{P}}$*(0.95)*						
No-action	1	0	0	0	0	0
1		1	0	1	0	0
2			1	0	0	1
3				1	0	0
4					1	0
5						1

is calculated by scaling the matrix containing the difference between the scores of each two alternatives for the set of specified criteria between one and zero by means of the factor ***c***. The power matrix $\mathbf{Z}^{\mathrm{P}}$ in Table 11, which is a function of the $\mathbf{Z}^2$ matrix, is used for cluster analysis through the evaluation of $\mathbf{Z}^{\mathrm{P}}$ (a), where $0 \leq a \leq 1$. The first row of $\mathbf{Z}^{\mathrm{P}}$ indicates that all the alternatives except the no-action alternative, cluster into a single group at 0.67. This implies that there is a clear distinction between no-action and take-action alternatives. The second, third, and fourth rows of $\mathbf{Z}^{\mathrm{P}}$ show that alternative 4 is slightly different than the alternatives 1, 2, 3, and 5, which group closely at more than 0.93. Alternative 4 is singled out reinforcing the suggestion of the explicit method that it is not economically justified compared to alternatives 3 and 5. Note that the cause of having alternative 4 in a different cluster is only clear through the explicit analysis.

The above cluster analysis can be further explained by evaluating $\mathbf{Z}^{\mathrm{P}}(a)$, at $a = 0.8$, $a = 0.9$, and $a = 0.95$. When $\mathbf{Z}^{\mathrm{P}}(a = 0.8)$ is evaluated, which is a high value for a, all the alternatives are clustered except for the no-action alternative, indicating similarity. When a is 0.9, only alternative 4 is eliminated from the previous clustering. When a is 0.95, two distinct clusters appear indicating similarity between alternatives 1 and 3, and alternatives 2 and 5. The cluster analysis for the 95th percentile of uncertainty and variability suggests that either the decision alternatives have a high degree of similarity, or the decision criteria are not sufficient to differentiate between the alternatives.

The results from both the explicit and implicit methods show that the explicit method produced a logical ranking of the alternatives subject to the information from the risk analysis. One reason for this observation is that the explicit method considers the decision criteria explicitly and weighs the criteria in the decision-making. The results obtained by the IOC method are identical to those obtained by the explicit method for the specified importance order of the decision criteria. The ordering of the decision criteria was such that it emphasizes the importance of reducing the health risk over economic considerations. This importance order is similar to the logical build in the explicit decision analysis approach. Thus, the alternative ranking is similar for the explicit decision analysis method and the IOC method.

However, the results obtained by the FDR method are not comparable to those obtained by the explicit decision analysis method or the IOC method. Fuzzy dominance analysis, by default, does not have a method of favoring a given decision criterion over other criteria. The only way to enforce a preference or an importance order is by assigning numerical weights to the criteria. The drawback of using numerical weights is that there is no unique procedure for estimating the weights. The results from the FDR method can be sensitive to the weights as well as the importance order of the criteria. The shortcomings of the FDR method can be overcome if a large number of unique decision criteria are employed, which can provide a clearer insight into the fuzzy similarities and differences between the different alternatives.

In summary, the explicit decision analysis provided a valuable insight into the decision problem. The IOC method produced a logical ranking of alternatives that is identical to that suggested by the explicit decision analysis. The FDR method failed to provide a logical ranking of the alternatives. The method may require the scaling of the decision criteria using weights to enforce an importance order of the decision criteria and such changes in the method may produce results that are more meaningful.

4. Summary and conclusions

The acceptable risk on any individual is defined here using two criteria; the maximum individual risk, and the expected individual risk. MIR is the maximum risk posed on the maximum exposed individual, while EIR is the average risk posed on the maximum exposed individual. MIR and EIR are both calculated at the 95th percentile of hydrogeologic uncertainty and population variability to avoid the effect of the outliers at the maximum percentiles. MIR and EIR convey important information to the decision-maker about the welfare of each individual in the population. Projecting the welfare of the population through the maximum exposed individual is arguably a fair measure, because it guarantees no individual in the population is more affected. The significance of the EIR is that it quantifies the uncertainty of the MIR.

