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Groundwater Contamination From Landfill Leachate:
A Risk Assessment Prototype For Western Kansas

by

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Abstract

This report demonstrates the applicability of the Probabilistic Risk Assessment (PRA) methodology to quantitatively evaluate risks of municipal landfill-related contamination. It focuses on exposure assessment of a landfill-vadose zone-underlying aquifer pathway connecting a western Kansas-type small landfill to a monitoring well at a point of compliance (POC)-downgradient position. The Wallace County, Kansas landfill and related data were employed in this study in combination with the HELP and MULTIMED models to perform a Monte Carlo type of uncertainty analysis using carbon tetrachloride as a risk agent. Different scenarios were considered involving one, five, and ten uncertain parameters representing alternative descriptions of uncertainty. We found that the probability of compliance to specified standards can increase or decrease depending on the number of uncertain variables and the nature of the impact each uncertain variable has on the resulting concentrations at the POC. Although the PRA results are more complex, they are also more informative and can alert the analyst about possible problems at a particular site. The advantage of this type of analysis is that the different sources of uncertainty can be explicitly recognized, and their impact on POC contaminant concentrations can be quantitatively evaluated without resorting to worst-case scenarios or safety factors. A number of recommendations for extending this type of analysis are presented.

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1. INTRODUCTION: MOTIVATION AND SCOPE

This report was prepared by the Kansas Geological Survey (KGS) as part of a contract with the Region 7 Office of the Environmental Protection Agency (EPA). The purpose of this contract is to provide the Bureau of Waste Management of the Kansas Department of Health and Environment (KDHE) with technical support to evaluate selected issues related to groundwater contamination from sanitary landfills. This report details the results of the activities carried out in the last quarter of the one-year project. The main topic is a risk assessment of ground-water contamination from landfill leachate under conditions typical of western Kansas. The purpose of the study is to demonstrate the applicability of a methodology - Probabilistic Risk Assessment (PRA) - to evaluate municipal landfill-related contamination.

The Wallace County landfill (Sophocleous et al., 1995) was selected for the study. Available information was used to define the characteristics of both the facility and the subsurface; climatic data correspond to the Sharon Springs and Dodge City, Kansas climatic stations. However, the need to incorporate additional variables/parameters led to the use of some generic information as well. Although this made the study more complete, the results obtained may not have site-specific validity. Instead, results should be interpreted as demonstrative of the conditions existing at small landfills in western Kansas.

2. SOME RISK ASSESSMENT CONCEPTS

One of the most important shifts in environmental policy in the 1980's was the acceptance of the role of risk assessment and risk management in environmental decision making. There is an abundant literature on risk assessment, covering both conceptual and applied aspects of the subject (e.g., NRC, 1983; Ang and Tang, 1984). We do not attempt to provide a complete review here. Instead, we selectively review some of the concepts needed to put the present study in perspective, and to define the methodology to be followed.

2.1. Basic Concepts

Risk is defined as the possibility of suffering harm from a hazard. A *risk agent* is a chemical substance, biological organism, radioactive material, or other potentially hazardous substance or activity. Under plausible circumstances, a risk agent can cause harm to human health or the environment. The goal of risk assessment is to estimate the severity and

likelihood of harm to human health or the environment occurring from exposure to a risk agent. In this report we focus on public health risk assessment.

A Risk Assessment consists of four steps (NRC, 1983): (1) hazard identification, (2) dose-response assessment, (3) exposure assessment, and (4) risk characterization. Hazard Identification involves finding out whether a particular risk agent is present in the system. Dose-Response Assessment is the process of characterizing the relationship between the received dose of a risk agent and the incidence of an adverse health effect (a typical example is that of a known carcinogen substance, for which toxicological studies are conducted on animals to infer effects on humans). Exposure Assessment is the estimation of the intensity, frequency, and duration of human exposure to a risk agent (either currently in the system or one that could result from a hypothetical release), for a given chain of events that create the possibility of harm. Risk Characterization is the actual estimation of the likelihood that harm will occur; in other words, this involves the calculation of a probability value using the results of the dose-response and exposure assessments. This step integrates the results of the previous steps into a risk statement (there is no new information generated in this step).

In the case of ground-water contamination from landfill leachate, we assume that adequate information is available to perform steps (1) and (2). In other words, the chemical characteristics of the leachate are known, and the appropriate toxicological studies for the identified risk agents are available. The result of risk characterization -step (4)- has been set a priori to meet a regulatory standard, for example a maximum contaminant level (MCL) - the maximum concentration admissible in ground water. Hence, the only step left for evaluation is step (3), Exposure Assessment. This restricted-scope risk assessment is typical of regulatory compliance analyses, and is applicable both to performance of existing landfills and design of new facilities.

Based on these assumptions, we restrict our attention to exposure assessment of a single pathway [landfill-vadose zone-underlying aquifer] connecting the landfill and a monitoring well at a point of compliance (POC) located a given distance downgradient from the landfill. For a risk assessment evaluation, the key variable to determine is the contaminant concentration at the well. Given that contaminant concentration, it is easy to calculate human ingestion over time, assuming that the well is to be used for water supply.

Although in this report we use the vocabulary of risk assessment, the application will be restricted to exposure assessment, as explained above. This choice, motivated only by simplicity, causes no lack of generality in the procedures to be followed.

2.2. Probabilistic Risk Assessment

Risk assessments, like many other calculations, can be conducted in either a deterministic or a probabilistic framework. Deterministic analyses seek to identify a single result, while probabilistic analyses allow for the existence of more than one answer. In the latter case, a probability is assigned to each possible answer to assess its likelihood. Probabilistic approaches are the natural choice when there is a measurable degree of uncertainty about some of the characteristics of the system under study. When some inputs and/or parameters are described probabilistically, so must the model results.

Of course the various uncertainties can be neglected. In fact, many risk assessments are conducted in a conservative fashion, making worst case assumptions to select values of different parameters and variables. This simple procedure can yield estimates of risk that are orders of magnitude larger than the true values. On the other hand, a probabilistic risk assessment (PRA) uses some form of uncertainty analysis to translate uncertain inputs and/or parameters into uncertain outputs. Uncertain input parameters are described in terms of probability distributions (rather than single deterministic values). Since PRA results are also expressed as probability distributions, it is straightforward to calculate values corresponding to a given probability or the probability that a particular value (e.g., a contaminant concentration) will be exceeded.

In our case, Exposure Assessment involves predicting leachate migration in the subsurface. Predictions are the result of a conceptual model of the landfill and the hydrogeologic system, expressed in the form of a mathematical model. However, a model is always a simplified representation of the real system, which can only partially capture the complex interactions between the different physical, chemical and biological processes involved in the migration of leachates (some of these processes are imperfectly understood). Furthermore, in natural systems like aquifers, there are complexities that may not even be represented in the conceptual model (e.g., aquifer properties vary in space but they may be conceptualized as homogeneous). Finally, there are uncertainties in the data, including measurement errors and errors in parameters that can only be indirectly estimated. Therefore, model results are subject to considerable uncertainty and should always be interpreted as estimates of ground-water flow and contaminant transport, and not as exact predictions. A recent study (National Research Council, 1990), strongly argues for a quantitative evaluation of uncertainty in the results of ground-water models. We will follow their recommendation and conduct the Exposure Assessment in a PRA framework.

A PRA (or the exposure assessment step in this study) consists of three sequential steps: (1) define uncertain inputs in probabilistic terms, (2) propagate uncertainty, and (3) analyze output to express it in probabilistic terms. The key step here is the propagation of uncertainty; this can be a simple task for a linear model involving three variables, but it can become quite involved for models of ground-water flow and contaminant transport that are nonlinear functions of many variables and parameters. Since the emphasis here is on the evaluation of uncertainty, these methods are also known collectively as *uncertainty analysis*. Different methods are available for uncertainty propagation, including analytical derivation, first-order analysis, and Monte Carlo simulations. While the first two methods are applicable under restrictive conditions, the third method -our choice for this study- is conceptually simple and widely applicable.

Since PRA inputs, parameters, and results are expressed as probability distributions, it seems worthwhile to review some basic concepts that pertain to this type of functions. *Probability distributions* are mathematical equations or graphical representations of the relationship between all possible values (or outcomes) a variable can have and the likelihood (expressed as a number from zero to one) that the variable will have a particular value. Probability distributions can be discrete or continuous. Discrete distributions can be represented as bar graphs that describe the probability of a specific, finite number of values a variable can have. Continuous distributions—sometimes called *probability density functions* (pdf)—are graphed as smooth curves and describe probabilities for variables that can have a continuous range and infinite number of possible values; the area under the smooth curve between two points represents the probability that the true value of the variable lies between those points. Such probabilities can be directly calculated from the *cumulative distribution function* (CDF), which measures the probability of a variable being equal to or less than a given value (the cumulative distribution is the integral of the pdf).

Probability distributions can be generated from data (e.g., from historical records or monitoring programs) or from knowledge of the underlying processes or systems. When derived from data, the pdf (or its discrete equivalent) displays the relative frequency of observed values. Probability distributions are useful vehicles for conveying the uncertainty in a risk estimate because important features of the estimate can be derived from the distribution. These features include measures of central tendency, such as the mean (or average), the median, and the mode; the variation around the central tendency (measured by the variance or standard deviation); the range of possible values; and the asymmetry, or skewness, in the distribution of probable values.

