INTRODUCTION

The management and long-term disposal of high-level radioactive waste and spent fuel produced by nuclear power generation and national defense activities is becoming an increasingly important issue. The waste inventory is already large and difficult to manage, and the future use of nuclear power is being questioned at least partly on the basis of waste disposal capability. Many options have been proposed for disposal of radioactive waste, including burial in deep excavations or boreholes, emplacement in the seabed, ejection into space, and others. The current option being pursued most actively is that of burial in mined repositories in deep, geologic formations. The formations under present consideration include tuff, basalt, domed salt, and bedded salt.

For any waste management option, the regulatory agencies require an assessment of the safety of the facility for the time period over which this option is designed to be effective. This time may be thousands of years, and therefore decisions relating to the acceptability of the facility must be based solely on its predicted behavior. This prediction is derived from the output of computer models which simulate the salient features and processes which affect the performance of the facility. The quantity of prime interest to regulatory agencies is the predicted radiation dose or risk to a specified individual, calculated as a function of time. This calculated dose or risk cannot be claimed to be a unique value for any instant in time, as the calculation has uncertainties associated with it. Since regulatory decisions are to be based on the model predictions, it is important to investigate the sources of uncertainty which affect these model predictions.

Uncertainty in the analysis of geologic waste disposal is generally considered to have three primary components: (1) computer code/model uncertainty, (2) model parameter uncertainty, and (3) scenario uncertainty. Computer code/model uncertainty arises from problems associated with determination of appropriate parameters for use in model construction, mathematical formulation of models, and numerical techniques used in conjunction with the mathematical formulation of models. Model parameter uncertainty arises from problems associated with selection of appropriate values for model input, data interpretation and possible misuse of data, and
DISCLAIMER

Portions of this document may be illegible in electronic image products. Images are produced from the best available original document.
variation of data. Scenario uncertainty arises from problems associated with the "completeness" of scenarios, the definition of parameters which describe scenarios, and the rate or probability of scenario occurrence. The preceding sources of uncertainty are discussed below.

SOURCES OF UNCERTAINTY

Uncertainty Associated with Computer Codes/Models

The time periods over which the performance of waste repositories in geologic media must be assessed are long - from at least a few thousand years to perhaps a few hundred thousand years. Obviously, experiments and monitoring to gain information on system behavior cannot be carried out over such time periods. Predictive modeling provides the only available way to evaluate candidate sites, waste forms and repository designs and to assess the safety of repositories. Computer codes/models are required in the following general areas: waste/rock interaction and feedback effects, groundwater flow and contaminant transport, surface transport and human uptake, and dosimetry and health effects.

A radioactive waste repository will experience a continuous evolution of state due to forces which are independent of the presence of the repository (i.e., externally-induced forces), forces which are caused by the presence of the repository (i.e., self-induced forces) and, perhaps, human intrusion. The modeling of such processes is never exact. Uncertainties arise from a lack of understanding of the processes, a limited capability to mathematically represent the processes, and an insufficient data base with which to describe a system or the processes acting on it. Each of these contributes to uncertainty in the results generated by a model.

Other sources of uncertainty associated with computer codes/models include coding errors and computational limitations. Since computers have finite word lengths, truncation errors in calculated values occur. In addition, algorithms used by computers to perform certain calculations (such as the square root function) have built-in limitations in accuracy. Also, one subtle problem which can arise is the use of data outside the ranges of validity of previously written algorithms.

Further, the programs which are required to model the relevant processes in nuclear waste disposal are large and complex. They are, therefore, particularly susceptible to input typing and programming errors.
Uncertainty Associated with Model Parameters

Once appropriate models have been selected to represent processes at a disposal site, one is confronted with the problem of obtaining suitable parameters for these models. There is uncertainty associated with such data for several reasons: measurement error, spatial variation, and misinterpretation of data. Further, there is the problem of quantifying these uncertainties for use in later uncertainty analysis. Several methods of representing this uncertainty are possible: point estimates, interval estimates, and probability distribution functions.