Population risk is another important criterion used in this methodology. PR quantifies the ultimate cost that the society has to bear in terms of the expected cancer cases as a result of a large-scale pollution event. We believe that PR provides an interesting alternative to the individual risk as a criterion of risk acceptability since the burden of remediation is eventually borne by the society. Similar criteria that quantify consequences to the society are used to describe the acceptable risks in different public safety projects. In dam safety projects, for example, there exists a definition of the acceptable societal risk defined as the expected number of the annual increase fatalities tolerated in any population, typically less than 0.01 fatalities (Bowles, 2001). Indeed, a similar acceptable population risk can be established for ground water contamination scenarios. However, we believe that the use of such criteria will raise a legitimate ethical question whether the collective welfare of the society is more important than the welfare of the most vulnerable individual in the population or not. Since we are not in a position to answer such a conflict, we introduced the risk index, which establishes a trade-off between the individual and population risk based on observations from published regulatory data. Thus, instead of attempting to select a condition from a list of criteria, we established a trade-off between the two most important decision criteria. Nevertheless, we recommend that a rigorous research of practices of the regulatory agencies towards the individual and population risk should be conducted, as we recognize that the proposed RI is not based on such a rigorous research. Yet, we agree with Travis and Richter (1987) on the general direction of the trade-off between individual and population risks.

Another important question we attempted to answer in this study is how to define the trade-off between the residual risk and the cost of risk reduction. Intuitively, if the risk is too high, then a high remediation cost does not justify a "no-action" response to lower the risk on the exposed population. On the other hand, a low risk does not trigger an immediate action of remediation, nor does it rule out the need for action. The appropriate action should be considered based on the trade-off between cost of remediation and the corresponding risk reduction. If the cost of a given risk reduction measure is small, then action might be required to avoid possible liabilities though it may not be cost-effective. Therefore, we proposed the use of CPLS as the cost-effectiveness criterion to convey to the decision-maker how costs are being employed to reduce the risk. Referring to the numerical experiment performed here, it was noted that for all the decision alternatives, the CPLS falls within a narrow range of US$8000–14,000 per unit risk reduced (see Table 6). This observation indicated that, at least for this case, the criterion of CPLS alone was not sufficient to address the trade-off between the increased cost and risk reduction. A better understanding of this trade-off is reflected through the **M** matrix in which the incremental CPLS was calculated (see Table 7). The **M** matrix helps to identify the point of diminishing return of the investment used in the risk reduction. The **M** matrix shows the otherwise undistinguishable cost-effectiveness and differences between the proposed alternatives, and therefore, provides a more meaningful insight into the risk-cost trade off.

In addition to the explicit decision analysis, two implicit methods from operations research were explored in this work. The IOC method provided a ranking of alternatives comparable to that of the explicit analysis. The IOC method is sensitive to the order of the criteria, which is based on the objectives of the decision-maker. The key advantages of using the IOC method in decision analysis are that the method is simple, accurate, and can avoid possible subjective biases of the decision-maker. The success to the use of the IOC method depends heavily on the correct order of importance of decision criteria applicable to a given problem such that the ranking of the remedial alternatives is meaningful and reflects the goals of the decision-maker.

The FDR method did not perform satisfactorily, at least in this demonstration example, compared to other methods. One possible avenue of improving the accuracy and applicability is the weighing of decision criteria to enforce an order of importance. Another possible course of action is the increase of the number of decision criteria, such that the fuzzy differences between alternatives are easier to detect. In addition, the fuzzy similarity analysis or the Level 2 analysis did not provide useful insight to the decision problem due to the same limitations that affected the Level 1 analysis.

We would like to emphasize that some of the observations we noted about the performance of ranking approaches should not be generalized. The simple demonstration example presented in this work was not intended to capture the complex nature of the decision-making context; rather it was intended to demonstrate the applicability of the proposed decision analysis framework. Hence, the generalization of the observations made from the single example of this study should be carried out with caution. Instead, future work related to decision analysis should consider the methodology proposed here and should evaluate the methods through the use of more complex field scenarios with a variety of decision criteria and alternatives. Such applications may provide better insight into the proposed methodology and help future work on improving the approaches suggested here.

Another limitation of this work is the limited scope of the decision criteria considered in the methodology. The decision criteria were limited to the most basic objectives of a decision-maker in a subsurface contamination scenario, i.e., risk reduction, cost minimization, and regulatory compliance. In a real world scenario, a variety of decision criteria would be relevant in the decision-making, e.g., duration of the remedial action and engineering reliability of a remedial technology. Another limitation is related to the design of remediation alternatives. Since the design of remediation is not the central theme of this paper, the optimal configuration of a given remediation alternative was not sought. In addition, the hydraulic conductivity fields used to describe spatial variability was generated using unconditional simulation, while realistically, conditional simulations are employed to represent site variability and to reduce the variability of hydraulic head (Gelhar, 1993).

Finally, we would like to acknowledge the anonymous reviewer's thoughtful comments questioning the applicability of the proposed methodology since it requires policy changes. Policy changes refer to the proposed definition of acceptable risk, which requires the trade-off between individual and population risk, and the trade-off between risk reduction and remediation cost. The proposed criteria may be employed to replace the definition of acceptable risk which is presently used as an individual risk of 10^{-6} by the US EPA. We recognize that this paper calls for both policy changes as well as management changes in risk-based management of subsurface contamination. Management changes are manifested in the adoption of multi-criteria decision analysis in place of a cost–benefit analysis framework. Our position related to the policy changes is that adopted policies should not dictate research debate but instead promote research-guided policies. It is the duty of the research community to introduce new concepts, debate their merits, and investigate their applicability. Once the consensus of the research community is finalized on the merits of a given methodology, then the timing is correct for necessary policy changes.