2.3. The Monte Carlo Method

The *Monte Carlo method* has a long tradition of application in science and engineering (e.g., Rubinstein, 1981). Given a number of input variables (or parameters) and a functional relationship between inputs and output, the method produces a probability distribution of the unknown output variable (either a pdf or a CDF). The name Monte Carlo has its origins in the casino games and their -hopefully- equally likely outcomes. In this case, equally likely probability values (between zero and one) are generated, and the corresponding values of each input variable are determined using its pdf. Then this generated set of input variable values is used to calculate the corresponding value of the output variable. After repeating this process many times, a frequency distribution of the output variable is calculated and interpreted as a discrete approximation to the output pdf. Integration of this function yields the output CDF, which can be used in the standard way to make probabilistic statements about the output. The Monte Carlo method is schematized graphically in Figure 1.

In the landfill application, the equations of flow and contaminant transport provide the functional relationship between inputs and output. The output is the contaminant concentration at the monitoring well. The MULTIMED model (Salhotra et al., 1993), used in this study, has a special module to perform Monte Carlo simulations without need for additional programming. The user only needs to provide the probability distributions of the different input variables and parameters. MULTIMED defines a distribution in terms of its functional form (e.g., lognormal) and four statistical parameters: the mean, standard deviation, minimum and maximum values. The minimum and maximum values specified by the user are actual bounds enforced by MULTIMED: If a value generated from the given distribution falls outside the range defined by the minimum and maximum, it is discarded and a new value is generated to replace it.

3. AN EXAMPLE FROM WESTERN KANSAS

As discussed in a previous section, this risk assessment exercise will be focused on exposure assessment at a monitoring well located downgradient from the landfill. According to existing regulations (K.A.R. 28-29-111; KDHE, 1994) the well is located at the maximum permissible distance of 150 meters from the facility.

3.1. Landfill and Site Characteristics

The basic characteristics of the landfill correspond to those of the Wallace County landfill, analyzed in a previous report (Sophocleous et al., 1995). The relevant information is reproduced here in Table 1 and Figure 2. Wallace County is located in west central Kansas, next to the border with Colorado. Annual average precipitation is about 441 mm (17 in), according to the Sharon Springs weather station data.

The conceptual picture of the system is as follows (Figure 2). The landfill consists of a soil cover, a waste layer, and is underlined by a 7-m-thick vadose zone; it has no liner. Leachate is produced only by local recharge from precipitation (i.e., there are no free liquids in the waste layer). The characteristics of the two layers are those of layers 1 and 2 of Case 1 analyzed by Sophocleous et al. (1995). Leachate seeps through the vadose zone and reaches the aquifer below. A contaminant plume develops in the aquifer, extending downgradient past the point of compliance (POC), as schematized in Figure 3. According to EPA Subtitle D regulations, we consider the contaminant concentration under steady-state conditions. As in Sophocleous et al. (1995), the two EPA models HELP and MULTIMED were employed to carry out the calculations. HELP calculates the leachate from the facility based on the soil and waste information shown in Fig. 2 and climatic data from Sharon Springs and Dodge City, Kansas. MULTIMED calculates contaminant transport through both the vadose zone and the aquifer; the values of the different parameters required by MULTIMED are listed in Table 2.

3.2. Exposure Assessment Under Uncertainty

We choose to assess contaminant exposure at the monitoring well with the steady state concentration calculated by HELP and MULTIMED for a single chemical, Carbon Tetrachloride (C-Tet) in our case. We assume that the corresponding maximum contaminant level (MCL) for C-Tet in ground water is the result of a risk characterization step; then our task is reduced to evaluating whether the MCL is exceeded at the well. For simplicity we will present relative concentrations of C-Tet, defined as the ratio of the concentration at the well to the leachate concentration at the source, which is assumed to have a unit concentration. Since a maximum allowable leachate concentration 100 times smaller than the MCL in ground water is normally used to define an acceptable Subtitle D landfill design, we arbitrarily specify such concentration at the facility to carry out our calculations. Then if the dilution caused by transport decreases the original concentration by a factor of 100 or more, the relative concentration at the well will be 0.010 or less.

The information listed in Table 2 and Figure 2 define a deterministic reference case where all parameter values are perfectly known. In this case the models predict a relative C-Tet concentration of 0.013 at the POC, which exceeds the maximum value of 0.010. Note that the result of a deterministic exposure assessment like this is either a yes or no answer to the question: Is the MCL exceeded at the well?

However, we are interested in assessing exposure under conditions of uncertainty (in this study, uncertainty in model parameters), so that the C-Tet concentration at the well becomes an uncertain variable. Its probability distribution can be obtained running MULTIMED in the Monte Carlo mode. From this distribution we can obtain the probability of compliance, that is, the probability of C-Tet relative concentration being less than 0.010 at the POC. This probability p can be compared to a (hypothetical) regulatory value p^* , a risk-based regulatory standard. For example, if $p^*=90\%$ and $p=95\%$, the facility would comply with the standard. Since we do not have risk-based standards at this time, our results will be expressed as probabilities of compliance (p).

3.3. Scenarios Considered

The transport of a contaminant from the landfill to the well under parameter uncertainty is analyzed under three different scenarios that correspond to different degrees of uncertainty. The model parameters selected are the ten variables to which MULTIMED results are most sensitive (identified by Sophocleous et al. (1995), for the Wallace County type landfill). The uncertainty about each variable is described with probability distributions chosen to adequately represent the range of parameter variability reported in the literature. Each distribution is summarized with four parameters: Mean, standard deviation, minimum, and maximum values. The values of these statistical parameters are listed in Table 3 under the heading Base Case.

The three scenarios are:

- (a). The first scenario assumes that there is uncertainty only about one parameter, the leachate percolation rate from the landfill (all other parameters are assumed known without uncertainty). Although the percolation rate is strictly an input to MULTIMED, it is a parameter of the combined HELP-MULTIMED model. The probability distribution used for the percolation rate is constructed with the results of a HELP run with 20 years of climatic data.
- (b). The second scenario assumes uncertainty in five of the most sensitive MULTIMED parameters (leachate percolation rate, transverse and vertical dispersivities, neutral hydrolysis rate, and unsaturated zone porosity).
- (c). The third scenario assumes uncertainty in ten parameters (in addition to the five previously listed, we included the hydraulic gradient, retardation

factor, unsaturated zone hydraulic conductivity, residual water content, and longitudinal dispersivity).

In addition, different cases (variants) are considered for each scenario. These cases represent alternative descriptions of uncertainty for each variable; that is, keeping the number of uncertain variables constant, these cases represent other sets of possible results. Four cases are defined by modifying the statistical parameters of the base case as follows: (1) the mean of each variable increased or decreased by a certain amount; (2) The variance (or standard deviation) of each parameter increased or decreased by a certain amount (with the mean value remaining constant). Table 3 lists these cases also.

3.4. Results

A Monte Carlo simulation is run with MULTIMED for each of the three scenarios and its variants. The result of each simulation is the cumulative distribution (CDF) of the C-Tet concentration at the point of compliance. However, it is important to realize that Monte Carlo results require a large number of independent runs to obtain a stable probability distribution of the output. As the number of runs becomes larger, the function converges asymptotically to the true distribution. The number of runs required cannot be prescribed in general, but has to be determined for each problem. To that end, we observed the results obtained with 100, 500, and 1000 runs, for the case of a single uncertain variable, the leachate percolation rate. Results are displayed as a cumulative distribution function (CDF) in Figure 4: note that the results for 500 and 1000 runs are virtually indistinguishable. Based on these results we decided to conduct the rest of the study with 500 runs for each calculation.

Then we considered the effect of uncertainty in the statistical parameters that describe the percolation rate distribution. The parameters that define the four variants of the first scenario can be found in Table 3 under the labels smaller and larger mean, and minimum and maximum range. The results are displayed in Figure 5. It is possible to check the consistency of these results as follows. A smaller mean brings more values to the left of the allowable range, so that the CDF moves to the left as well, increasing the probability of compliance (values less than the 0.01 threshold); the reverse is true for a larger mean. The maximum range case corresponds to both a smaller minimum and a larger maximum, but because the lognormal distribution considered here has the mean closer to the minimum than the maximum, an increase in the range has a similar effect as moving the mean to the left, and therefore a larger probability of compliance p ; the reverse holds for a smaller range.

Next we considered the combined effect of 5 uncertain variables: leachate percolation rate, longitudinal and transverse dispersivities, unsaturated zone hydraulic conductivity and porosity. Analyzing the effect of more than one variable is not always straightforward because of the possibility of "canceling" effects. This can occur for example when the output (concentration at the well) is directly proportional to one variable (e.g., leachate percolation rate) but inversely proportional to another variable (e.g., transverse dispersivity). Figure 6 displays the results for the base case and the four cases that change the mean and the range. These results have qualitative similarities with the single variable case: decreasing the mean values of the 5 uncertain parameters increases the probability of compliance at the POC (and vice versa), and decreasing their variance decreases the probability of compliance (and vice versa). However, we also note the following apparently striking results: the range of probabilities of compliance - base case and four variants - is smaller in the five variable case than in the single variable case (0.17 to 0.71 versus 0.01 to 0.73, respectively). This demonstrates that there are opposite effects between some of the variables considered. The conclusion is that the final result (e.g., probability of compliance) can move either way (smaller or larger) depending on the strength of the different variables that have opposite effects. Hence, there is no substitute for a carefully conducted simulation to obtain the combined result in each particular case.