There are several possible sources of measurement error. First, there is the possibility that the measuring technique is either incorrect or misapplied. For example, laboratory tests to determine distribution coefficients might be conceptually incorrect or conceptually correct but misapplied. Also, measurement error could have a physical source due to the treatment of the material to be studied. For example, a specimen is sampled from depth, removed to a laboratory and then tested. In the course of this, the ambient stresses on the specimen are released and the specimen may be damaged. A new stress and thermal state are then applied and measurements are taken. The result is that the measured properties often differ from those in existence in the field. Finally, measurement error could have a statistical source. For example, commonly used estimators for the autocovariance of spatial variability may be statistically biased.

Data measurements often display significant scatter across a site due to spatial variation of rock properties. These properties would vary in space even if it were possible to measure them without error. Uncertainty is introduced by replacing such spatial variability by lumped-parameters (i.e., averages) or by distributed but deterministic parameters (e.g., trend surfaces). Spatial variation is a serious problem. Better characterization of a site by more sampling (e.g., more drill holes) may lead to compromising the integrity of the site. There are various techniques available for spatial interpretation and extrapolation of data. The most prominent technique of this type is kriging. (see, e.g., Doctor, 1980)

Uncertainty can also arise due to misinterpretation of data. For example, even for similar rock and groundwater conditions, measured data for distribution coefficients may vary over several orders of magnitude. A possible explanation for this variation is an overly simplistic interpretation of distribution coefficients and a resultant misinterpretation of field data. For this example, more detailed models for the causes of radionuclide partitioning may be required for more meaningful interpretation and use of field data.
Uncertainty Associated with Scenarios

To perform an analysis of a disposal site, it is necessary to determine the various scenarios which could affect the performance of the site. A scenario is defined to be a collection of related events, features and processes potentially affecting radionuclide movement away from a repository and eventual human exposure to these radionuclides. There are several types of uncertainty which arise in the consideration of scenarios: uncertainty associated with "completeness" of scenarios, uncertainty associated with screening of scenarios, and uncertainty associated with analysis of scenarios.

First, there is the question of "completeness": Are all possible scenarios being considered? To provide some confidence as to completeness, a systematic method of compiling scenarios is needed. Further, as it is usually not possible to immediately ascertain the consequences associated with individual scenarios, it is necessary to describe the scenarios in suitable detail and then to use models to predict their consequences. The organizational method must work to group events, features and processes into scenarios in a manner that facilitates the use of available models to predict consequences. Unfortunately, it is not possible to prove "completeness" in the sense of unequivocally establishing that all possible scenarios have been compiled. Through care in scenario development and appropriate independent review, assurance can be sought that a collection of scenarios is acceptably complete. However, this cannot be proved.

Next, there is uncertainty associated with the screening of scenarios. The scenario generation technique will probably generate more scenarios than can be incorporated into the final analysis of a site. Indeed, the first effort at scenario development will probably be to generate as comprehensive a collection of scenarios as possible. Then, a suitable subcollection of these scenarios must be selected for use in a comprehensive site analysis. With the assumption that the scenario development process disallows physically unreasonable scenarios, there are two criteria left which can be used to screen scenarios for inclusion in the final site analysis: consequence and probability. Scenarios with very low consequences can be omitted because of their small potential to affect risk and to cause uncertainty in the analysis of risk. Similarly, scenarios with very low probabilities can also be omitted. It is also possible that scenarios with "intermediate" consequences and probabilities may be screened on the basis of risk. Due to the large computational effort required to perform a site analysis, it is important to reduce
the number of scenarios as much as possible. An additional technique that may be useful is to seek out scenarios which are "similar" and to find ways to pool such collections into single scenarios.