References

Asante-Duah DK. Hazardous waste risk assessment. Florida, USA: Lewis Publishers; 1993.

Barker JF, Wilson JT. Natural biological attenuation of aromatic hydrocarbon under anaerobic conditions. In: Ward CH, Cherry JA, Scalf MR, editors. Subsurface restoration. Chelsea, MI: Ann Arbor Press, 1997. p. 289–300.

Bedient PB, Rodgers AC, Bouvette TC, Tomson MB, Wang TH. Groundwater quality at a creosote waste site. Ground Water 1984;22(3):318–29.

Bogen KT, Spear RC. Integrating uncertainty and individual variability in environmental risk assessment. Risk Anal 1987;7(3):427–36.

Bordon RC, Bedient PB, Lee MD, Ward CH, Wilson JT. Transport of dissolved hydrocarbons influenced by oxygen-limited biodegradation: 1. Theoretical development. Water Resour Res 1986;():(13):1973–82.

Bowles DS. Evaluation and use of risk estimates in dam safety decision-making. Proceedings of the

United Engineering Foundation Conference on Risk-Based Decision-Making in Water Resources IX, 20-Year Retrospective and Prospective of Risk-Based Decision-Making, Santa Barbara, CA. Reston, VA: American Society of Civil Engineers, 2001. p. 17–32.

Clemen RT. Making hard decisions: an introduction to decision analysis. 2nd ed. Pacific Grove, CA: Brooks/Cole Publishing, 1996.

Clement TP, Sun Y, Zheng C. RT3D—A MODFLOW-family reactive transport simulator. In: MODFLOW 98 conference proceedings, October 4–8, Golden, Colorado vol. 1. Golden, CO: International Groundwater Modeling Center, 1998. pp. 397–403.

Cohen J, Lampson MA, Bowers TS. The use of two stage Monte Carlo simulation technique to characterize variability and uncertainty in risk analysis. Hum Ecol Risk Assess 1996;2(4):939–71.

Dagan G. Models of groundwater flow in statistically homogeneous porous formations. Water Resour Res 1979;15(4):47–63.

Fetter CW. Contaminant hydrogeology. NJ: Prentice Hall; 1999.

Finley B, Paustenbach D. The benefits of probabilistic exposure assessment: three case studies involving contaminated air, water, and soil. Risk Anal 1993;14(1):52–73.

Freeze RA, Massmann J, Smith L, Sperling T, James B. Hydrogeological decision analysis: 1. A framework. Ground Water 1990;28(5):738–66.

Gelhar LW. Stochastic subsurface hydrology. NJ: Prentice Hall; 1993.

Harbaugh, AW, McDonald, MG. User's documentation for MODFLOW-96, an update to the U.S. Geological Survey modular finite-difference ground-water flow model. U.S. Geological Survey Open-File Report, 96-485; 1996. 56 pp.

Hope BK. A multiple criteria decision-making model for comparative analysis of remedial action alternatives. In: EL-Swaify SA, Yakowitz DS, editors. Multiple objective decision making for land, water, and environmental management, Proceeding of the First International Conference on Multiple objective decision support systems (MODSS) for land, water, and environmental management: concepts, approaches, and applications. Lewis Publishers; 1996. p. 143–52.

Kaufman A. Introduction to the theory of fuzzy subsets, vol. I. New York: Academic Press; 1975.

Khadam I, Kaluarachchi JJ. Applicability of risk-based management and the need for risk-based economic decision analysis at hazardous waste contaminated sites. Environ Int 2003;29(4):503–19.

Lahkim MB, Garcia LA. Stochastic modeling of exposure and risk in a contaminated heterogeneous aquifer: 1. Monte Carlo uncertainty analysis. Environ Eng Sci 1999;16(5):315–28.

Massmann J, Freeze RA. Ground water contamination from waste management sites: the interaction between risk-based engineering design and regulatory policy: 1. Methodology. Water Resour Res 1987a;23(5):351–67.

Massmann J, Freeze RA. Ground water contamination from waste management sites: the interaction between risk-based engineering design and regulatory policy: 2. Results. Water Resour Res 1987b;23(5):368–80.

Massmann J, Freeze RA, Smith L, Sperling T, James B. Hydrogeological decision analysis: 2. Application to ground water contamination. Ground Water 1991;29(4):536–48.

