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Analysis of Infiltration Uncertainty

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Introduction

In a total-system performance assessment (TSPA), uncertainty in the performance measure (e.g., radiation dose) is estimated by first estimating the uncertainty in the input variables and then propagating that uncertainty through the model system by means of Monte Carlo simulation. This paper discusses uncertainty in surface infiltration, which is one of the input variables needed for performance assessments of the Yucca Mountain site. Infiltration has been represented in recent TSPA simulations by using three discrete infiltration maps (i.e., spatial distributions of infiltration) for each climate state in the calculation of unsaturated-zone flow and transport. A detailed uncertainty analysis of infiltration was carried out for two purposes: to better quantify the possible range of infiltration, and to determine what probability weights should be assigned to the three infiltration cases in a TSPA simulation. The remainder of this paper presents the approach and methodology for the uncertainty analysis, along with a discussion of the results.

Approach

This analysis involves two main tasks: (1) development of an uncertainty distribution for infiltration using a probabilistic sampling of relevant input parameters combined with simulations of surface hydrologic processes and (2) calculation of weighting factors for the three infiltration cases based on the uncertainty distribution. The approach for the first task involves a system of linked software codes that has been developed to automate and streamline the process shown in Figure 1. The automation also ensures reproducibility and traceability. The core component of the analysis uses the Monte Carlo method with Latin Hypercube Sampling (LHS)[1,2] to sample various input parameters such as precipitation, hydraulic conductivity, evapotranspiration, etc. (Table 4-1 in reference 3). LHS is a form of stratified sampling whereby the input distribution is divided into intervals of equal probability. An equal number of samples are drawn from each of the intervals, ensuring a more complete sampling of the distribution. The main advantage in using LHS is that fewer samples are needed to derive a representative output distribution when compared to random sampling methods. For the infiltration uncertainty analysis, 100 realizations were used, with 12 stochastic input variables. After the input values were sampled, a numerical code (a modified version of the U.S. Geological Survey [USGS] code INFIL[4]) was used to simulate surface and near-surface hydrologic processes to produce spatially variable infiltration maps.[3] The infiltration was then

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averaged over a rectangle that represents the potential repository (Figure 2). The averaged infiltration rate for each of the 100 realizations constitutes the desired infiltration distribution.

For the second task, weighting factors were calculated by comparing the infiltration distribution described above to the mean infiltration for the three discrete infiltration cases that are used in TSPA simulations. The mathematical derivation for the weighting factors is presented in the next section. It is worth noting that infiltration distributions and weighting factors were not developed for present-day conditions, but rather for a projected future climate state called the glacial-transition climate, which dominates the first 10,000 years. However, similar analyses could also be performed for the modern climate or other projected climates if needed.

Discussion of Analyses and Results

The mean and standard deviation for the distribution of 100 realizations and their common logarithms are presented in Table 1. A histogram of the logarithms ($\log_{10}$) of the averaged infiltration rates for the 100 realizations is shown in Figure 3, along with the logarithmic means of the three discrete infiltration maps, which are denoted "lower bound," "middle bound," and "upper bound."

Table 1. Mean and Standard Deviation of Infiltration Rate for 100 Realizations

Infiltration Rate [mm/yr]	Log_{10} Infiltration Rate
Mean = 25.5	Mean (log) = 1.25
StDev = 19.2	StDev (log) = 0.42

Because the distribution of infiltration rates is roughly log-normal, it was decided that the logarithms of the infiltration rates would be used to evaluate the weighting coefficients. Thus, in log space, the following three equations hold:

$$w_1 + w_2 + w_3 = 1.0 \qquad (1)$$

$$w_1 \bullet R_1 + w_2 \bullet R_2 + w_3 \bullet R_3 = \overline{R} \qquad (2)$$

$$w_1 \bullet (R_1)^2 + w_2 \bullet (R_2)^2 + w_3 \bullet (R_3)^2 = \sigma^2 + \overline{R}^2 \qquad (3)$$

where w_1, w_2, and w_3 are the weights applied to the lower, middle, and upper discrete infiltration cases; R_1, R_2, and R_3 are the means of the three discrete infiltration maps, spatially averaged over the simulated rectangular region of Figure 2; σ and $\overline{R}$ are the standard deviation and mean of the computed uncertainty distribution (all in log space). These equations are based on the definitions of normalized weighting factors, mean, and standard deviation. Equation 3 is merely a restatement of the definition of variance. In log space, R_1 = 0.37, R_2 = 1.32, and R_3 = 1.59

(determined from USGS infiltration maps[4]), and $\sigma = 0.42$ and $\overline{R} = 1.25$ (from Table 1). Solving Equations 1–3, the weighting factors for the lower, middle, and upper infiltration cases are 0.17, 0.48, and 0.35, respectively. The derived weighting factors indicate that the middle infiltration case is the most likely of the three discrete cases, followed by the upper case and the lower case. Table 2 summarizes the mean infiltration rates derived from the analog infiltration maps along with the associated weighting factors determined in this analysis.