Finally, there is the uncertainty associated with the analysis of individual scenarios. This uncertainty has two components: the probability that the scenario will occur and the state of the repository system after the occurrence of the scenario. The preceding are needed to screen scenarios on probability and consequence and to perform risk calculations. Determination of the variables needed to describe the scenarios associated with a disposal site is dependent on both the individual scenarios and the particular site. It is difficult to give specific techniques for their determination in a general paper such as this; indeed, the thrust of this paper is, given that these variables can be determined, how can the uncertainty which they impose on assessments of a site be studied? However, the following six general approaches might be used: application of known physical relationships, laboratory measurements of properties and processes, field measurements of geologic conditions and processes, investigation and interpretation of past historic and geologic records, synthesis of expert opinion, and deliberate conservatism. All of these techniques are most useful when their application is as site-specific as possible. Various of these techniques have been applied in radioactive waste isolation problems. Such applications can be found in the following papers and reports: Beckman and Johnson (1980), Cranwell et al. (1982), and Cranwell and Donath (1980).

METHODS OF TREATING OR REDUCING UNCERTAINTIES

Computer Code/Model Uncertainty

1) Mathematical Description of Processes

In order to predict the performance of a facility, relevant events and processes must be described in a series of mathematical equations. The equations are encoded in a computer program, site-specific data are added, and the output predictions are generated. The uncertainty associated with the incompleteness of a mathematical description of reality can be addressed by comparing model predictions with experimental data, or with the predictions of models previously compared with experimental data. This is defined as validation of a model. It is possible to obtain a performance statistic for comparison of two model predictions. For example, by calculating the suitably-normalized sum of the squares of the differences between corresponding points on two model prediction curves. This performance assessment, however, does
not distinguish between uncertainties associated with incompleteness of the mathematical description, computational limitations or coding errors.

2) **Computational Limitations**

Uncertainty can be introduced into model predictions because of the nature of numerical solution procedures. Truncation or round-off errors exist, in addition to errors due to approximations used in numerical integration, square root extraction, etc. In general, the uncertainties introduced because of computational limitations are considerably smaller than those from other sources. A practical limitation may also arise when large and complex models need to be run many times (several hundred) in order to generate suitable output distributions. The cost of computer time and the need for large computer systems may force analysts to further truncate sampling schemes. This results in either lower confidence in the results or in the possibility that critical combinations of parameters are overlooked.

3) **Quality Assurance of Codes**

Once the mathematical equations describing the relevant physical processes are assembled, they must be solved to obtain the model predictions. In general, the equations cannot be solved in a closed form, i.e. by obtaining an analytical solution, and so recourse must be made to computers, which than use numerical techniques to obtain the desired solutions.

Errors in the output predictions can occur from the following sources:

1. Transcription (coding) errors, e.g., inserting a "+" sign in the code, when the original equation reads "-";

2. Use of wrong data, e.g., using a value for porosity when permeability is required;

3. Incorrect transfer of data between sections of the program, e.g., using the stored inverse of a matrix, instead of the matrix itself;

4. Use of insufficient precision in algorithms;

5. Use of sub-routines or sub-models beyond their ranges of validity.

The magnitude of the errors from these sources cannot be estimated, either qualitatively or quantitatively. However, use of sufficiently powerful software Quality Assurance procedures can significantly reduce the number of such errors.
An example of the extensive implementation of software QA procedures is found in the Canadian deep geological disposal analysis program (Lyon, 1981).

Parameter Uncertainty

Because of the complexity of the systems being modeled and the time frames over which these systems are modeled, one is often faced with the problem of what numerical values to use for model parameters. This difficulty can arise from the physical processes themselves if system parameters are not constant, but vary in some manner about nominal values. For example, data measurements across a site often display large amounts of scatter caused by natural spatial variation of rock properties. These properties vary in space even if one were able to measure them without error. Additional variations or uncertainty in data can arise from measurement error and from misinterpretation of data. Consequently, many of the variables used to characterize a disposal site will not be known as single values.

