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An Economic Decision Framework Using Modeling for Improving Aquifer Remediation Design

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An Economic Decision Framework Using Modeling for Improving Aquifer Remediation Design

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ABSTRACT

Reducing cost is a critical challenge facing environmental remediation today. One of the most effective ways of reducing costs is to improve decision-making. This can range from choosing more cost-effective remediation alternatives (for example, determining whether a groundwater contamination plume should be remediated or not) to improving data collection (for example, determining when data collection should stop). Uncertainty in site conditions presents a major challenge for effective decision-making. We present a framework for increasing the effectiveness of remedial design decision-making at groundwater contamination sites where there is uncertainty in many parameters that affect remediation design.

The objective is to provide an easy-to-use economic framework for making remediation decisions. The presented framework is used to 1) select the best remedial design from a suite of possible ones, 2) estimate if additional data collection is cost-effective, and 3) determine the most important parameters to be sampled. The framework is developed by combining elements from Latin-Hypercube simulation of contaminant transport, economic risk-cost-benefit analysis, and Regional Sensitivity Analysis (RSA).

The framework is demonstrated using a hypothetical contamination problem. In this problem, ^{90}Sr placed in an unlined trench 40 years ago is leaching into the groundwater and forming a plume at the site boundary in concentrations above compliance levels. Three remediation design alternatives are considered: no action, isolating the source trench, and installing a plume containment and treatment system. Uncertainty in remediation design performance is due to uncertainty in 13 flow and transport parameters including hydraulic conductivity, retardation factor, and source strength.

Model results show that, for the assumed parameter distributions, plume containment is the most cost-effective at low compliance limits (<100 pCi/L), while monitoring alone is the most cost-effective at higher compliance limits (> 10,000 pCi/L). In the areas between these extremes, costs are fairly close among the alternatives and more data are needed to reduce uncertainty. Data worth analysis suggests that hydraulic conductivity of the C soil horizon is the key parameter in helping to determine the most cost- effective course of remedial action.

The methodology applied to this specific example can be applied to a variety of transport situations.

1.0 INTRODUCTION

Reducing costs is one of the critical challenges facing environmental remediation today because of high costs of present cleanup practices, large number of contaminated sites, and declining remediation resources. One of the most effective ways of reducing costs is to

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improve decision-making, such as choosing more cost-effective remediation alternatives or improving data collection. A major challenge facing effective decision-making is uncertainty in site conditions. This is particularly true at groundwater contamination sites where uncertainty may exist in a large number of parameters affecting remediation design, ranging from contaminant plume location to transport parameters such as hydraulic conductivity and source strength. For example, it can be difficult to determine whether a plume should be contained or not, if there is great uncertainty in whether the plume poses a future environmental threat. In addition, a large number of uncertain parameters can make it difficult to determine which parameter is the most cost-effective to sample in order to reduce uncertainty.

We present a decision framework for increasing the effectiveness of remediation decision-making for groundwater contamination sites having uncertainty in many parameters. The objective is to provide a generic, easy to use, robust methodology for making remediation decisions. Three particular decisions are addressed by the framework. The first is determining the best remedial action alternative. The best alternative is defined as the lowest-cost, acceptable alternative. The second is determining if additional data collection is likely to be cost-effective. Additional data collection is valuable if it helps to choose a better alternative than one chosen with existing information alone. Finally, if additional data collection is warranted, what are the most important parameters to sample? This question is addressed by ranking the uncertain parameters, according to the sensitivity of the remedial alternative to these parameters. The parameters that have the most effect on the decision are the most important ones to sample.

The framework is demonstrated using a hypothetical contamination problem. The physical situation is based on similar contamination problems found at Oak Ridge National Laboratory. In this problem, ^{90}Sr placed in an unlined trench approximately 40 years ago is leaching into the groundwater and discharging into a nearby creek in concentrations that are above compliance levels. Consequently, remedial action must be considered. Three remediation design alternatives are considered: 1) no action, 2) isolation the source trench, and isolation of a plume containment and treatment system. There is uncertainty in remediation design performance due to uncertainty in 13 hydrogeological parameters ranging from hydraulic conductivity and retardation to source strength.

The framework is developed by combining elements from Latin-Hypercube simulation of contaminant transport, economic risk-cost-benefit analysis, and Regional Sensitivity Analysis (RSA). Latin Hypercube simulation is used to model contaminant transport for a wide variety of combinations of unknown parameters. Economic risk-cost-benefit analysis is used to select the best remedial alternative and to estimate whether additional data are worth collecting. RSA is used to rank the importance of collecting information about different parameters.

One of the major advantages of this framework is that it is relatively easy to understand and to apply. It also accounts for the multivariate relationship between parameters as opposed to a standard sensitivity analysis where one varies a single parameter at a time. The methodology is also adaptable to a variety of problems. For instance, while only uncertainty in hydrogeological parameters is dealt with in the hypothetical example, uncertainty in economic parameters can also be accounted for. However, the framework is also dependent on simplifying assumptions. For example, the unknown parameters are assumed to be independent.

The remainder of the paper will first present a review of previous work and then outline the framework. The framework will then be applied to the hypothetical example. Finally, strengths and limitations of the framework will be discussed.

2.0 LITERATURE REVIEW

Much of the earlier work in developing data worth decision frameworks in hydrogeology/hydrology using economic risk-cost-benefit analysis are based on Bayesian decision analysis. Bayes' equation is used to evaluate the worth of gathering additional information in situations where there is uncertainty in one parameter that is an independent random variable. Example applications include evaluating the worth of additional stream flow measurements in the design of a bridge (Davis et al. 1972), determining the optimal sampling frequency for contamination at a water supply well (Grosser and Goodman 1985), and evaluating the worth of drilling a borehole when determining the hydraulic connection between and a contaminated an uncontaminated aquifer (Ben-Zvi et al. 1988).

More recent work is much more complex in nature, where the worth of gathering additional information about a spatially correlated parameter is evaluated. These solutions are based on extensive numerical simulation. Example applications include evaluating worth of boreholes when searching for aquitard discontinuities (James and Freeze 1993), and designing sampling programs when searching for contamination (Christakos and Killam 1993 and James and Gorelick 1994).

The framework presented here differs from the above work in a number of ways. First, the objective of this framework is to provide an easy-to-apply method for making preliminary remediation decisions. As such the data-worth analysis is not as rigorous as in the above work and is simpler to apply. Second, the framework evaluates data worth in situations where there are numerous uncertain parameters. Much of the above work is geared to evaluating the worth of 1 unknown parameter. Refer to Benjamin and Cornell (1970) or Freeze et al. (1990) for a discussion of Bayesian decision analysis.

In the work that is most similar to the work presented here, Maddock (1973) examined the management of a farm. He provided a means of estimating the value of collecting additional information when there is uncertainty in a large number of parameters. Maddock's work differs from our work in that it is analytical in nature whereas ours is numerical and can incorporate more complex situations. Gates and Kisiel (1974) evaluated the worth of information about several uncertain hydraulic parameters when predicting hydraulic heads. However, the worth of data was quantified in terms a costs associated with the precision of predicted heads rather than a design decision.

It is important to note that the risk-cost-benefit approach discussed here will work in concert with human health and ecological risk in remediation decision making (Sutter et al. 1995).

3.0 DATA WORTH DECISION FRAMEWORK

The framework consists of three major components: 1) a prior analysis that determines the lowest total cost alternative, based on given information, 2) a data worth analysis that gives a ball park estimate of whether additional data collection is cost-effective, and 3) a mechanism based on Regional Sensitivity Analysis (RSA) that determines the most important parameters to sample. The steps in the framework are outlined in Figure 1.

3.1 Prior Analysis: Choosing Lowest Total-Cost Remediation Alternative, Based on Existing Information

The purpose of the prior analysis is to choose the lowest total-cost alternative, from a suite of available alternatives, based on given information.