Table 2. Summary of Mean Infiltration Rates for Lower, Middle, and Upper Cases and Associated Weighting Factors

Analog for Glacial-Transition Climate	Mean Infiltration[a] [mm/yr]	Log_{10} Mean Infiltration	Weighting Factor[b]
Low	2.36	0.37	0.17
Middle	20.79	1.32	0.48
High	39.22	1.59	0.35

Notes:

[a]The numbers in the second column are calculated using the lower, middle, and upper infiltration maps developed by the USGS for the glacial-transition climate,[4] averaged over the simulated rectangular region in Figure 2

[b]Weighting factors are solutions to Equations 1–3

Conclusions

This paper has presented the analysis used to derive weighting factors for three discrete infiltration cases representing low-, middle-, and high-infiltration scenarios for TSPA simulations. Spatially variable infiltration maps were developed using stochastic input parameters and a model for surface and near-surface hydrologic processes. One hundred realizations were simulated to create a distribution of the infiltration averaged over a rectangular region that represents the potential repository. The statistics for this distribution were then used to derive weighting factors for the three discrete infiltration cases. The weighting factors are used in probabilistic calculations of total-system performance assessment to define the fraction of system realizations that use the three infiltration cases. Thus, in a TSPA simulation the lower-bound infiltration case is used in 17 percent of the realizations, the middle bound is used in 48 percent of the realizations, and the upper bound is used in 35 percent of the cases. The approach of using three discrete infiltration cases rather than a more general distribution such as the one shown in Figure 3 has been adopted primarily because of the large amount of effort required to compute unsaturated-zone flow and transport for each infiltration case.

Acknowledgments

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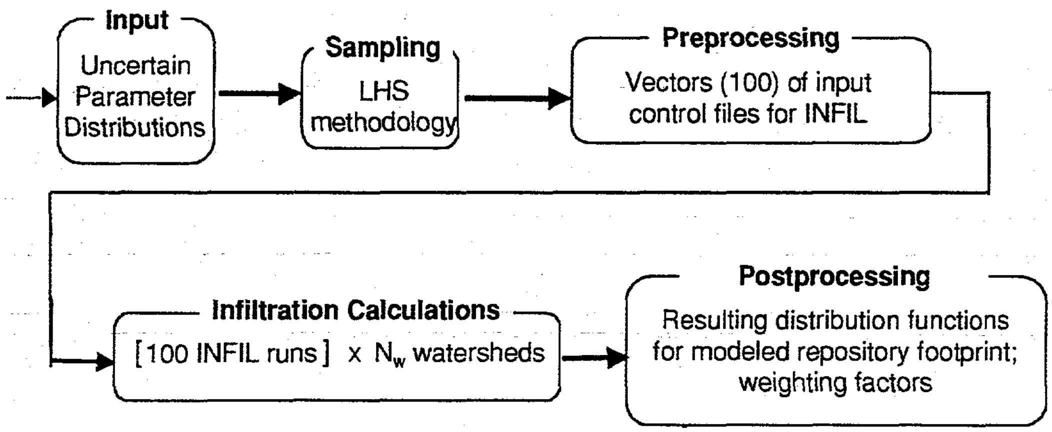