Several procedures exist for handling parameter uncertainty in the modeling of geologic waste disposal processes. The more common approaches include: (1) the use of deterministic models with statistical sampling of model parameters, (2) the use of stochastic models, (3) the use of kriging to estimate a surface from spatially distributed data, and (4) the geostatistical approach. Each of these are discussed in more detail below.

1) Deterministic Models with Statistical Sampling

Most computer models produced to date accept only a single input value for each parameter. These are so-called "deterministic" models. In order to accommodate the acknowledged variation in model parameter values, the parameters are treated as random variables with a distribution of values. Specific values for model input are then selected using a statistical sampling procedure. The sampled values are used to generate a distribution of output values. This procedure is commonly referred to as a "Monte Carlo" simulation.

Where it is necessary to treat a parameter as a random variable in uncertainty analysis, the variable will usually be expressed in terms of a probability density function as indicated in Figure 1. The probability density function may be one of the more familiar forms, for example uniform, log-normal, gamma or (as is more likely for naturally stochastic or measured data) presented as a histogram. Where parameters are treated as random variables by virtue of ignorance, an appropriate choice of density function from the common analytical forms will often suffice. Parameters with
probability density functions in the form of histograms will also occur when they are the output of a sub-model and used as inputs to a subsequent sub-model. For example, the output probability distribution for the quantity of a particular nuclide from a geosphere sub-model is used as the input parameter distribution for a biosphere and consequence sub-model.

![Probability density of occurrence](image)

It should be noted that, in general, complete experimental data are lacking and therefore estimates of the probability density function must be used. These estimates are subject to change with the addition of new information. In other words, perturbations on the input probability density functions can propagate through the model, to produce changes in model output values. Further it may be necessary to treat the density distributions as functions of time, since certain parameters may vary over sufficiently long time scales. To date, this time dependence has not been incorporated in performance assessments.

The method used to select specific values for model input is dictated by the requirements for information about model input and model predictions (output) and by the type of estimates to be made concerning model predictions. For example, it is common to desire the following:

(a) probability related statements, such as those regarding the mean, variance, or cumulative distribution function (cdf) of the output variable;

(b) estimates that are close to the real value of the quantities being estimated;
(c) an assessment of the relative importance of each input variable;

(d) correlations which occur in reality.

A number of sampling techniques exist which might be used to generate input data for models: random sampling, factorial stratified sampling, Latin hypercube sampling, and quadrature-based sampling. Several of these methods are compared in McCay, Conover and Beckman (1979) and Filshtein, Goldstein and Kozmin (1981). Whatever statistical sampling procedure is used to select specific values for model input from the ranges of values specified for each input parameter, it is essential for improved modeling that this sampling procedure allow for correlation between the input parameters (item (d)) as such correlations exist in nature. For example, experimental data gathered for porosity and permeability have definitely indicated a correlation between these two parameters (see, e.g. Musket, 1937) Other examples undoubtedly exist where correlations occur. For correlated parameters, the range of one parameter will control the range of the second. Furthermore, parameter correlations will play a role in arriving at ranges of values for parameters. Techniques to handle parameter correlation are still evolving and further work in this field is needed.

2) Stochastic Models

One approach to handling parameter uncertainty is to treat the varying parameters as spatially random fields and then solve the appropriate stochastic equations for the mean quantities and the variance of their respective fluctuations. This approach has been adopted in the past seven years in the area of transport modeling of dissolved species in ground water (Bakr et al. 1978; Gelhar, Gutjhar and Naff 1979; Gutjhar et al. 1978). For example, the one dimensional equation for the concentration of solute undergoing radioactive decay as it moves through a medium with random velocity is (Gelhar and Gutjhar, 1982).

\[
\frac{\partial C}{\partial t} + u \frac{\partial C}{\partial x} - \alpha V \frac{\partial^2 C}{\partial x^2} + BC = 0
\]
where

\[ C = C(x,t) = \text{concentration at location } x, \text{ time } t. \]
\[ U = U(x) = \text{velocity} \]
\[ \alpha = \text{local dispersivity (constant)} \]
\[ \beta = \text{a decay constant for the given species}. \]

In the stochastic framework, the pore velocity \( U(x) \) is viewed as a stochastic process in space. Thus, not only is \( U(x) \) a random variable for each \( x \), but \( U(x) \) also has a continuity expressed through its correlation structure or covariance function. This in turn implies that the concentration \( C(x,t) \) at location \( x \) and time \( t \), is also a stochastic process. Thus \( U(x) \) and \( C(x,t) \) are decomposed into a mean and a mean zero perturbation.