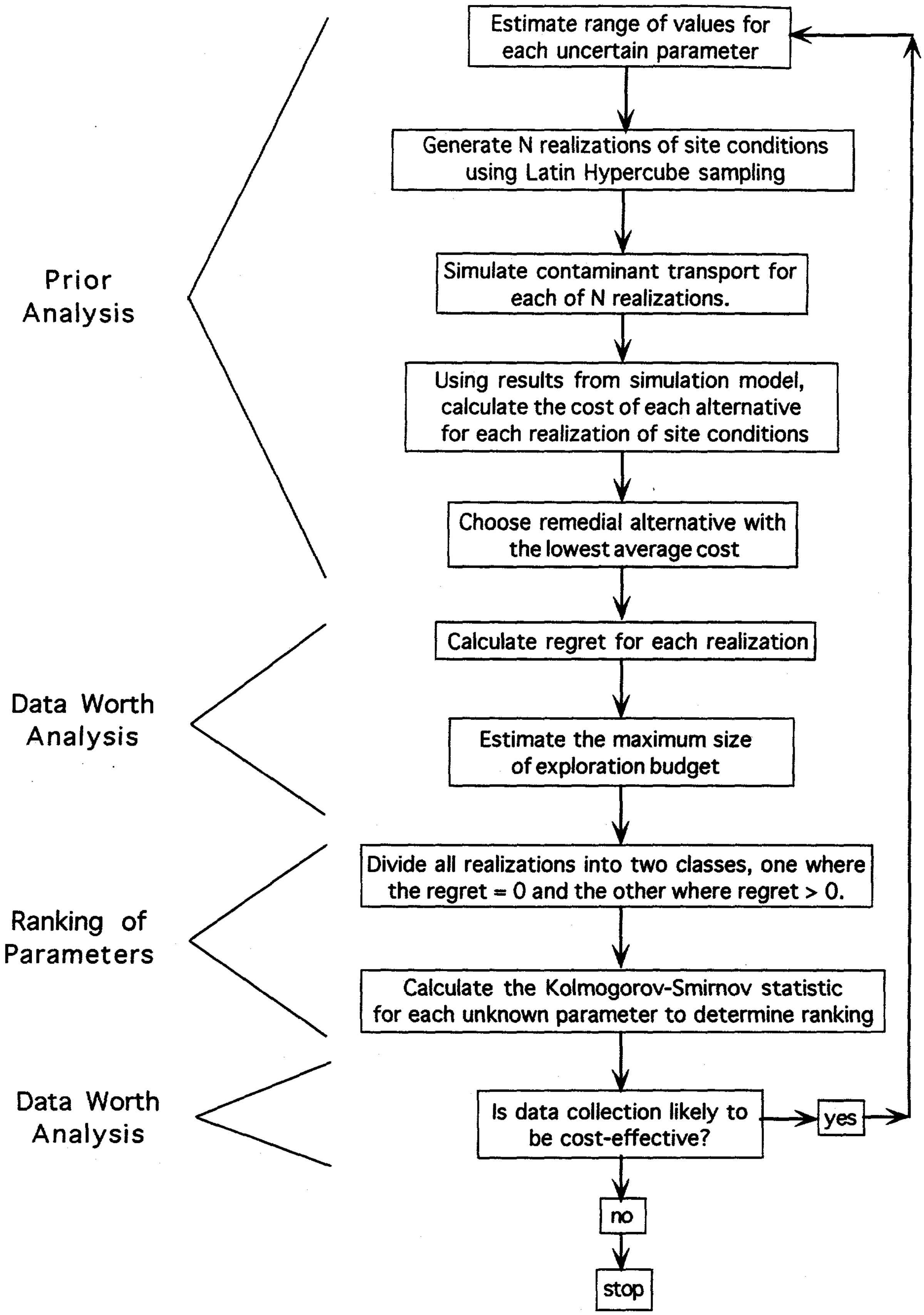

Figure 1: Outline of major steps in carrying out an analysis using framework.

3.1.1 Total Cost of an Alternative

The total cost of an alternative can be calculated using the following equation, based on economic risk-cost-benefit analysis (Freeze et al. 1990):

$$C_{tot} = \sum_{t=0}^{T} \frac{1}{(1+i)^t} \left[C(t) + R(t) \right] \tag{1}$$

where,

C_{tot}	total cost of an alternative ($);
t	time (years);
T	engineering time horizon (years);
i	discount rate (decimal %);
C(t)	known costs in year t ($);
R(t)	risk in year t ($).

C_{tot} represents net present value of all future costs associated with a given alternative. The best alternative is the one with the lowest C_{tot}. C(t) represents the known costs in year t, such as cost of monitoring or construction cost associated with remediation. The risk, R(t), represents the expected cost of failure, where failure is defined as an alternative not performing as expected. For example, failure will occur if the source trench is hydraulically contained, but the level of contamination reaching the stream does not achieve compliance levels. It is calculated by:

$$R(t) = P_f(t) C_f(t) \tag{2}$$

where, $P_f(t)$ represents the probability of failure in year t (decimal fraction),and $C_f(t)$ is the cost of failure in year t. The cost of failure includes all costs associated with a design alternative failing, including secondary remedial actions as well as regulatory fines or penalties. It is noted that equation (2) can also incorporate a term to account for the risk adverseness of a decision maker (Freeze et al. 1990). In general, the higher the consequences of making a wrong decision are, the more risk adverse a decision maker is likely to be.

Combining equations (1) and (2) yields:

$$C_{tot} = \sum_{t=0}^{T} \frac{1}{(1+i)^t} \left[C(t) + P_f(t) C_f(t) \right] \tag{3}$$

which is the equation used here to calculate the total cost of an alternative. Note that i, $C_f(t)$, and C are known while are $P_f(t)$, and t are unknown. They are unknown because they depend on many unknown transport parameters. The next step is to estimate the total cost for each remediation alternative despite this uncertainty.

3.1.2 Estimating Total Cost Using Latin Hyper Cube Simulation

The expected (or average) total cost of each alternative is estimated using Latin Hypercube simulation. The details of the methodology can be found in Iman and Conover (1980). The basic technique is to statistically generate equally likely realizations, or scenarios, of what the site conditions could be. Latin Hypercube simulation is a form of Monte Carlo simulation. However, the advantage of the former is that fewer realizations are needed to get a reliable estimate the total cost. As a general rule of thumb, six times as many realizations should be generated as the number of unknown parameters (Morris 1995) in order to obtain a reliable estimate of the predicted variable, which here is total cost. Parameters are assumed to be independent or weakly correlated

The first step in generating the realizations is to estimate probability distributions for each of the uncertain parameters. Latin Hypercube simulation then uses these probability distributions to generate a series of N realizations of site conditions on the computer. Each realization consists of one possible value for each of the unknown parameters. Every realization is assumed to be equally likely to represent a picture of the real, but unknown, site conditions. Contaminant transport is then simulated for every realization for each remedial alternative using a computer model to determine if failure occurs or not, and also the failure time. The probability of failure for an alternative for each realization will be either zero or one. The total cost for each alternative can then be calculated using equation (3). The best remediation alternative is the one with the lowest expected total cost and will be referred to hereafter as the prior design, or A_D for short.

It is important to note that since A_D is based on uncertain information, it may not actually be the best alternative. Consequently, it may be worth spending money gathering additional information to help choose a better alternative. This issue is addressed next.

3.2 Evaluating the Maximum Size of an Exploration Budget

The purpose of this section is to estimate the maximum size of an exploration budget. In economic risk-cost-benefit analysis, additional data are only worth collecting if they will change the choice of best design, or prior design, based on existing information. New data that cannot change A_D have no value. Data worth can be explained using the concept of regret. The regret represents the monetary loss incurred by not making the best decision. The regret in selecting A_D, $Reg(A_D)$ is calculated by (Freeze et al. 1992):

$$Reg(A_D) = C_{tot}(A_D|truth) - C_{tot}(A_T|truth) \qquad (4)$$

where

$C_{tot}(A_D|truth)$ the total cost of the prior design given the truth, i.e. complete knowledge of site conditions;
A_T the true best design alternative;
$C_{tot}(A_T|truth)$ the total cost of the true best alternative, given the truth.

Note that $C_{tot}(A_D|truth)$ represents the actual total cost for A_D given complete knowledge of site conditions; it is not the value estimated in the prior analysis. In other words, equation (4) represents the difference between the actual total cost of A_D and the total cost of best alternative, A_T. If A_D is the same as A_T (i.e. we really did choose the true best design in the prior analysis) then the regret is zero.

The regret represents the maximum amount of money that should be spent gathering additional data, or in other words, the maximum size of an exploration budget. Unfortunately we do not know what the regret is because the true site conditions are unknown. However, we have N equally likely realizations of the site conditions that were generated using Latin Hypercube simulation. We can calculate the regret for each realization number n by comparing the actual cost of A_D, based realization n, to the cost of the true best design for realization n:

$$\mathrm{Reg}(A_D|\bar{x}_n) = C_{tot}(A_D|\bar{x}_n) - C_{tot}(A_T|\bar{x}_n) \tag{5}$$

where

$\bar{x}_n$	vector containing a value generated for each uncertain parameter representing site conditions for realizations number n;
$\mathrm{Reg}(A_D|\bar{x}_n)$	regret of choosing A_D, assuming that $\bar{x}_n$ represents the true site conditions;
$C_{tot}(A_D|\bar{x}_n)$	total cost of the prior design, assuming that $\bar{x}_n$ represents the true site conditions;
$C_{tot}(A_T|\bar{x}_n)$	total cost of the true best design, assuming that $\bar{x}_n$ represents the true site conditions.

Realizations where the regret = \$0 indicate that A_D is the true best design. Realizations where the regret > \$0 indicate that A_D is not the true best design. The maximum size of an exploration budget is represented by the average regret of the N realizations:

$$\text{Maximum exploration budget} = \frac{1}{N}\sum_{n=1}^{N}\left[C_{tot}(A_D|\bar{x}_n) - C_{tot}(A_T|\bar{x}_n)\right] \tag{6}$$

If the maximum exploration budget is very large, additional data collection is likely to be cost-effective.