Figure 1. Simplified Diagram of Process Flow for Uncertainty Analysis

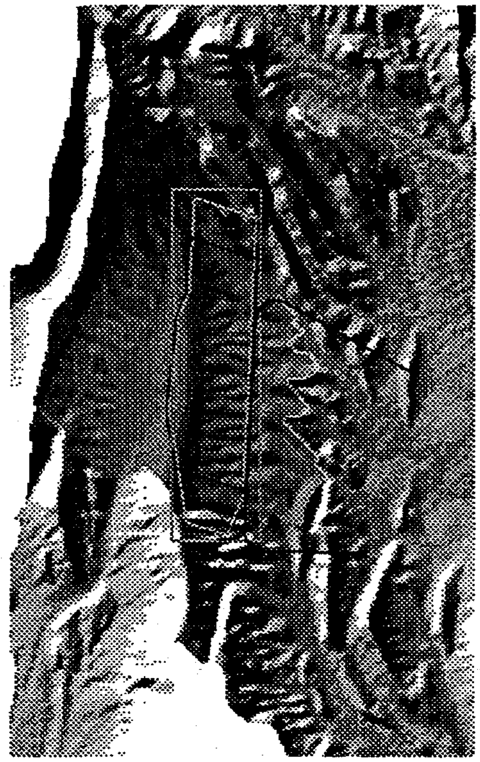

Figure 2. Map of Yucca Mountain and Vicinity. The outer rectangular outline indicates the region used in the uncertainty analysis of infiltration. The larger enclosed outline indicates the potential repository "footprint," and the smaller enclosed outline indicates the "loaded" region that would contain waste.

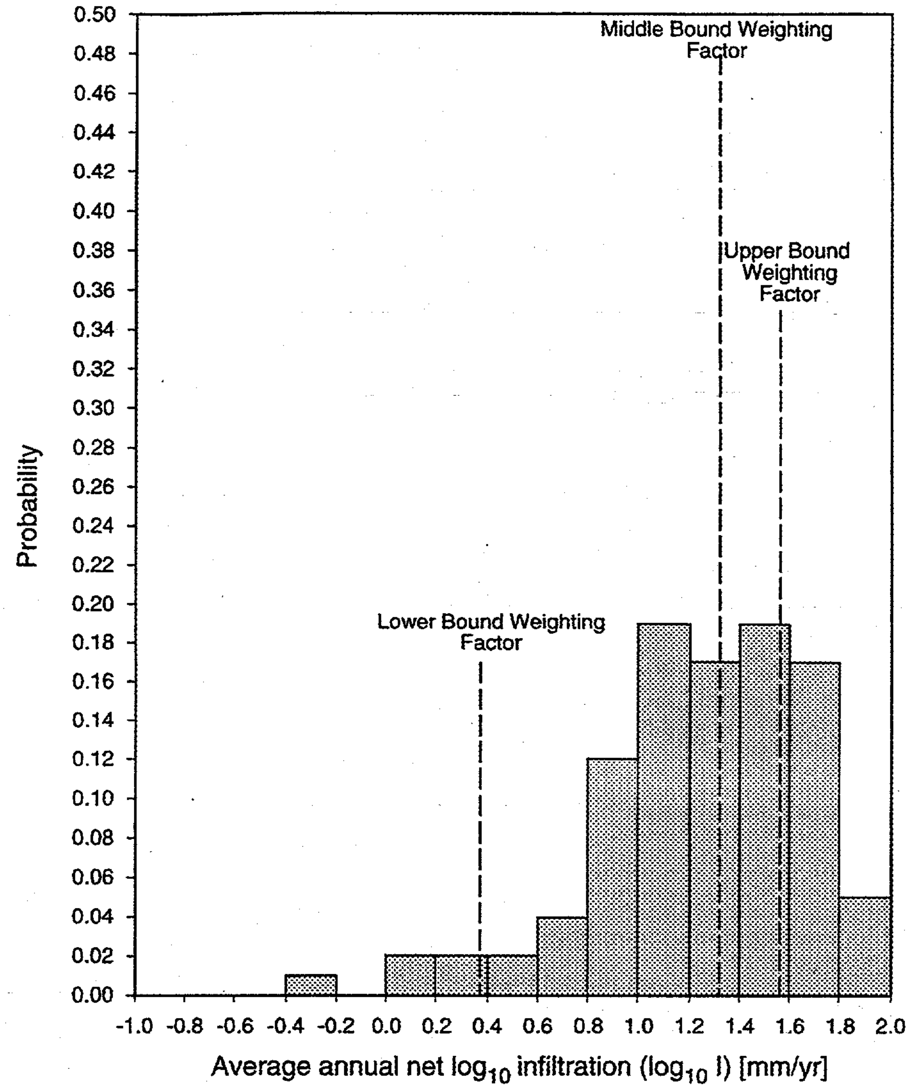

Figure 3. Histogram of Log Average Annual Infiltration for Glacial-Transition Climate