Finally, we considered the effect of the ten uncertain variables listed in Table 3. The results were qualitatively similar to those with the above-mentioned 5 uncertain variables. By collecting the results obtained so far we can assess the effect of the number of uncertain variables: Figure 7 displays the results for the base case (reference statistical parameters) for one, five, and ten variables. Figure 7 shows that the probability of compliance (values less than the 0.01 threshold) increases with increasing number of uncertain variables: p values are 0.35, 0.45, and 0.54, respectively. This result can also be interpreted in physical terms as a direct consequence of most of the ten variables having the effect of increasing dilution (decreasing concentration] at the POC (e.g., transverse dispersivity]. However, when the number of uncertain parameters excluded variables related to dispersion (such as dispersivities and parameters affecting ground-water velocity), the probability of greater dilution at the POC did not increase with increasing number of uncertain parameters (Figure 8 and Table 4).

How good are Monte Carlo results given that they are based on a limited number of simulations? This is always a valid question, which can be investigated by analyzing the complete set of Monte Carlo results. From the frequency values at a given probability level, confidence intervals can be determined about the mean values displayed in the previous figures. A *confidence interval* is a range of numbers believed to include an unknown parameter. Associated with the interval is a measure of the confidence we

have that the interval does indeed contain the parameter of interest. The resulting confidence intervals for one, five, and ten uncertain variables described earlier, are shown in Figure 9. We see that as the number of uncertain variables increases, the width of the confidence bounds (i.e., the width of the relative concentrations between the lower and upper limits) also increases.

How are the PRA results different than those of the deterministic RA? Consider for example the base case for five uncertain variables (Figures 6 and 9). The actual value of the relative concentration of C-Tet at the POC is uncertain, but from the cumulative distribution shown in figure 6 we can read different values of interest. For example, the mean value is about 0.012 (not far from the deterministic estimate: 0.013). From figure 9 we can also read confidence intervals, like a 95% probability of values less than 0.055, for example; however, many of the values in this range are much larger than the acceptable limit (0.010). The corresponding probability density function (pdf) is shown in Figure 10 for reference. From that figure we can see that there is indeed a finite and appreciable probability of C-Tet relative concentrations at the POC being 0.055 for example, which exceed the considered threshold value of 0.010. Hence, although PRA results are more complex, they are also more informative and can alert the analyst to possible problems at a particular site.

In summary, this study has shown that groundwater contamination can be evaluated with probabilistic analysis tools. Here we have conducted an exposure assessment, an integral component of a probabilistic risk assessment (PRA). The advantage of this type of analysis is that the different sources of uncertainty can be explicitly recognized, and their impact on the final result quantitatively evaluated without resorting to safety factors or worst-case assumptions. Another advantage is that uncertainty about site-specific data can always be reduced by collecting more information; PRA results can reflect these changes automatically.

4. POSSIBLE EXTENSIONS OF THIS STUDY

The scope of this study has been of a demonstrative nature. We have conducted a simplified probabilistic risk assessment of groundwater contamination from a landfill, using assumptions and generic information when needed. In this last section we briefly consider some of the possible extensions of this type of analysis. The following is an incomplete list of such extensions.

Replace assumptions by site-specific data. This is the most obvious modification to the present study. Not only will parameters more closely represent a given reality, but also the uncertainty of the final result -

contaminant concentration- will be greatly reduced. For example, input concentrations can be more accurately assessed if chemical analyses of leachate samples are available.

Evaluation of alternative models. A PRA can be conducted with alternative models that can simulate contaminant transport from a landfill (e.g., EPACML, EPRI models). Each model is built upon a different set of assumptions and simplifications, so that different results can be obtained with each one of them. It is the modeler's job to use a model whose features more closely approximates the conditions prevalent at a particular site.

Modification of existing models to include additional processes. This can be done on an ad-hoc basis if warranted by the need to incorporate site-specific or regional characteristics.

Repeat the exercise for a handful of representative regional cases. By doing this with the best available information -a composite of various facilities, as well as representative regional geology- a PRA can produce bounds on the range of values that can be expected in different regions in Kansas. Such information can be valuable for regulatory agencies that conduct reviews of modeling studies conducted by other interested parties: if enough variability is built into a PRA to represent regional conditions, one expects the site-specific model calculations to fall within the range of values obtained by the original PRA.

Focus on transient calculations. The present study adopted a steady-state point of view both for simplicity and because of its more conservative nature. However, it is always advisable to conduct the same calculation under transient conditions because often the time scale required to approach steady-state conditions can be larger than either the time frame of interest or the maximum time that a landfill owner has any liability for the facility. An example of transient calculation is given in Sophocleous et al. (1995).

Assessment of alternative standards. This includes, for example, relaxing the requirement that a dilution attenuation factor of at least 100 has to be attained between the facility and the POC, or how the results change when the POC location is changed to be either closer or further away from the facility.

Development of risk-based standards. This is possible in principle because a PRA gives much more information than a deterministic risk assessment. Tradeoffs between cost and probability of non compliance can be analyzed with this methodology.

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Table 1. Wallace County Landfill Profile

Location: 17.8 hectares (44 acres) located in the SE 1/4 of Section 3, and the NE 1/4 of Section 10, both located in Township 14 South, Range 40 West, approximately 3 km south of the town of Sharon Springs, Kansas. Latitude 38° 51' 01" N, longitude 101° 45' 00" W.

Operation Authorization: 1974

Topography: The active portion of the landfill is situated along the north side of a northeasterly running intermittent stream channel. Side slopes are up to twenty percent at the east end of the property.

Site History and Operation: Trenches have been dug and filled on the west-central portion of the landfill property, all on the north side of the draw. Expansion room is left to the north and east.

Geology and Soils: The local geology consists of soils of the Colby-Kim-Midway Association underlain by Pleistocene Loess of the Sanborn Formation. These formations are underlain by the Miocene Ogallala Formation. The Ogallala is an unconfined aquifer and is the primary groundwater aquifer in the region. Bedrock is the Cretaceous Pierre Shale.

Ground-water and Monitoring : Groundwater availability in this area is limited. Three monitoring wells ranging in depth from 15 to 17.5 m (50 to 58 ft) were installed at the landfill in 1993. The static water level was 12.5 to 14 m (41 to 46 ft). One well was dry. Water analyses from the wells indicate no adverse impact on the groundwater has occurred at this landfill.

Table 2. Base Case MULTIMED Input Parameters (abridged)

| Aquifer Parameters | | Unsaturated Zone | |
|-----------------------------------|-------------------|----------------------------------|---------------------|
| Parameters_ | | | |
| <u>Name</u> | <u>Base Value</u> | <u>Name</u> | <u>Base Value</u> |
| Aquifer Porosity | 0.25 vol/vol | Number of Different Materials | 1 |
| Bulk Density | 1.40 g/cc | Number of Different Layers | 1 |
| Aquifer Thickness | 3.35 m | Depth of Unsaturated Zone | 7.0 m |
| Hydraulic Conductivity | 11,125 m/yr | Sat. Hydraulic Conductivity | 0.175 cm/hr |
| Hydraulic Gradient | 0.0015 | Porosity | 0.47 vol/vol |
| Longitudinal Dispersivity | 15.0 m | Air Entry Pressure Head | 0.2 m |
| Transverse Dispersivity | 5.0 m | Residual Water Content | 0.2 vol/vol |
| Vertical Dispersivity | 0.84 m | Alpha van Genuchten Coeff. | 0.02 |
| Aquifer Temperature | 16 °C | Beta van Genuchten Coeff. | 1.41 |
| Groundwater pH | 7.0 pH units | Longitudinal Dispersivity | 0.174 m |
| Organic Carbon Content | 0.015 | Percent Organic Matter | 0.015 |
| Point of Compliance | 150 m | Bulk Density | 1.50 g/cc |
| Angle off Center | 0 degrees | Biological Decay Coeff. | 0.0 1/yr |
| Source Parameters | | Chemical Parameter | |
| <u>Name</u> | <u>Base Value</u> | <u>Name</u> | <u>Base Value</u> |
| Type of Source | Gaussian | Chemical | Carbon Tetrachloric |
| Leachate Percolation Rate | 0.0406 m/yr | Acid Catalysis Hydrolysis Rate | 0.0 l/M yr |
| Landfill Area | 3710 sq. m | Neutral Hydrolysis Rate Constant | 0.017 1/yr |
| Recharge Rate | 0.04 m/yr | Base Catalysis Hydrolysis Rate | 0.0 l/M yr |
| Source Decay Constant | 0.0 1/yr | Reference Temperature | 25.0 °C |
| Initial Concentration at Landfill | 1.0 mg/l | Normalized Distribution Coeff. | 257.0 ml/g |
| | | Biodegradation Coefficient | 0.0 1/yr |