The next step is determining the most cost-effective parameters to sample.

3.3 Determining the Most Important Parameters to Sample

The parameters that are the most important to sample are the ones that have the greatest effect on changing the prior decision. Parameters that have little effect on the prior decision are the least important to sample. The ranking of cost-effectiveness is done using Regional Sensitivity Analysis (RSA), a technique developed by Spear and Hornberger (1980) and Hornberger and Spear (1980).

RSA is conceptually very simple. The approach is to separate the N realizations into two classes. Class 1 represents realizations where the best alternative is the same as A_D ($\mathrm{Reg}(A_D) = \$0$). Class 2 represents realizations where the best design is not A_D ($\mathrm{Reg}(A_D) > \$0$). The number of realizations in classes 1 and 2 are represented by N_1 and N_2, respectively, where $N_1 + N_2 = N$. Recall that each realization consists of one value for each unknown parameter. Let us refer to an unknown parameter as X_i. The cumulative probability function, $F_{X_i}(x_i)$, is then estimated for each X_i, for both classes. The cumulative probability function for X_i is defined as $F_{X_i}(x_i)_1$ for class 1 and $F_{X_i}(x_i)_2$ for class 2.

The measure of importance of a parameter, X_i, is based on the difference between $F_{X_i}(x_i)_1$ and $F_{X_i}(x_i)_2$. The basic principle is that if $F_{X_i}(x_i) = F_{X_i}(x_i)_1 = F_{X_i}(x_i)_2$ then parameter X_i has no effect on the decision. The greater the difference between $F_{X_i}(x_i)_1$ and

$F_{X_i}(x_i)_2$, the greater the importance in obtaining more information about parameter X_i. The difference between $F_{X_i}(x_i)_1$ and $F_{X_i}(x_i)_2$ is calculated by:

$$d_i = \max_{-\infty < x_i < \infty} \left| S_{X_i}(x_i)_1 - S_{X_i}(x_i)_2 \right| \qquad (7)$$

where,

d_i	is the Kolmogorov-Smirnov two sample statistic for X_i;
$S_{X_i}(x_i)_1$	is the sample $F_{X_i}(x_i)_1$ for class 1;
$S_{X_i}(x_i)_2$	is the sample $F_{X_i}(x_i)_2$ for class 2.

The d_i represents the maximum vertical distance between $S_{X_i}(x_i)_1$ and $S_{X_i}(x_i)_2$. The greater the size of d_i, the greater the sensitivity of the A_D to X_i, and the more important it is to sample X_i. Conceptual results are shown in Figure 2 for the cases of a sensitive and a non sensitive parameter.

One way to accentuate the difference in importance between different parameters is to calculate the confidence that d_i is indicating that the realizations in classes 1 and 2 are truly different. This confidence is quantified by (Press et al. 1987):

$$\mathrm{Prob}(D_i > d_i) = 2\sum_{j=1}^{\infty}(-1)^{j-1} e^{-2j^2\lambda^2} \qquad (8)$$

and λ is calculated by

$$\lambda = d_i \sqrt{\frac{N_1 N_2}{N_1 + N_2}} \qquad (9)$$

where D_i is the Kolmogorov-Smirnov statistic for two samples drawn from the same population. Hence D_i represents the random difference between the cumulative probability distributions of two samples that are from the same population. The $\mathrm{Prob}(D_i > d_i)$ represents the probability that d_i is not just a random event. If the $\mathrm{Prob}(D_i > d_i) = 0.9$ then there is a 90% chance that the calculated d_i is simply a random event and the realizations of X_i in classes 1 and 2 are from the same population. In this case we have no confidence that A_D is sensitive to X_i. If the $\mathrm{Prob}(D_i > d_i) = 0.001$ then there is a 0.1% chance that the realizations of X_i in classes 1 and 2 are from the same population. In this case we are very confident that A_D is very sensitive to X_i.

Therefore, the lower the $\mathrm{Prob}(D_i > d_i)$, the more important the parameter is to sample. The value of $\mathrm{Prob}(D_i > d_i)$ can be used to accentuate the difference in importance between the different parameters because small increases in d_i yield large increases in $\mathrm{Prob}(D_i > d_i)$. Consequently, $\mathrm{Prob}(D_i > d_i)$ can be used to quickly pick out the most sensitive parameters.

It is noted that one cannot set a certain value of $\mathrm{Prob}(D_i > d_i)$ to indicate whether a parameter is significant or not because $\mathrm{Prob}(D_i > d_i)$ is dependent upon the number of realizations used in the analysis. The value of $\mathrm{Prob}(D_i > d_i)$ is only valuable for picking out the important parameters in the relative sense.

Equation (10) is only an approximation of λ that becomes asymptotically accurate as N_1 and N_2 become large. In practice N_1 and N_2 should be ≥ 20 (Press et al. 1987). An

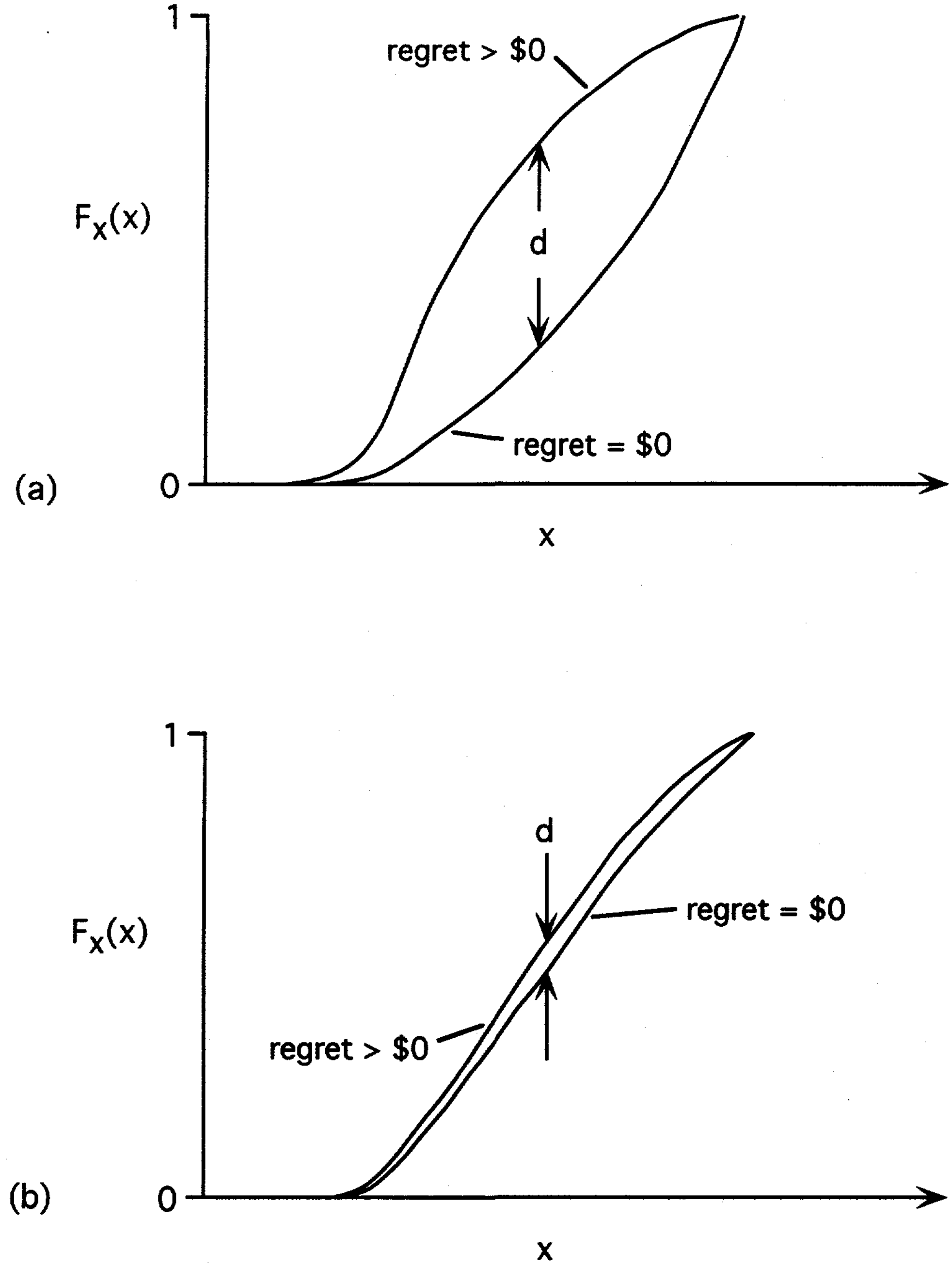

Figure 2: Cumulative probability distributions for realizations where regret = $0 and regret > $0 for (a) a sensitive parameter and (b) a nonsensitive parameter.

important point is that as long as N_1 and N_2 are ≥ 20, the number of realizations needed to achieve a given level of confidence in the conclusions is independent of the number of uncertain parameters because the Kolmogorov-Smirnov two sample test is only a function of N_1 and N_2 and not of the number of uncertain parameters (Auslander et al. 1982).