That is,

\[ U(x) = \bar{U} + U' \]
\[ C(x,t) = \bar{C} + C' \]

where

\[ E(U) = \bar{U}, E(C) = \bar{C} \]

and the perturbations \( U' \) and \( C' \) satisfy

\[ E(U') = E(C') = 0. \]

In this approach, \( U(x) \) is generally modeled as a second order stationary process with covariance function \( R(y) = \text{cov}[U(x+y), U(x)] \). Using a perturbation procedure, equations are derived for the mean concentration \( \bar{C}(x,t) \) and the perturbation \( C'(x,t) \). The equation for \( C' \) is then used to evaluate the covariance between \( U' \) and \( C' \) (and hence to derive a new mean equation for \( C \)), and to obtain an expression for the variance of the concentration \( C(x,t) \) (Gutjhar, Bonano, and Cranwell, 1985).

3) **Kriging**

Kriging is a statistical technique that can be used to estimate a surface from spatially distributed data. It was named after D. R. Krige, who first applied some of the concepts underlying this technique to problems of ore content.
assessment. The general formulation of the theory was provided, however, by Matheron (1969, 1970) and a number of applications have been made by the Ecole des Mines de Paris (e.g., Delhomme, 1976 and Delfiner, 1976). As developed by Matheron the theory of kriging considers the observation record as coming from the realization of a random function of some sort and seeks to construct linear estimators that have the properties of unbiasedness and minimum variance, i.e., estimators that will have a satisfactory average behavior when applied to many realizations of the random function.

Kriging has several advantages over alternative approaches such as least squares, polynomial interpolation and distance weighting of the data. It restitutes the measured values as estimates at the data points whereas the least squares method does not, since it is meant for regression rather than interpolation. Kriging will not produce the contortions that result from trying to force a polynomial to fit the data and makes a minimum of assumptions for the structure of the field. Finally, kriging also provides an assessment of the accuracy of the estimates.

The problem to be solved using the kriging technique is typically the following: Given the values \( Z(x_i) \), \( i = 1, 2, \ldots, n \), of a surface \( Z(x) \) in the plane at the data points \( x_i \), it is required to estimate the value of \( Z(x_0) \), say \( Z^*(x_0) \), of the surface at the point \( x_0 \). The kriging estimate of \( Z \) at \( x_0 \) is a linear combination of the surrounding data points in a neighborhood about \( x_0 \):

\[
Z^*(x_0) = \sum_i \lambda_i Z(x_i).
\]

The weights \( \lambda_i \) are calculated such that \( Z^*(x_0) \) is an unbiased estimate of \( Z(x_0) \), and that the variance

\[
E[Z^*(x_0) - Z(x_0)]^2
\]

is a minimum (Doctor, 1980).

4) Geostatistical Approach

Kriging is frequently thought of as a subset of a broader more general statistical parameter estimation technique called "geostatistics." The geostatistical approach referred to in this paper is a modification of nonlinear regression techniques combined with kriging, and is associated with the inverse problem solution proposed by Clifton and Neuman (1982). This approach addresses some of the weaknesses of conventional approaches to parameter estimation. These weaknesses include: the non-use of measured data, overparameterization, physically implausible solutions, excessive computational effort, and overdependence on assumptions about the spatial distribution of the property of interest.
The geostatistical approach is essentially a two-step process:

1. The structure of the property field is identified. In essence, at this step the modeler determines how much variability at a point is small-scale (compared to the smallest separation distances between measurements) and how much can be explained through measurements at neighboring points. Furthermore, a mathematical model is selected to describe how two property measurements are correlated as a function of their location. Mathematically, the structure of the field may be represented through drifts (or trends) and covariance functions or variograms. Structure identification is applied in an iterative fashion with three substeps: model selection, parameter estimation, and model validation or diagnostic checking.