Maxwell RM, Pelmulder SD, Thompson AFB, Kastenberg WE. On the development of a new methodology for ground water risk assessment. Water Resour Res 1998;34(4):847–83.

Maxwell RM, Kastenberg WE, Rubin Y. A methodology to integrate site characterization information into ground water-driven health risk assessment. Water Resour Res 1999;35(9):2841–55.

McDonald MG, Harbaugh AW. A modular three-dimensional finite-difference ground-water flow model. Technical Report, U.S. Geological Survey, Reston, VA; 1988.

McKone TE, Bogen KT. Predicting uncertainties in risk assessment. Environ Sci Technol 1991; 25(10):1674–5.

National Research Council. Alternatives for ground water cleanup. Committee on Ground water cleanup alternatives, Water Science and Technology Board, Board on Environment and Resources, National Research Center; 1994.

Newell CJ, Winters JA, Rifai HS, Miller RN, Gonzales J, Wiedemeier TH. Modeling intrinsic remediation with multiple electron acceptors: results from seven sites. Proceedings of the Petroleum

Hydrocarbons and Organic Chemicals in Ground Water: Prevention, Detection and Restoration. Houston, TX: National Water Well Association; 1995. p. 33–47.

Rifai HS, Bedient PB, Wilson JT, Miller KM, Armstrong JM. Biodegradation modeling at aviation fuel spill site. J Environ Eng 1988;5(6):1007–29.

Rosen L, LeGrand HE. An outline of a guidance framework for assessing hydrological risk at early stages. Ground Water 1997;35(2):195–204.

Russell KT, Rabideau AJ. Decision analysis for pump and treat design. Ground Water Monit Remediat 2000:159–68.

Semprini L, McCarty PL. Comparison between model simulations and field results for in situ biorestoration of chlorinated Aliphatics: Part 1. Biostimulation of metanotophic bacteria. Ground Water 1991;4(2):475–87.

Smalley JB, Minsker BS, Goldberg DE. Risk-based in situ bioremediation design using a noisy genetic algorithm. Water Resour Res 2000;36(10):3043–52.

Talisman Partners. RACER software for environmental cost management and liability evaluation. Englewood, CO; 1999.

Thompson AFB, Ababou R, Gelhar LW. Implementation of three-dimensional turning bands random field generator. Water Resour Res 1989;25(10):2227–43.

Travis CC, Richter S. In: Whipple C, editor. On defining a de minimis risk level for carcinogen. De minimis risk. NY: Plenum; 1987.

US EPA. Exposure factors handbook. Office of Health and Environmental Assessment. EPA/600/8/8-89/043. Washington, DC: United States Environmental Protection Agency; 1989a.

US EPA. Risk Assessment guidance for superfund: Volume 1—Human Health Evaluation Manual (Part A, Baseline Risk Assessment). Interim final. Office of Health and Environmental Assessment. EPA/540/1-89/022. Washington, DC: United States Environmental Protection Agency; 1989b.

US EPA. Risk assessment guidance for superfund: Volume 1—Human health evaluation manual (Part B, Development of risk-based preliminary remediation goals), Interim. EPA/540/R-92/003. Office of Emergency and Remedial Response. Washington, DC: United States Environmental Protection Agency; 1991.

US EPA. Supplemental guidance to RAGS (RAGS III part A): the use of probabilistic risk analysis in risk assessment, working draft. Washington, DC: Office of Emergency and Remedial Response; 1999.

Waldis D, Rosen L, Kros H. Risk based analysis of atmospheric emission alternatives to reduce ground water degradation on the European scale. Ground Water 1999;37(6):818–26.

Wang AT, McTernan WF. The development and application of a multilevel decision analysis model for the remediation of contaminated groundwater under uncertainty. J Environ Manag 2002;64(6):221–35.

Wenger RB, Rong Y. Two fuzzy set models for comprehensive environmental decision-making. J Environ Manag 1987;25(6):167–80.

Xu M, Eckstein Y. Use of weighted least square method in evaluation of the relationship between dispersivity and field scale. Ground Water 1995;33(6):905–8.

Yakowitz DS. A multiplattribute tool for decision support: ranking a finite number of alternatives. In: EL-Swaify SA, Yakowitz DS, editors. Multiple objective decision making for land, water, and environmental management, Proceeding of the First International Conference on Multiple objective decision support systems (MODSS) for land, water, and environmental management: concepts, approaches, and applications. Lewis Publishers; 1996. p. 205–15.

Yakowitz DS, Lane LJ, Szidarovszky F. Multiattribute decision-making: dominance with respect to an importance order of the attributes. Appl Math Comput 1993;54(6):167–81.

Zhao Q, Kaluarachchi J. Risk assessment at hazardous waste contaminated sites with variability of population characteristics. Environ Int 2002;28(6):41–53.