Once the important parameters are selected, the next step is to determine which sampling program is the most cost-effective.

3.4 Cost-Effectiveness of a Proposed Sampling Program

The purpose of this section is to determine whether a proposed sampling program is cost-effective. A sampling program is worthwhile if it will reduce remediation costs by an amount greater than its cost of acquisition. This section will only provide an approximate estimate of the cost-effectiveness of a proposed sampling program.

There can be four possible outcomes for a sampling program: (a) failure conditions are indicated when failure conditions exist, (b) non failure conditions are indicated when in reality failure conditions exist, (c) non failure conditions are indicated when non failure conditions exist, and (d) non failure conditions are indicated when in reality failure conditions exist. Outcomes (b) and (d) will be referred to here as false indications of failure and non failure conditions, respectively.

Estimating the worth of a sampling program that accounts for all four possible outcomes can be done, but is beyond the scope of this paper. For simplicity we focus on evaluating the worth of a sample survey that gives no false indications of failure. For example, say that a potentially dangerous contaminant exists at a site. A sample survey that can give a false indication of failure may suggest that the dangerous contaminant exists when in reality it does not. The worth of a sample survey with no false indications of failure can be calculated by (James and Freeze 1993):

$$\text{Sample worth} = (\text{Sample reliability})\ (\text{EVPI}) \qquad (10)$$

where the sample reliability represents the probability that the sample survey will detect failure conditions given that failure conditions exist. The reliability ranges from 0 to 1. A sampling survey with a reliability of 1 represents a perfect measurement that reduces uncertainty to zero, while one with a reliability of 0 represents a useless survey that gives no useful information.

One can obtain a very approximate estimate of the worth of a proposed sample survey by intuitively estimating what the precision is of the proposed sampling program, for example determining if the sample reliability is high (say >0.7), medium (say 0.3 to 0.7) or low (say <0.3). If the sample cost is much lower than the estimated worth then the sample survey is likely to be cost-effective, whereas if it is higher then the sample survey is not likely to be cost-effective.

4.0 HYPOTHETICAL EXAMPLE: REMEDIATION OF A DISPOSAL TRENCH CONTAINING ^{90}Sr

4.1 Introduction

In this section, the framework is demonstrated using a hypothetical example. However, the site conditions are based on one found at Waste Area Grouping 6 (WAG6) at Oak Ridge National Laboratory (ORNL), Oak Ridge Tennessee.

In the hypothetical problem, waste contaminated with strontium-90 (^{90}Sr) was disposed of in an unlined earthen trench 40 years ago. Since disposal, ^{90}Sr has been leaching out of the trench into the groundwater system. Monitoring wells adjacent to the site boundary indicate that the activity of ^{90}Sr in the groundwater is above the compliance level, which is assumed to be 1,000 pCi/l. Consequently, remedial action must be considered. It is noted that this is not the contamination problem being faced at ORNL.

However, spending limited financial resources carrying out remediation immediately may not be the best course of action. First, the contamination presently poses no direct human health risk. Second, the contamination will remediate itself naturally as the source strength weakens through dilution and radioactive decay (the half life of strontium is 28.5 years). Given these circumstances, it may be more cost-effective to spend limited financial resources on other higher priority sites.

It has been determined through negotiation with involved stakeholders that the average activity level of ^{90}Sr contamination in the groundwater leaving the site must achieve the compliance level within 10 years.

4.1.1 Remedial Action Alternatives

Three remedial alternative courses of action are considered. The first is containment of the groundwater contamination by a pump and treat system at an assumed cost of $5 million. It is assumed that this alternative will be 100% effective in bringing the site within compliance. The second is isolation of the source trench with a impermeable cap and slurry walls at an assumed cost of $1 million. This alternative will be effective in cutting off the source trench, but it will not prevent remobilization of ^{90}Sr that is already sorbed to soil matrix outside of the trench area. This remobilization represents a secondary source of contamination. Therefore, this second alternative may not achieve compliance levels within 10 years. The third is to monitor-only at zero cost. Monitoring costs will be incurred; however, they are not considered in the analysis here because monitoring will be carried out for all remediation alternatives. This alternative relies solely on natural cleanup to achieve compliance. As such it is the least effective at reducing discharge levels of contamination, but has the lowest cost up front.

In the event that compliance is not achieved within 10 years, failure will occur. It is assumed that the cost of failure will be $15 million, payable at the time of failure. This cost will include regulatory fines as well as having to remediate a much more serious contamination problem. A discount rate of 4.5% is assumed.

4.1.2 Geology and Hydrogeology

The physical situation consists of three layers (Fig. 3). The top layer is the B soil horizon and is approximately 1 m in thickness. The next layer is the C horizon which is composed of highly fractured saprolite that ranges in thickness from 5 to 10 m. The bottom is a layer of limestone/shale which has fracturing to a depth of 10 to 20 m. The water table is located in the saprolite layer and is below the waste trench. Contaminants are leached from the trench in the unsaturated zone down to the water table, where they are transported by the groundwater through the saprolite and limestone/shale layers. In addition to three layers, a series of clay lenses also exist which effect contaminant transport.

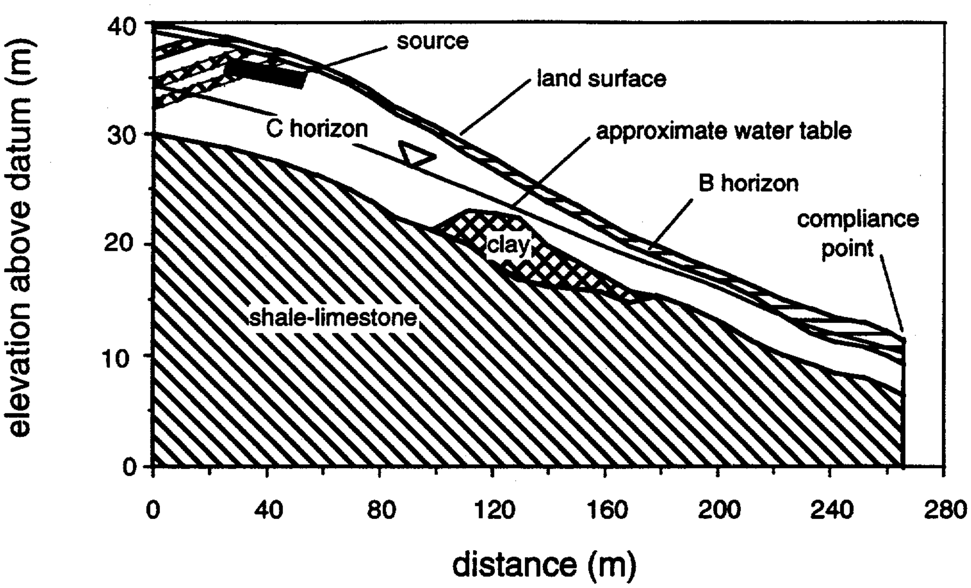

Figure 3: Cross section used in the hypothetical example. The cross section consists of B and C soil horizons, a shale-limestone layer, and clay lenses.

4.1.3 Numerical Model of Contaminant Transport

The modeled system is shown in Figure 3. It consists of three layers as well as clay lenses. All geological units are assumed to be homogeneous and the transport parameters are independent random variables. It is assumed that the average activity level of ^{90}Sr can be adequately modeled using an equivalent porous media two dimensional flow and transport model.

Groundwater flow is modeled using the finite element code PFEM, a parallelized version of 3DFEMWATER (Yeh 1987) while contaminant transport was modeled using 3DLEWASTE, a parallelized version of LEWASTE (Yeh and Gwo 1990). The finite element mesh consisted of 8262 nodes and 4000 elements. The groundwater flow calculations were run assuming steady state conditions. The leaching rate through the unsaturated zone is based on tabulated soil moisture properties from the ORNL site.

Present day conditions were generated by modeling transport from 40 years ago until the present. Given the 40 year period of time, it is assumed that flow is in steady state conditions. The monitor-only alternative was simulated by continuing to model each realization of present day conditions for another 10 years. The source isolation alternative was simulated by turning off the source term at the present time and then continuing to simulate transport for another 10 years.

For this hypothetical example, it is assumed that any modeled realization of present day activity level is equally likely, as long as the activity level is above compliance levels. Monitoring data will not be used to condition any present day realizations that are above compliance levels for two reasons. First, only limited monitoring data maybe available with which to provide bounds of plume activity levels. Furthermore, in extremely heterogeneous setting where there is fracture flow, such as at ORNL, there can be tremendous variability in the contaminant concentrations measured by different monitoring wells, depending on whether a significant flow zone is intersected or not. Finally, the modeled activity level will not correspond exactly to the real activity level because of model simplifications. For example, fracture flow is represented as an equivalent porous media and only steady state flow conditions are modeled.