Table 3. Uncertainty Analysis - 10 Uncertain Parameters

Base Case

| Parameter | Min | Max | Mean | Std Dev | Distribution |
|------------------------------------|---------|------|--------|---------|--------------|
| Transverse Disp. (m) | 0.01 | 10 | 2 | 2.1587 | Normal |
| Vertical Disp. (m) | 0.01 | 2 | 0.84 | 0.4081 | Normal |
| Leachate Perc. Rate (m/yr) | 0.005 | 0.15 | 0.0406 | 0.0308 | Log Normal |
| Unsaturated Zone Porosity | 0.1 | 0.57 | 0.4 | 0.0972 | Normal |
| Neutral Hydrolysis Rate (1/yr) | 0.00001 | 0.1 | 0.017 | 0.0218 | Normal |
| Hydraulic Gradient | 0.00001 | 0.05 | 0.0015 | | Exponential |
| Retardation Factor | 1 | 100 | 22.6 | 21.2514 | Normal |
| Longitudinal Disp. (m) | 0.01 | 50 | 15 | 10.4731 | Normal |
| Unsat. Zone Hydraulic Cond. (m/yr) | 0.01 | 5 | 0.174 | 1.1573 | Log Normal |
| Residual Water | 0.08 | 0.3 | 0.2 | 0.0450 | Normal |

Minimum Range

| Parameter | Min | Max | Mean | Std Dev | Distribution |
|------------------------------------|---------|-------|--------|---------|--------------|
| Transverse Disp. (m) | 0.02 | 5 | 2 | 1.0236 | Normal |
| Vertical Disp. (m) | 0.02 | 1 | 0.84 | 0.2146 | Normal |
| Leachate Perc. Rate (m/yr) | 0.01 | 0.075 | 0.0406 | 0.0133 | Log Normal |
| Unsaturated Zone Porosity | 0.2 | 0.465 | 0.4 | 0.0564 | Normal |
| Neutral Hydrolysis Rate (1/yr) | 0.00002 | 0.05 | 0.017 | 0.0104 | Normal |
| Hydraulic Gradient | 0.00002 | 0.025 | 0.0015 | | Exponential |
| Retardation Factor | 2 | 50 | 22.6 | 9.8307 | Normal |
| Longitudinal Disp. (m) | 0.02 | 25 | 15 | 5.1327 | Normal |
| Unsat. Zone Hydraulic Cond. (m/yr) | 0.02 | 2.5 | 0.174 | 0.5673 | Log Normal |
| Residual Water | 0.1 | 0.2 | 0.15 | 0.0204 | Normal |

Maximum Range

| Parameter | Min | Max | Mean | Std Dev | Distribution |
|------------------------------------|----------|------|--------|---------|--------------|
| Transverse Disp. (m) | 0.005 | 20 | 2 | 4.4962 | Normal |
| Vertical Disp. (m) | 0.005 | 4 | 0.84 | 0.8603 | Normal |
| Leachate Perc. Rate (m/yr) | 0.0025 | 0.3 | 0.0406 | 0.0661 | Log Normal |
| Unsaturated Zone Porosity | 0.05 | 0.75 | 0.4 | 0.1429 | Normal |
| Neutral Hydrolysis Rate (1/yr) | 0.000001 | 0.2 | 0.017 | 0.0453 | Normal |
| Hydraulic Gradient | 0.000001 | 0.1 | 0.0015 | | Exponential |
| Retardation Factor | 1 | 200 | 22.6 | 44.5777 | Normal |
| Longitudinal Disp. (m) | 0.005 | 100 | 15 | 22.0157 | Normal |
| Unsat. Zone Hydraulic Cond. (m/yr) | 0.005 | 10 | 0.174 | 2.3362 | Log Normal |
| Residual Water | 0.04 | 0.6 | 0.2 | 0.1178 | Normal |

Smaller Mean

| Parameter | Min | Max | Mean | Std Dev | Distribution |
|------------------------------------|---------|------|---------|---------|--------------|
| Transverse Disp. (m) | 0.01 | 10 | 1 | 2.2471 | Normal |
| Vertical Disp. (m) | 0.01 | 2 | 0.42 | 0.4290 | Normal |
| Leachate Perc. Rate (m/yr) | 0.005 | 0.15 | 0.0203 | 0.0325 | Log Normal |
| Unsaturated Zone Porosity | 0.1 | 0.57 | 0.2 | 0.1011 | Normal |
| Neutral Hydrolysis Rate (1/yr) | 0.00001 | 0.1 | 0.0085 | 0.0226 | Normal |
| Hydraulic Gradient | 0.00001 | 0.05 | 0.00075 | | Exponential |
| Retardation Factor | 1 | 100 | 11.3 | 22.2203 | Normal |
| Longitudinal Disp. (m) | 0.01 | 50 | 7.5 | 11.0068 | Normal |
| Unsat. Zone Hydraulic Cond. (m/yr) | 0.01 | 5 | 0.087 | 1.1672 | Log Normal |
| Residual Water | 0.08 | 0.3 | 0.1 | 0.0497 | Normal |

Larger Mean

| Parameter | Min | Max | Mean | Std Dev | Distribution |
|------------------------------------|---------|------|--------|---------|--------------|
| Transverse Disp. (m) | 0.01 | 10 | 4 | 2.0529 | Normal |
| Vertical Disp. (m) | 0.01 | 2 | 1.68 | 0.4363 | Normal |
| Leachate Perc. Rate (m/yr) | 0.005 | 0.15 | 0.0812 | 0.0296 | Log Normal |
| Unsaturated Zone Porosity | 0.1 | 0.57 | 0.5 | 0.1035 | Normal |
| Neutral Hydrolysis Rate (1/yr) | 0.00001 | 0.1 | 0.034 | 0.0208 | Normal |
| Hydraulic Gradient | 0.00001 | 0.05 | 0.003 | | Exponential |
| Retardation Factor | 1 | 100 | 45.2 | 20.2469 | Normal |
| Longitudinal Disp. (m) | 0.01 | 50 | 30 | 10.2719 | Normal |
| Unsat. Zone Hydraulic Cond. (m/yr) | 0.01 | 5 | 0.348 | 1.1384 | Log Normal |
| Residual Water | 0.08 | 0.3 | 0.25 | 0.0471 | Normal |

Table 4. Uncertainty Analysis - 4 Uncertain Chemical Parameters

| <u>Parameter</u> | <u>Min</u> | <u>Max</u> | <u>Mean</u> | <u>Std Dev</u> | <u>Distribution</u> |
|---------------------------|------------|------------|-------------|----------------|---------------------|
| Acid Hydrolysis Rate | 0.00E+00 | 0.1 | 0 | 0.0236 | Normal |
| Neutral Hydrolysis Rate | 1.00E-05 | 0.1 | 0.017 | 0.0218 | Normal |
| Base Hydrolysis Rate | 0.00E+00 | 0.1 | 0 | 0.0236 | Normal |
| Norm. Distribution Coeff. | 10 | 500 | 257 | 100.02 | Normal |