2. Point or block-averaged estimates of the unknown property are obtained.

The first step is equivalent to "model estimation" in time series and to "structural analysis" in mining geostatistics. The representation through drifts and covariance functions, although mathematically not generally complete, is convenient and adequate for most practical purposes. The model is selected and fitted using all available measurements of the property of interest and input-output variables, and prior information, if available. The second step, which is equivalent to prediction in time-series analysis, uses cokriging, or general linear estimation theory, to yield unbiased and minimum mean square error estimates of the property field given all available information.

Details of the geostatistical approach can be found in Kitanidis and Vomvoris (1983) and Hoeksema and Kitanidis (1984a and 1984b).

Scenario Uncertainty

There are two aspects of uncertainty relating to modeling scenarios. The first is completeness. The predicted performance of a site may be affected by whether or not the suite of scenarios considered is complete, in that all processes or events which could conceivably occur are included in the modeling considerations.

The second aspect is truncation of the set of scenarios considered. Each scenario is not certain to occur in the design lifetime of the waste management facility. This uncertainty in whether or not a particular scenario is likely to occur is best expressed in the language of probability:
Each scenario is assigned a probability of occurrence. A scenario is not included in the modeling procedure if its probability is considered to be so low that it can be neglected in accordance with accepted social norms. The estimate of the probability of occurrence is itself a source of uncertainty.

Omission of a scenario from the suite considered can therefore arise in two ways: a) Failure to identify its existence, and b) Rejection of the scenario as too improbable. These two facets affect the accuracy, but not the precision, of model output predictions. There is no known way of assessing the change in model predictions due to facet a). In principle, changes in model predictions as a result of facet b) can be addressed simply by repeating the modeling calculations with the previously-excluded scenarios included. However, the fact that a scenario is considered unlikely is closely related to the fact that the detailed modeling of the related physical processes is itself uncertain (for example, glaciation mechanisms and its related processes are not at all well understood), and so the value of such a procedure is not clear.

In summary, the contribution of scenario uncertainty to model output uncertainties cannot be expressed quantitatively. At most, one can simply assert that, to the best of currently-available knowledge, the suite of scenarios considered is judged to be acceptably complete and that decisions based on the overall assessment are adequately justified.

Sensitivity Analysis

One approach to reducing uncertainty in model parameters is through the use of sensitivity analysis. The term sensitivity analysis generally refers to a means of quantitatively estimating the amount of variation in model output due to arbitrary variation in model input parameters. That is, it is a means of identifying so-called key or important parameters.

A sensitivity analysis can be beneficial in the reduction of uncertainty in two ways. First, it can be used to direct future research and efforts towards understanding the behavior and influence of the important parameters. In turn, this refined knowledge could result in reduced uncertainty due to more realistic ranges of values for these parameters, improved concepts of how to model these parameters, or perhaps alterations in repository design or locations. Second, the identification of important parameters can be beneficial in the refinement of a computer code or model or in the development of a more efficient, less costly code. For example, complex sophisticated codes are beneficial for improved understanding of the system being modeled. However, because of their
complexity there is more chance of errors occurring in these codes or of being misused by the uninformed user. Furthermore, these complex codes are generally costly to use in terms of demands on the user and computer time. Therefore sensitivity analysis can aid in the development of more efficient less costly codes by identifying those parameters or processes which can be ignored without significantly decreasing the confidence in model predictions.