The next section discusses the setting of values for the uncertain transport parameters.

4.1.4 Setting of Values for Uncertain Transport Parameters

In this section, we choose the range of values for the different uncertain flow and transport parameters. It is assumed that all parameters are known except for the hydraulic conductivity (K), distribution coefficient (Kd), and longitudinal dispersivity (α_L) of the three layers and clay lenses as well as the source strength. Consequently there were 13 uncertain parameters. It was assumed that the likelihood of each parameter is uniformly distributed between a maximum and a minimum value. Parameter ranges for the uncertain parameters were based on knowledge from the ORNL site known as Waste Area Grouping 6 (WAG6), where possible. These values are summarized in Table 1. The choice of these values is discussed next.

The ranges of hydraulic conductivity (K) of the different units were based on observed values rounded to an order of magnitude difference (Moore and Toran 1992; Wilson et al. 1992).

Parameter	minimum	maximum
conductivity Limestone (m/h)	3.6e-6	3.60e-3
conductivity C horizon (m/h)	0.00036	0.036
conductivity clay lenses (m/h)	3.6e-6	3.60e-3
conductivity B horizon (m/h)	0.036	0.360
Kd, Limestone, (ml/g)	0	5.0
Kd, C horizon, (ml/g)	0	5.0
Kd, clay lenses, (ml/g)	0	5.0
Kd, B horizon, (ml/g)	0	5.0
dispersivity, Limestone (m)	10.0	100.0
dispersivity, C horizon (m)	10.0	100.0
dispersivity, clay lenses (m)	10.0	100.0
dispersivity, B horizon (m)	10.0	100.0
source strength (pCi/l)	2.e4	2.e5

Table 1: Assumed ranges of transport parameters.

The dispersivity cannot be easily measured in the field, and there are no well-calibrated model plumes on which to base a site-specific value. Therefore, we used an order of magnitude range (10-100 meters) that is typical for modeling at this scale (Anderson 1984 and Gelhar et al. 1992). Model dimensions were 250 meters in length with a variable grid spacing that never exceeded 10 m. Each hydrogeologic unit had the same range in dispersivity, with the transverse dispersivity (α_T) fixed at one-tenth the selected value of the longitudinal dispersivity (α_L).

The upper bound for Kd is set at 5.0 and is based on field observations of plumes located near WAG 6 (Jardine 1995). We arbitrarily used a lower bound of Kd = 0 to represent a conservative (fast) travel time with a retardation factor of 1.

One estimate for the present source strength is approximately 2 x 10^4 pCi/l based on estimates from the WAG6 environmental monitoring plan (SAIC 1993). This is assumed to represent the lowest possible value for the original source strength. It is arbitrarily assumed that the maximum possible value is 10 times greater than the minimum one.

Fixed parameters included porosity (0.39 for limestone, 0.41 for C horizon, 0.48 for clay lenses, and 0.45 for B horizon) and half-life of ^{90}Sr (28.5 y).

4.2 Results

A total of 100 realizations of site conditions were generated. However, two of the realizations were rejected because breakthrough of contamination had not occurred at the compliance point when present day conditions were modeled. Consequently, only 98 of the 100 realizations were used in the analysis

4.2.1 Prior Analysis

Results from the prior analysis indicated that plume containment was the best alternative, with cost of $5 million. However, the expected costs of the monitor-only alternative and of source isolation were both not much higher at values of $5.5 and $6.3 million, respectively. The probability of failure for monitoring-only was 0.57 while the probability of failure for source isolation was slightly smaller at 0.55. These values are summarized in Table 2.

This small reduction in probability of failure from 0.57 to 0.55 indicates that source isolation was only slightly more effective at reducing the level of ^{90}Sr activity than natural remediation with monitoring alone. This slight reduction illustrates the importance of the secondary source, which continues to leach after the primary source in the trench is cut off.

4.2.2 Maximum Size of an Exploration Budget

The expected regret of the 98 realizations was calculated to be $2.2 million using equation (6). Therefore, the maximum size of an exploration budget is approximately $2.2 million. Given this magnitude of exploration budget, it is highly likely that additional data collection is cost-effective because many sampling programs will cost much less than $2.2 million. The next question is to determine which are the most important of the 13 uncertain parameters to sample in order to reduce uncertainty.

Remediation Alternative	Average Total Cost ($ million)	Probability of Failure
seepage containment	5.0	0.0
source isolation	6.3	0.55
monitor-only	5.5	0.57

Table 2: Result of prior analysis for base case.

4.2.3 Ranking of the Most Important Parameters to Sample

Recall that the ranking was done by the RSA algorithm. The RSA analysis indicated that the most sensitive parameter is K of the C horizon. It had a Kolmogorov-Smirnov statistic of 0.475 and the probability of its being a random event, or level of significance, is 3.6 x 10^{-5} (Table 3). The next two most important parameters to sample are the α_L of C horizon and the source strength, which had Kolmogorov-Smirnov statistics of 0.399 and 0.38, and levels of significance of 8.9 x 10^{-4} and 1.8 x 10^{-3}, respectively. One can also see that uncertainty in the transport parameters for the B horizon and the clay lenses in general have little effect on choosing the best remediation alternative, as would be expected because lateral flow occurs primarily in the C horizon. For example the Kolmogorov-Smirnov statistic for K_d of clay lenses is 0.1 and its level of significance of 0.97. This means that there is a 97% chance that there is no significant difference between the realizations K_d for the clay lenses in classes 1 and 2. Consequently, it is not worth gathering additional information about these less important parameters. The cumulative probability distributions for realizations with a regret = \$0 and > \$0 for K for the C horizon (a sensitive parameter) and K of the clay lenses (a non-sensitive parameter) are shown in Figures 4 and 5.

The importance of source strength is clear, but muted somewhat because of the development of the secondary source. Note that the results from the monitoring only and the source isolation realizations are nearly identical. This similarity also indicates the importance of the secondary source. The dominance of dispersivity over retardation is a function of the maturity of the plumes. Most of the plumes have reached their peak concentration and already crossed the compliance point. In the tailing portion of the plume, dispersivity is more important than retardation in determining the concentration.

Note that the levels of significance are at least an order of magnitude less for α_L of C horizon and the source strength, than that for K of the C horizon, showing that K of the C horizon is clearly dominating the uncertainty. Consequently, any sampling program should likely focus solely on K of the C horizon. This is especially true since both the α_L of C horizon and the source strength will be difficult parameters to measure.

4.2.4 Estimating Cost-Effectiveness of Proposed Sampling Program

A field sampling program for K of the C horizon is highly likely to be cost-effective. First, the likely cost of the program will be much less than the estimated \$2.2 million maximum size of the exploration budget. Second, a well designed field program should be reliable in greatly reducing uncertainty in K of the C horizon from its present 2 orders or magnitude spread. Consequently, from equation (10), the worth is likely greater than the sample cost.

5.0 SENSITIVITY ANALYSIS

In this section, we study the sensitivity of the base case analysis to the compliance limit and the cost of failure. We will first examine the sensitivity to the choice of the best remediation design in the prior analysis, then the maximum size of an exploration budget and finally the ranking of parameters. This exercise is valuable at showing how decisions may change under different assumptions.

The choice of best remediation design determined in the prior analysis is sensitive to both the cost of failure and the compliance limit. The expected total cost for both the monitor-only and source isolation alternatives both decrease with increasing compliance limit for a cost of failure = \$15 million (Fig. 6). At lower (more strict) compliance limits, the best

Parameter	d_i	Prob(d_i<D)
K of C horizon	0.475	3.6E-05
α_L of C horizon	0.399	0.00089
Source Strength	0.38	0.0018
K of limestone	0.317	0.015
K_d of C horizon	0.295	0.03
K of B horizon	0.244	0.11
K_d of limestone	0.234	0.14
α_L of clay lenses	0.205	0.26
K of clay lenses	0.194	0.32
α_L of limestone	0.164	0.53
K_d of B horizon	0.162	0.54
α_L of B horizon	0.141	0.72
K_d of clay lenses	0.1	0.97

Table 3: Ranking for parameters to be sampled from RSA analysis for base case. The Kolmogorov-Smirnov statistic = d_i and the level of significance = Prob(d_i<D).