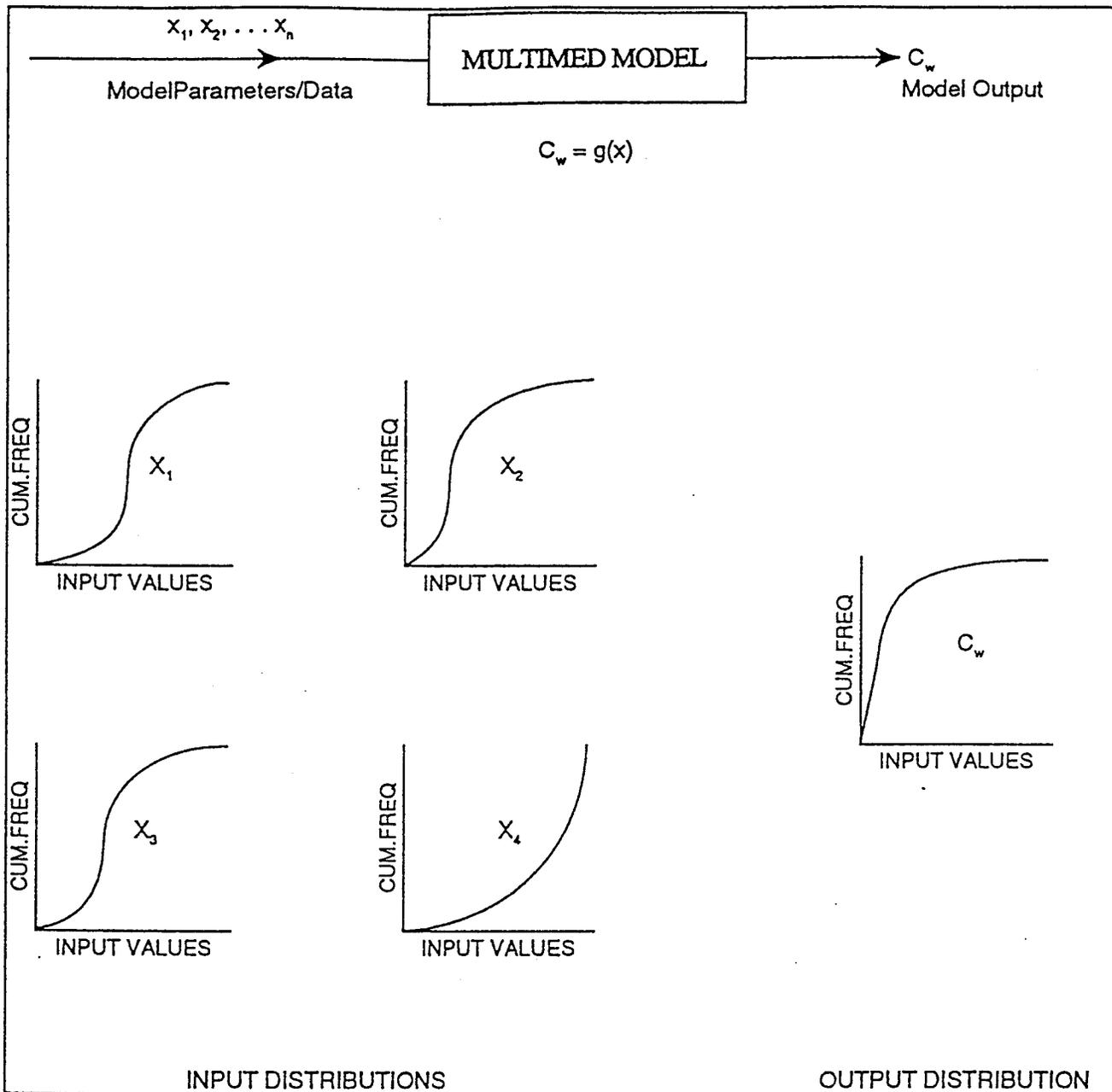


Figure 1. A schematic description of the Monte Carlo method of uncertainty analysis.
(Adapted from Salhotra et al., 1993)

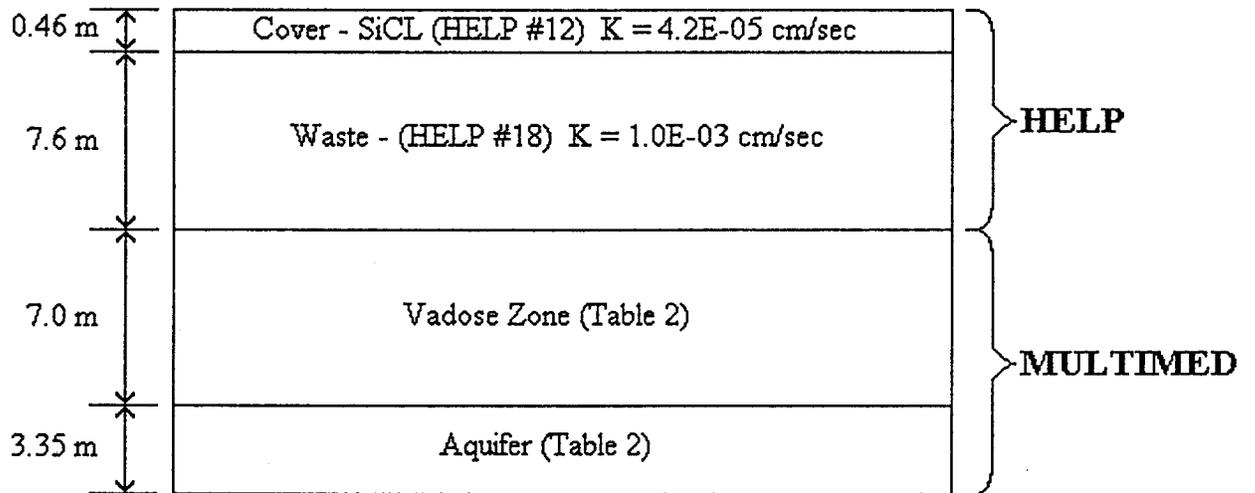


Figure 2. Conceptual Model of Wallace County Landfill

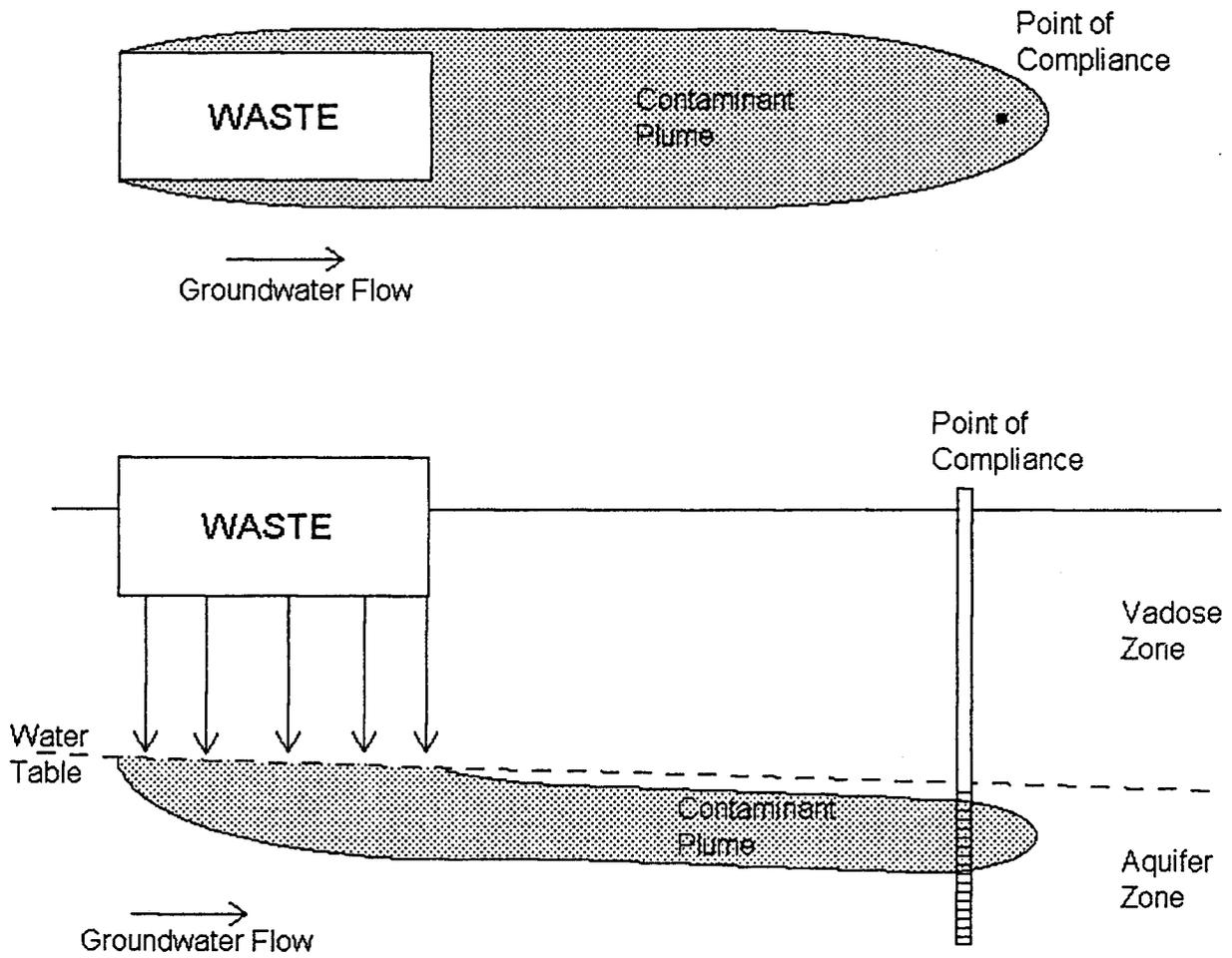


Figure 3. Conceptual model of the waste facility and leachate migration through the vadose and aquifer zones.