For computer codes which do not use a stochastic description of the system being modeled, two major approaches exist for performing sensitivity analyses. The first involves the use of statistical sampling of input parameter values commonly followed by stepwise regression analysis of output values as a function of input parameter values to identify key parameters (Iman, Helton, and Campbell, 1978). Statistical methods such as this typically fit a polynomial to describe the relationship between input and output parameters. The second approach, sometimes referred to as the differential or deterministic approach, uses the explicit relationship between input and output as described in the computer code. Key parameters are then identified using either a direct method or the adjoint method (Harper, 1983). This approach is generally more difficult than statistical methods in that it requires knowledge of the mathematical relationship used in the code whereas statistical methods do not. However, its primary advantage is that it supplies information on the importance of all parameters of interest with one run of the computer code. This can result in savings in computer costs as compared to statistical methods for which multiple runs are required. Both approaches nevertheless, provide a suitable means for performing sensitivity analyses with neither technique being universally superior over the other. The suitability of one method over the other depends on the type of problem being analyzed.

It must be clearly recognized that sensitivity analysis is not equivalent to uncertainty analysis. It is, however, an essential precursor to a full understanding of overall system uncertainty.

RECOMMENDATIONS AND CONCLUSIONS

The following points must be seen in the context of large complex models containing hundreds of even thousands of individual parameters:

- Uncertainty analysis is needed as a part of overall systems performance analysis for use in the decision-making process:
• Methods are available to conduct uncertainty analysis wherever uncertainties can be quantified:

• The results of uncertainty analysis may need to be taken into account when regulatory statements are formulated:

• Where uncertainties cannot be quantified, as for scenario selection, there is a need to develop methods as none currently exist:

• Sensitivity analysis is an essential process which must be carried out prior to an uncertainty analysis:

• Sensitivity analysis combined with modeling experience can identify which are the most sensitive parameters. However, the most sensitive ones can depend on the particular performance assessment indicator which is selected:

• Worst case analysis or single point analysis is not appropriate when dealing with large complex models:

• Methods for handling correlation between parameters during an uncertainty analysis need to be improved:

• The details of how specific parameters within models correlate with each other also need to be improved by obtaining more information on the modeled processes:

• A quality assurance program must be implemented for computer codes in order to help reduce uncertainty:

• Extensive efforts are still needed to validate codes:

• There is a need to conduct an intercomparison of performance assessment methodologies and, in particular, uncertainty assessment methods.

REFERENCES


Hoeksema, R. J., and P. K. Kitanidis. 1984b. "The Geo-
statistical Approach to the Inverse Problem in
Two-Dimensional Steady State Groundwater Modeling," IIHR
Tech. Report No. 282, University of Iowa, Iowa City.

"Risk Methodology for Geologic Disposal of Radioactive
Waste: Sensitivity Analysis Techniques," SAND78-0912,
NUREG/CR-0394, Sandia National Laboratories, Albuquerque,
NM.

Approach to the Inverse Problem in Groundwater Modeling
(Steady State) and One-Dimensional Simulations." Water
Resources Research, 19(3), 677-690.

Lyon, R. B. February 1981. "Environmental and Safety
Assessment for Nuclear Waste Disposal, The Canadian


Matheron, G. 1970. "The Theory of Regionalized Variables and
Fontainebleau.

"A Comparison of Three Methods for Selecting Values of
Input Variables in the Analysis of Output from a Computer
Code," Technometrics, 21(2).


DISCLAIMER

This report was prepared as an account of work sponsored by an agency of the United States
Government. Neither the United States Government nor any agency thereof, nor any of their
employees, makes any warranty, express or implied, or assumes any legal liability or responsi-

bility for the accuracy, completeness, or usefulness of any information, apparatus, product, or
process disclosed, or represents that its use would not infringe privately owned rights. Reference
herein to any specific commercial product, process, or service by trade name, trademark,
manufacturer, or otherwise does not necessarily constitute or imply its endorsement, recommenda-
tion, or favoring by the United States Government or any agency thereof. The views
and opinions of authors expressed herein do not necessarily state or reflect those of the
United States Government or any agency thereof.

-17-