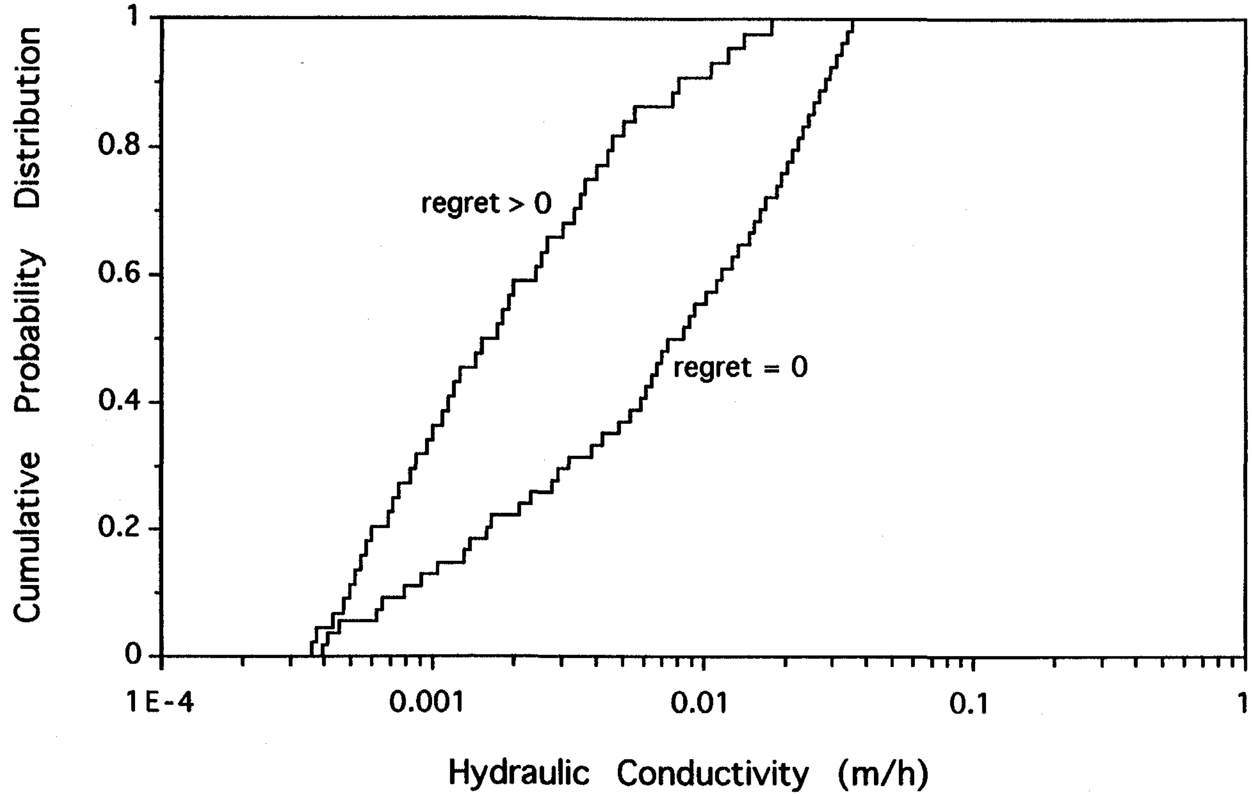

Figure 4: Cumulative probability distribution for realizations of K for the C horizon for classes where regret = \$0 and regret > \$0. The prior design is very sensitive to uncertainty in K for the C horizon.

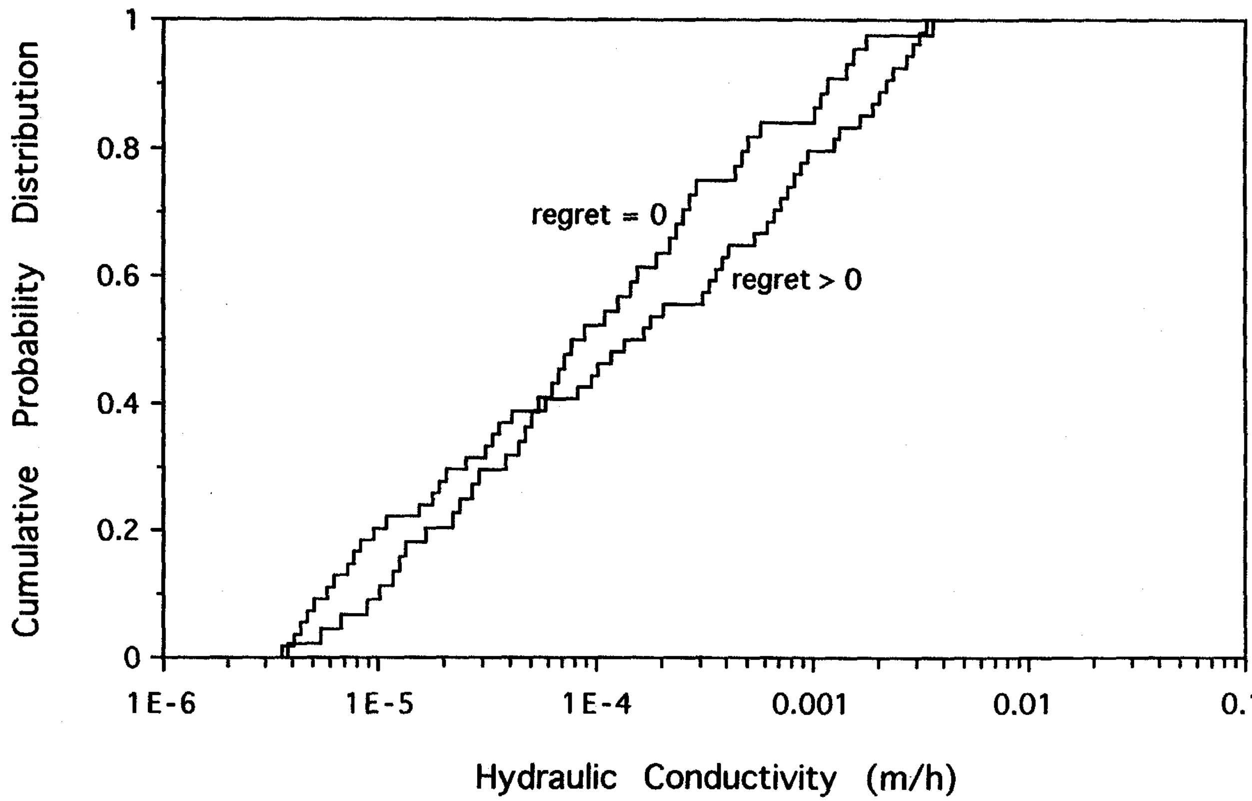

Figure 5: Cumulative probability distribution for K of clay lenses for realizations classes where regret = \$0 and regret > \$0. The prior remediation design is not sensitive to uncertainty in K of the clay lenses.

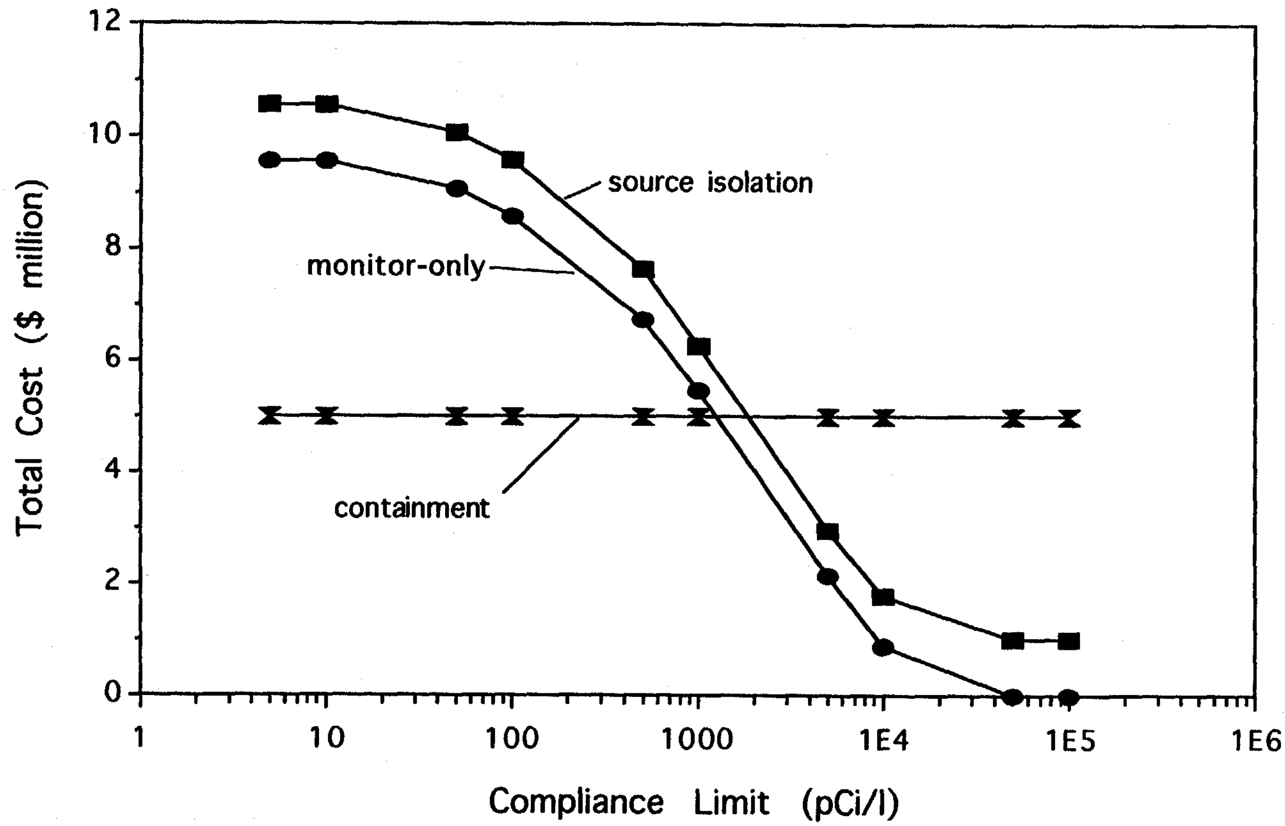

Figure 6: Average total cost of the containment, monitor-only, and source isolation alternatives versus compliance limit. Cost of failure = $15 million.