Uncertainty Analysis - Base Case 100, 500 and 1000 Runs

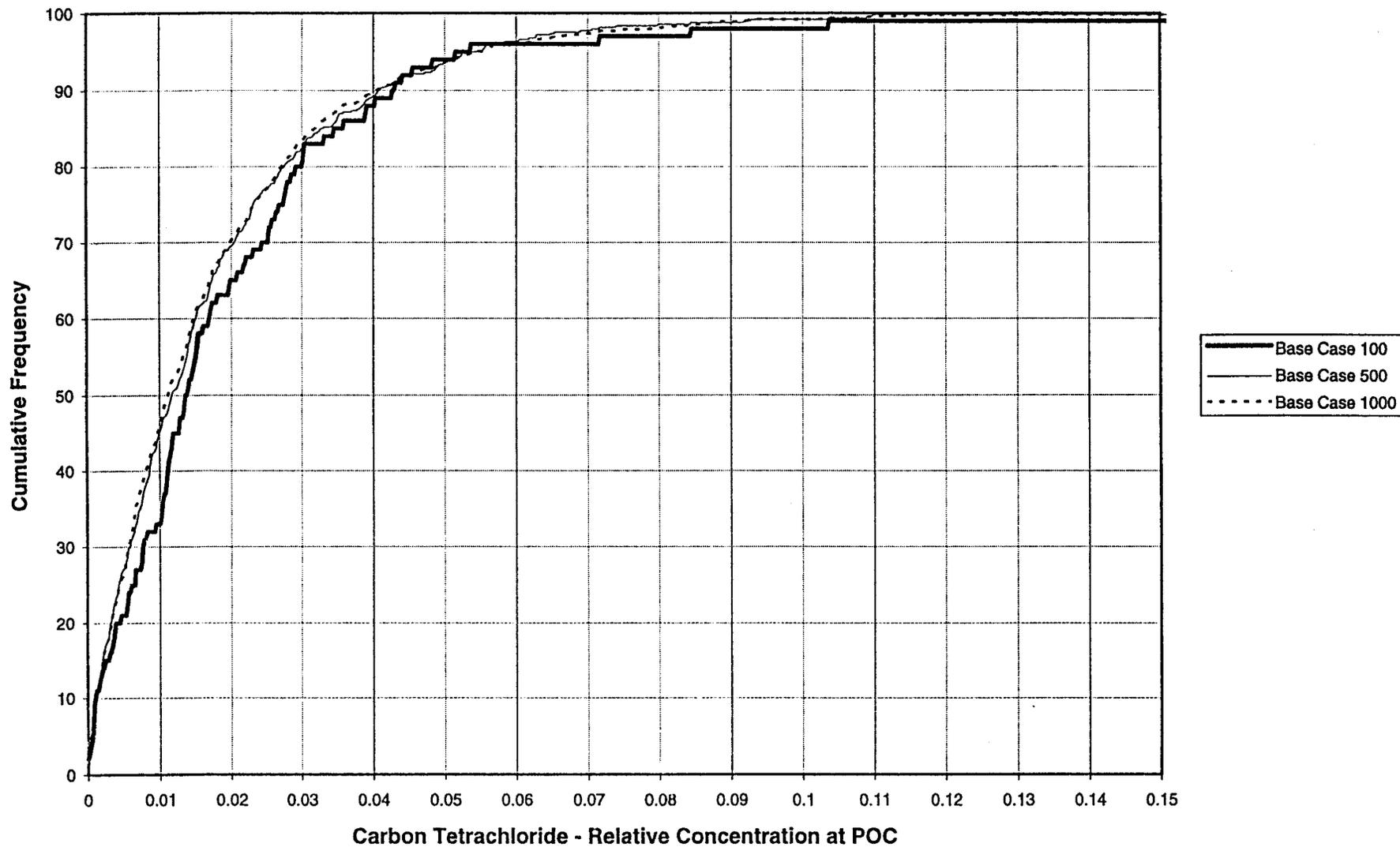


Figure 4

Uncertainty Analysis - 1 Variable (Leachate Perc Rate)

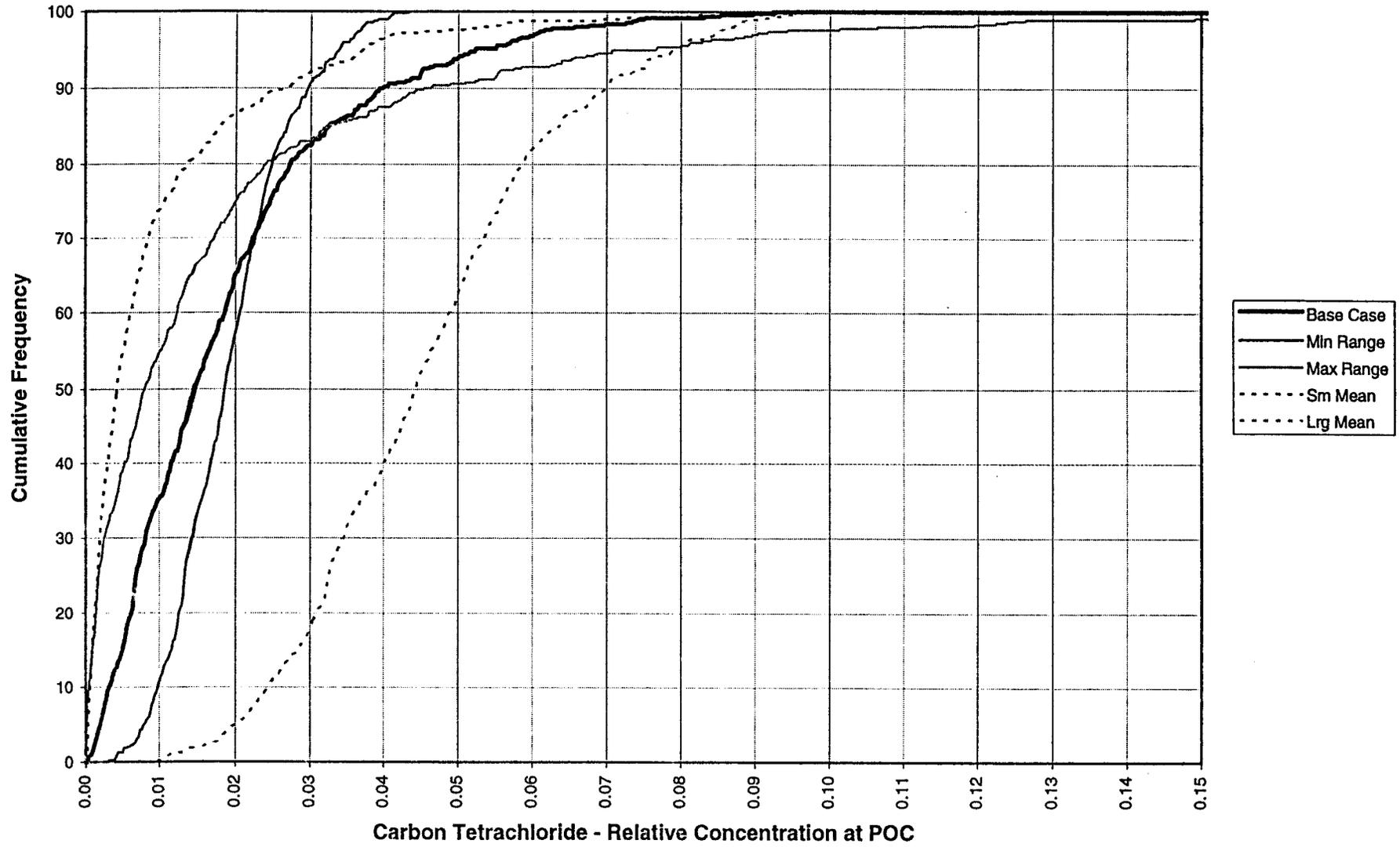


Figure 5

Uncertainty Analysis - 500 Runs

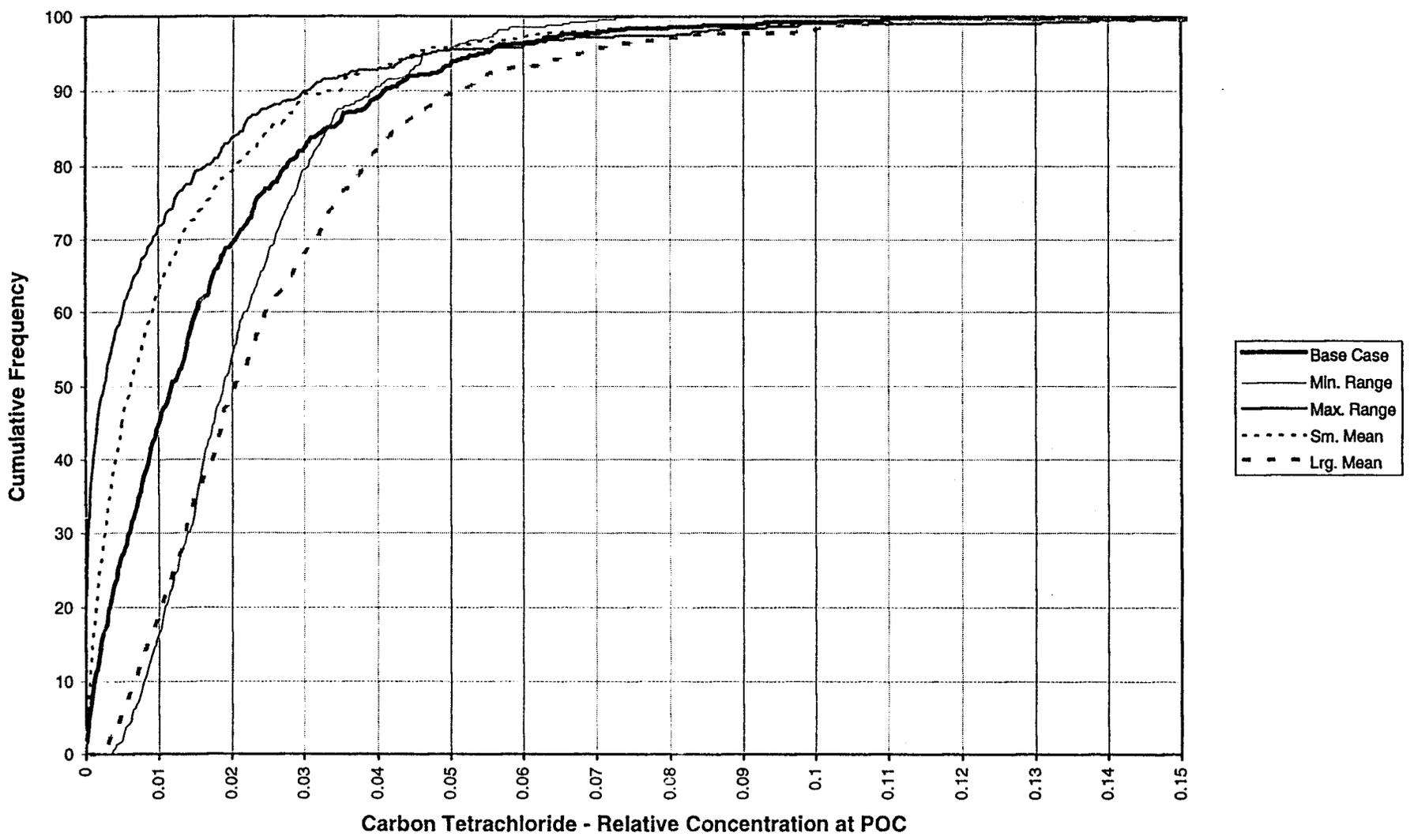


Figure 6

Uncertainty Analysis - 1, 5 and 10 variables

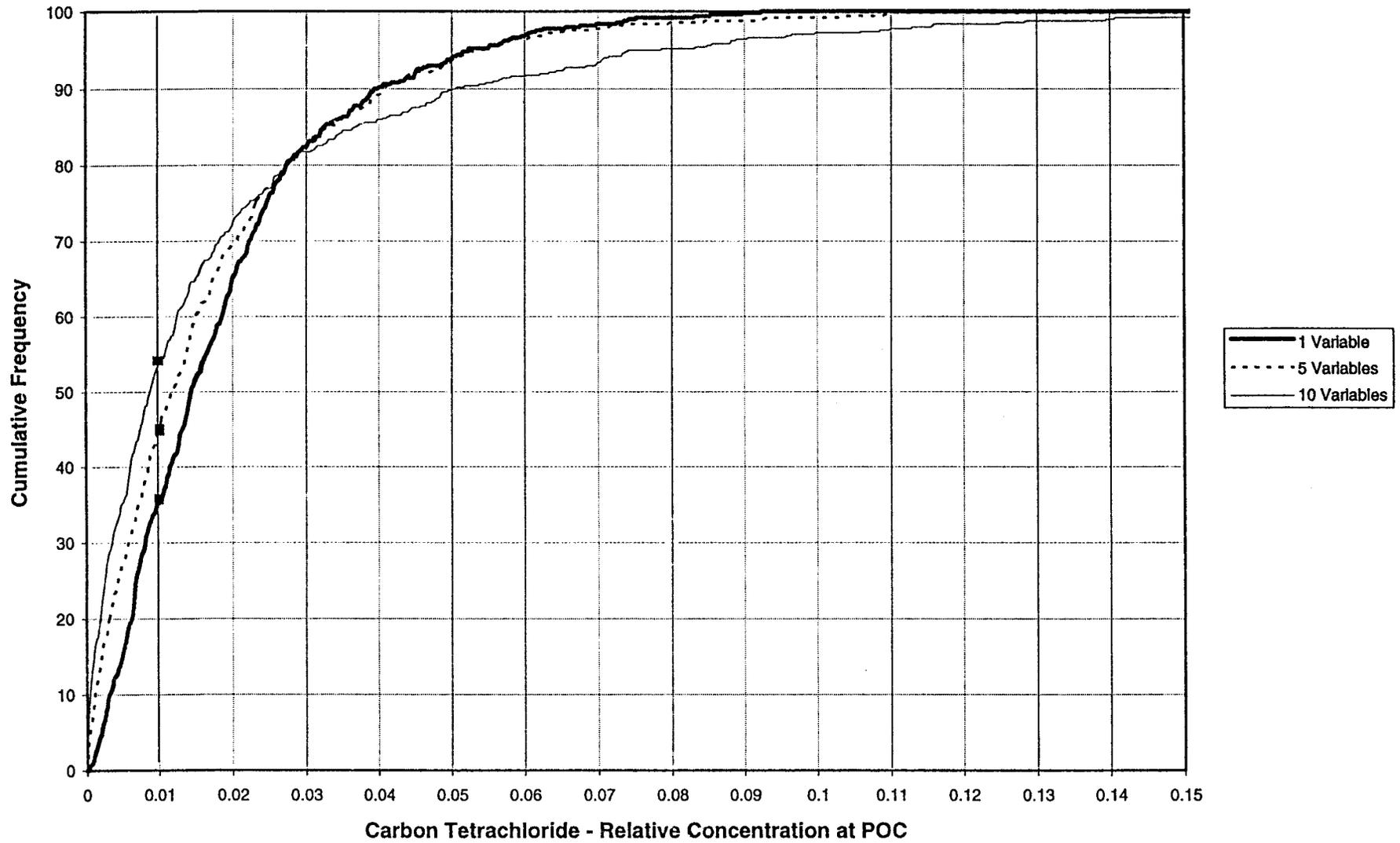


Figure 7

Uncertainty Analysis - 4 Uncertain Chemical Variables