remediation alternative is to be conservative and contain the plume at a cost of $5 million. However, at higher compliance limits (less strict), the best remediation alternative is to monitor-only, and accept the risk of failure. A similar behavior is shown for a cost of failure of $10 million (Fig. 7). Note that for both costs of failure of $10 million and $15 million that the expected total cost of monitor-only is always less than that for source isolation. Note also, for the base case compliance limit of 1000 pCi/l, that changing the cost of failure from $15 million to $10 million changes the best design from containment to monitor-only.

The estimated maximum size of an exploration budget is also sensitive to both the cost of failure and the compliance limit (Fig. 8). For a cost of failure of $15 million, as the compliance limit increases from 10 pCi/l, the maximum size of the exploration budget increases and reaches a maximum ≈ $2.2 million at a compliance limit of approximately 1,000 pCi/l. It then decreases and reaches $0 at a compliance limit of approximately 50,000 pCi/l. A similar phenomenon also occurs when the cost of failure is $10 million, except that the maximum size of the exploration budget is only approximately $1 million.

This change in size of exploration budget reflects the change in the degree of uncertainty in selecting the best design as the compliance level changes. At low, or more strict, compliance levels (≤ 10 pCi/l) the seepage containment is clearly the best. Its $5 million cost is much less than the next best alternative of source isolation which costs over $9 million (Fig. 6). This large difference in costs shows that there is little uncertainty in which alternative is the best design. In fact the maximum size of an exploration budget is $0, indicating that no data collection is cost-effective. As the compliance limit increases to near 1,000 pCi/l, the estimated total costs for the three alternatives are all relatively close together (Fig. 6). At this point there is great uncertainty as to which is the best design alternative. Consequently, the estimated maximum size of an exploration budget reaches a peak. At higher, less strict, compliance limits (≥ 50,000 pCi/l) the degree of uncertainty again decreases as monitor-only clearly becomes the best alternative (Fig. 6). The maximum size of an exploration budget then decreases to $0 again.

The sensitivity of the parameter ranking was also studied. The parameter ranking was calculated for three different compliance limits of 500, 1000 and 5000 pCi/l for a cost failure = $15 million (Table 4). Note that it is worth collecting data at each of these three limits. The ranking of the three most important parameters (K of C horizon, α_L of the C horizon, and source strength) does not change with changing compliance limit. However, the ranking of the less important parameters is sensitive to the compliance limit. For example, α_L of the limestone is the 4th most important parameter at a compliance limit of 5,000 pCi/l, but it is only the 10th most important parameter at a compliance limit of 1,000 pCi/l.

The ranking of the three most important parameters was insensitive to changing the cost of failure from $15 million to $10 million (Table 5). As in the above case, only the ranking of the less important parameters was sensitive to changes in the cost of failure.

6.0 STRENGTHS AND LIMITATIONS

There are a number of strengths and limitations associated with the framework. The strengths will be discussed first. The first strength is that the framework is conceptually simple to understand and relatively easy to implement on the computer. For example, two of the needed computer routines for carrying out the analysis are readily available. Latin Hypercube sampling routines are commercially available. A program for carrying out the RSA analysis is available as part of the Numerical Recipes programs (Press et al. 1987).

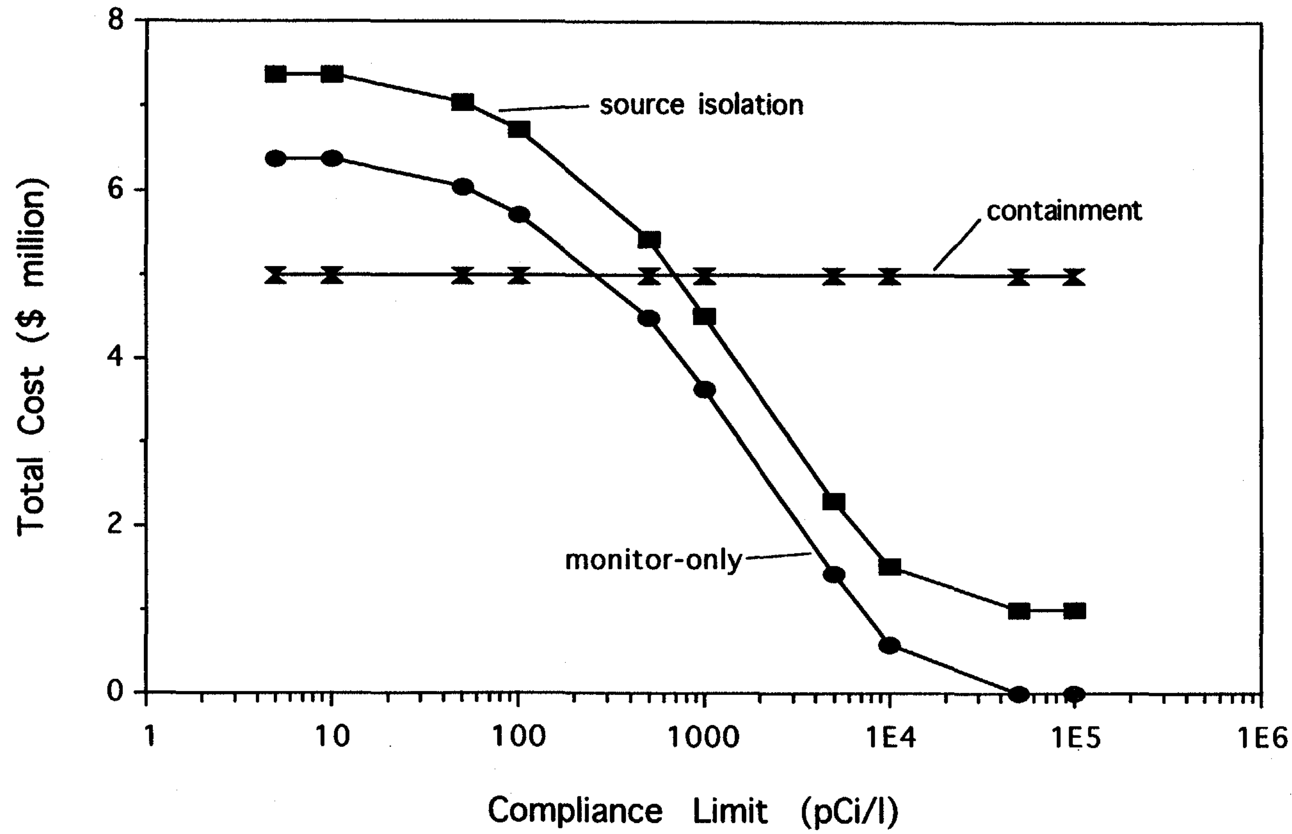

Figure 7: Total cost of the source isolation, monitor-only, and contaiment alternatives versus compliance limit. Cost of failure = $10 million.