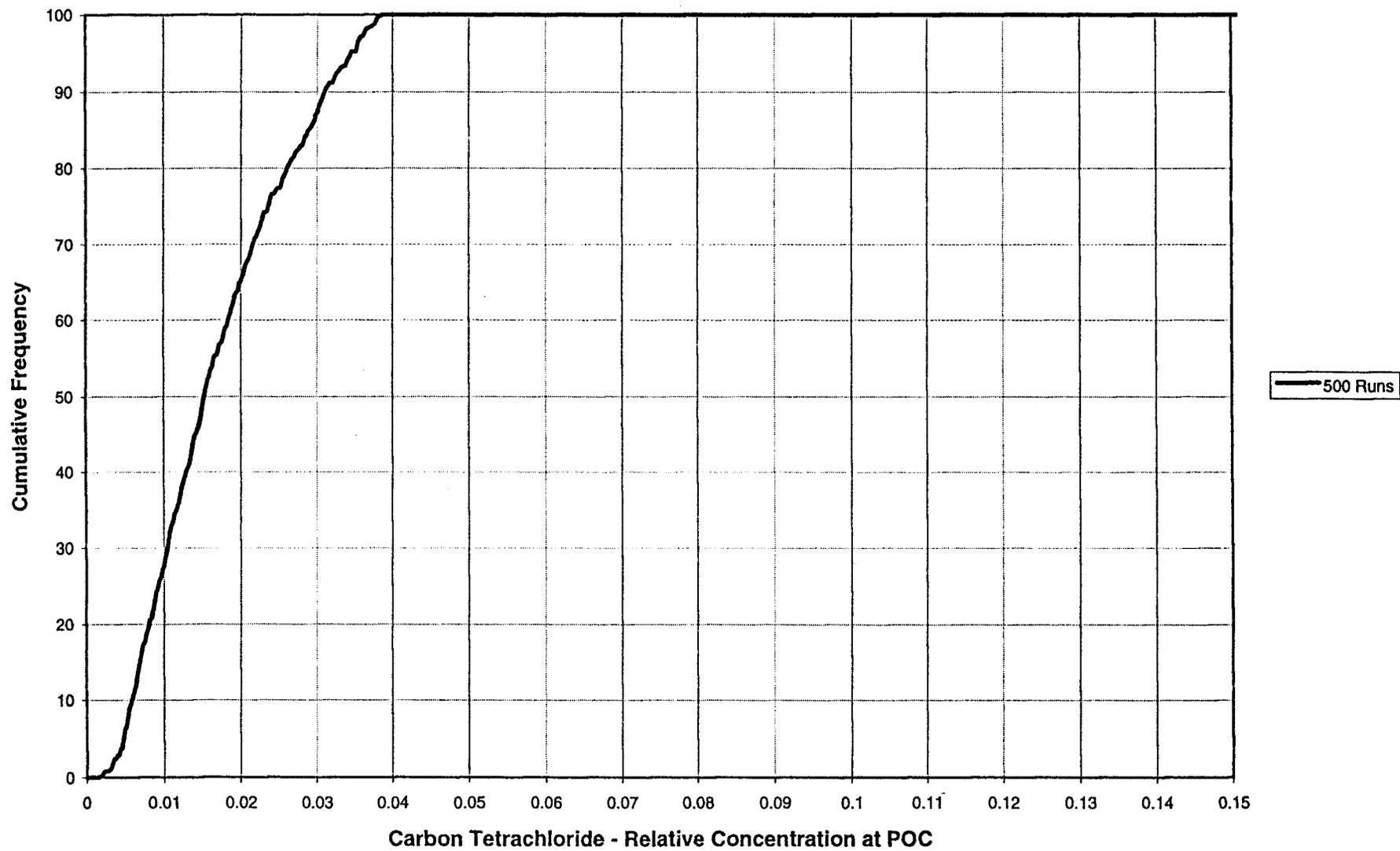


Figure 8

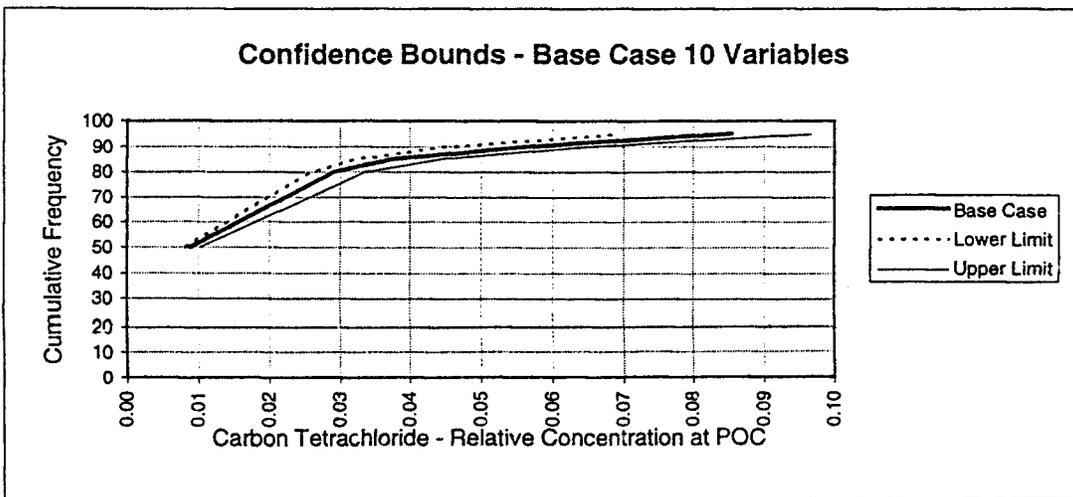
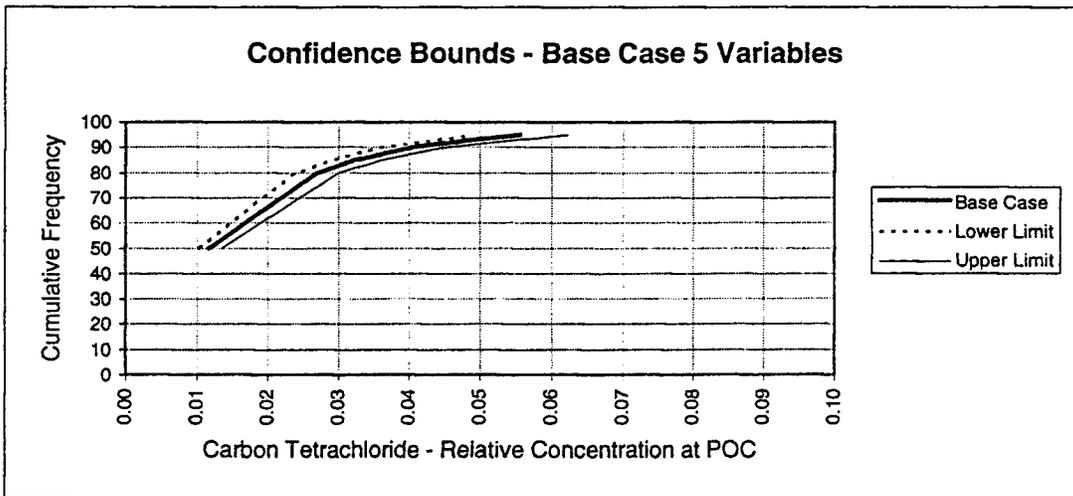
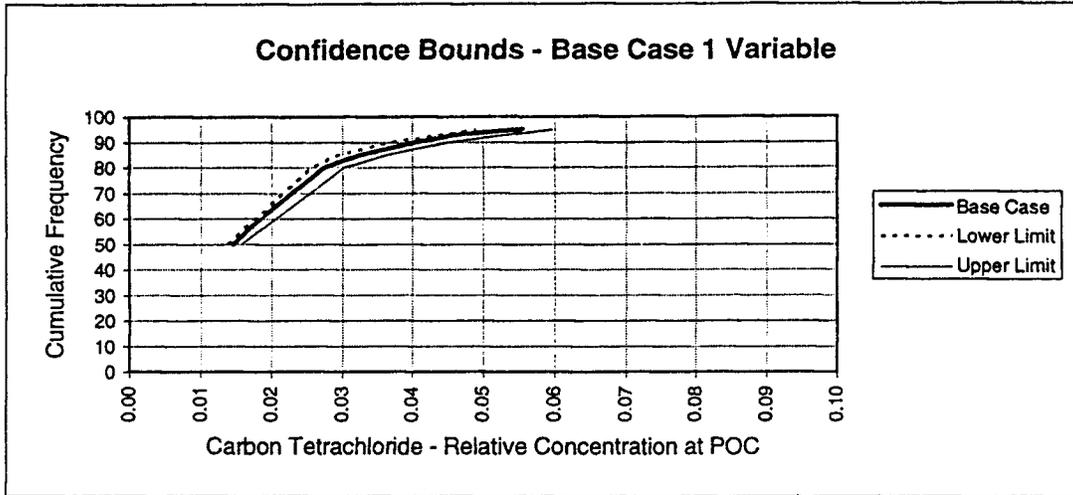


Figure 9

Uncertainty Analysis - 5 Variables

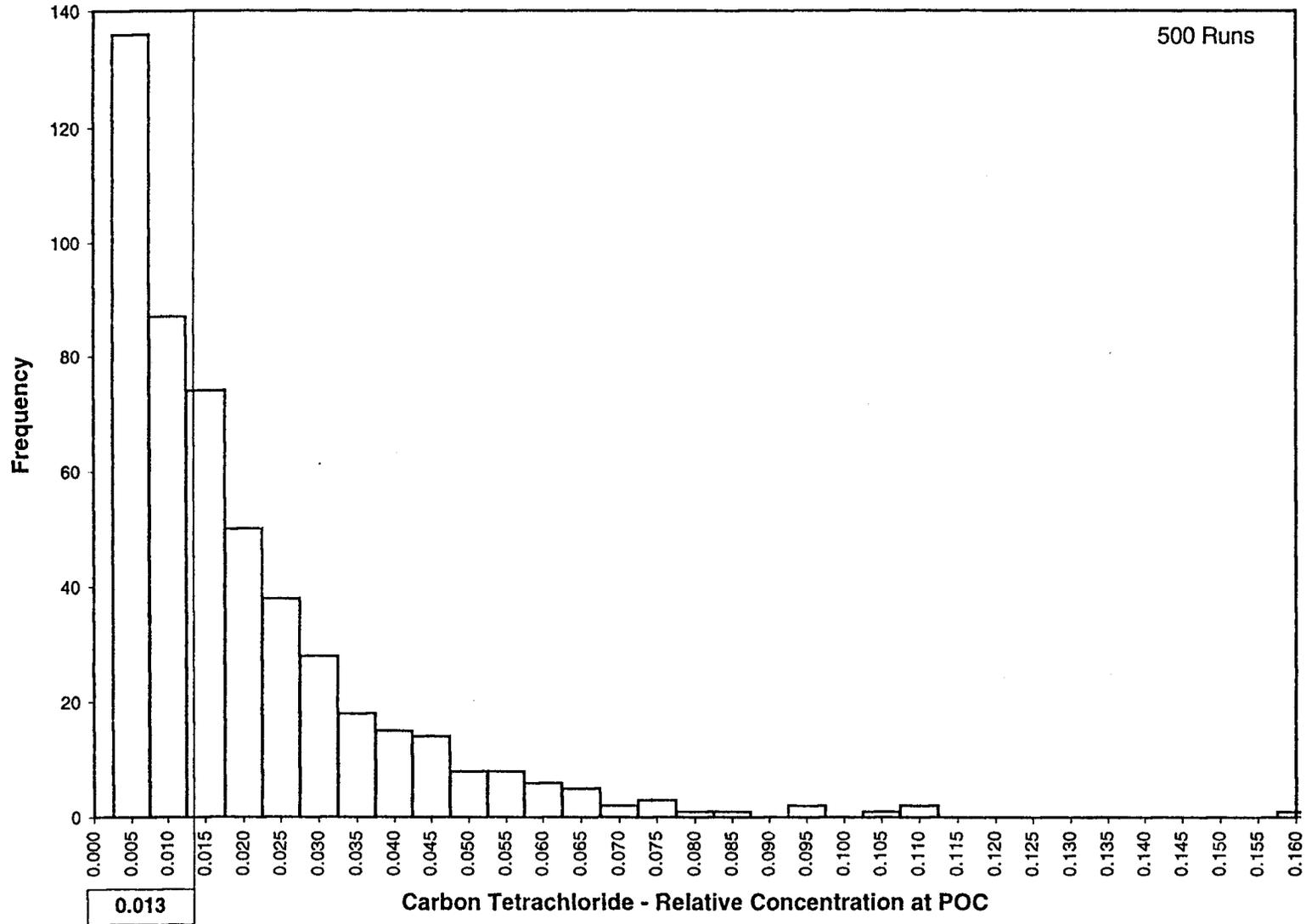


Figure 10