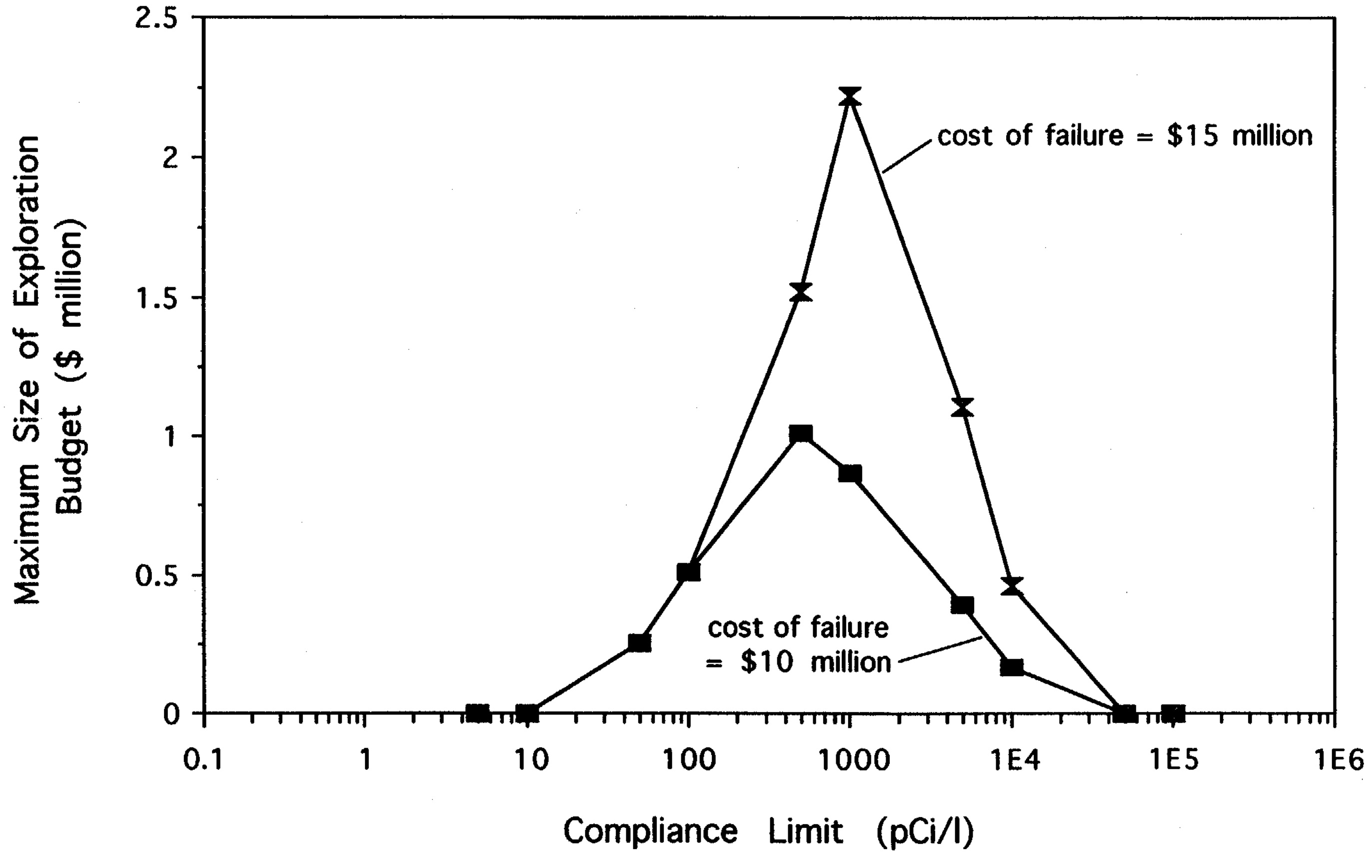

Figure 8: The maximum size of exploration budget for different compliance limits.

Parameter	Compliance Level (pCi/l)					
	500		1000		5000	
	d_i	$Prob(d_i<D)$	d_i	$Prob(d_i<D)$	d_i	$Prob(d_i<D)$
K of C horizon	0.498	6.5×10^{-5}	0.475	3.6×10^{-5}	0.706	8.3×10^{-8}
α_L of C horizon	0.417	0.0015	0.399	0.00089	0.458	0.0016
Source Strength	0.33	0.021	0.38	0.0018	0.385	0.013
K of limestone	0.317	0.031	0.317	0.015	0.279	0.14
K_d of C horizon	0.247	0.16	0.295	0.03	0.267	0.18
K of B horizon	0.257	0.13	0.244	0.11	0.121	0.96
K_d of limestone	0.125	0.9	0.205	0.26	0.269	0.17
α_L of clay lenses	0.202	0.36	0.234	0.14	0.2	0.5
K of clay lenses	0.145	0.77	0.194	0.32	0.187	0.59
α_L of limestone	0.162	0.65	0.162	0.54	0.324	0.055
K_d of B horizon	0.158	0.68	0.164	0.53	0.12	0.97
α_L of B horizon	0.248	0.15	0.141	0.72	0.112	0.98
K_d of clay lenses	0.138	0.82	0.1	0.97	0.118	0.97

Table 4: Ranking of parameters for different compliance levels. Cost of failure = $15 million. The Kolmogorov-Smirnov statistic = d_i and the level of significance = $Prob(d_i<D)$.

Parameter	Cost of Failure			
	\$10 million		\$15 million	
	d_i	Prob(d_i<D)	d_i	Prob(d_i<D)
K of C horizon	0.53	2.8E-06	0.475	3.6E-05
α_L of C horizon	0.381	0.0019	0.399	0.00089
Source Strength	0.345	0.0066	0.38	0.0018
K of limestone	0.28	0.047	0.317	0.015
K_d of C horizon	0.273	0.097	0.295	0.03
K of B horizon	0.304	0.024	0.244	0.11
K_d of limestone	0.214	0.22	0.234	0.14
α_L of clay lenses	0.19	0.35	0.205	0.26
K of clay lenses	0.208	0.25	0.194	0.32
α_L of limestone	0.149	0.66	0.164	0.53
K_d of B horizon	0.167	0.52	0.162	0.54
α_L of B horizon	0.143	0.71	0.141	0.72
K_d of clay lenses	0.125	0.85	0.1	0.97

Table 5: Ranking of parameters for cost of failure = \$10 million and \$15 million. Compliance level = 1000 pCi/l (base case). The Kolmogorov-Smirnov statistic = d_i and the level of significance = Prob(d_i<D).

Second, it is adaptable to a wide variety of problems and a relatively large number of uncertain parameters. The framework can also be adapted to handle uncertainty in other parameters besides contaminant transport parameters. For example, uncertainty in economic parameters, such as the cost of failure, can easily be incorporated into the analysis. This incorporation can be particularly valuable in situations where uncertainty in economic parameters may be more important than uncertainty in hydrogeological parameters. Such a situation was found by Maddock (1973) in his study of the management of a farm.

Finally, the framework is relatively robust. For example the application of the RSA approach is essentially independent of the complexity of the modeled situation because the classification scheme is based on a binary system (Beck 1987). For the same reason, the number of simulations required to achieve a given level of confidence in d_i is independent of the number of uncertain parameters. The value of d_i is also sensitive not only to the difference in the central tendency of the two distributions, but also to any difference in the distribution functions (Spear and Hornberger 1980).

The most significant limitation is that the modeled situation is a simplified version of reality. For example, the RSA approach is limited to uncertain parameters that are independent random variables or correlated to just one other random variable (Beck 1987). Hence, situations with many correlated random variables may not be handled adequately. Another limitation is that the framework does not carry out a complete data worth analysis. The framework gives ball park estimates as to whether additional information may be cost-effective and indicates what are the most important parameters to sample. It does not estimate how much money should actually be spent gathering information on each individual parameter.

Another limitation of the adaptation here is that conditioning of realizations of present day contamination was only based on whether the modeled activity levels were greater or less than compliance. In reality, measured activity levels would be useful in conditioning likely realizations of reality.

Given these strengths and limitations, the framework is most applicable to making "big picture" decisions such as the best remedial alternative, the cost-effectiveness of additional data collection, and the choice of parameters to sample. One area of potential application is in the preliminary stages of remediation design.

7.0 SUMMARY AND CONCLUSIONS

We present an economic decision framework for improving remediation design at groundwater contamination sites where there is uncertainty in many flow and transport parameters. The framework is specifically used to address broad decisions regarding remediation design and data worth.

The framework is applied to a hypothetical example, but the physical conditions are based on a field site located at ORNL. In this example, the cost-effectiveness of three alternatives for remediation of ^{90}Sr contamination are compared. The three alternatives include: 1) monitor only, 2) source isolation, and 3) plume containment. There is uncertainty in which is the best alternative because of uncertainty in 13 flow and transport parameters.

The prior analysis indicates that plume containment at a cost of $5 million is the most cost-effective remediation alternative. However, there is significant uncertainty in this choice and a data-worth analysis indicates that up to $2.2 million could be spent on exploration to reduce uncertainty in site conditions.

The ranking analysis indicates that K of the C horizon was by far the most important parameter to sample. Dispersivity of the C horizon and source strength were also important. However, since they are difficult to measure, exploration effort should likely focus solely on obtaining a better estimate of K of the C horizon.

A sensitivity analysis indicated that the choice of best remediation alternative, based on existing information, was dependent on the compliance limit and the assumed cost of failure. However, it was more sensitive to the compliance level. At compliance limits greater than the base case level of 1,000 pCi/l, monitoring only was the best, while at compliance limits much less than 1,000 pCi/l, containment was the best.

Data worth was a maximum at the base case compliance limit because the estimated costs of the three alternatives were relatively close together. At higher and lower compliance limits, there is a greater spread in the remediation costs of the different alternatives; therefore, uncertainty in which is the best alternative is reduced and the amount of money that should be spent on exploration declines. The ranking of the most important parameters was insensitive to changes in the compliance limit and cost of failure. However, the ranking of the less important parameters was.

The advantage of the methodology is that it is easy to apply and relatively robust. The disadvantage is that site conditions are simplified. However, the methodology is adaptable to more complex problems.

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