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Date: March 20, 2018
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REVIEWER: G. P. Flach, 773-42A

Topic 3.8: Proposed Approach to Uncertainty Quantification and Sensitivity Analyses in the next PA

Recommendation 153: The analysis must capture the total system uncertainty. This includes such factors as infiltration (HELP modeling and associated meteorological data), inventory uncertainty, special waste forms, and plume interaction.

Method for Including Uncertainty in Infiltration Rates in the E-Area PA System Model

Scope

This memorandum builds upon earlier reports whose purpose is to lay the foundation for the infiltration data package that will be assembled during the next revision of the E-Area Low-Level Waste Facility (LLWF) Performance Assessment (PA):

- Dyer (2017a) establishes the conceptual modeling framework for the E-Area PA HELP infiltration model simulations.
- Dyer (2017b) confirms closure of the water mass balance for scenarios involving cap subsidence resulting from the disposal of non-crushable waste.
- Dyer and Flach (2017) describe a probabilistic model for estimating subsided-area infiltration rates for vadose-zone PORFLOW simulations.
- Flach (2017) lays out the overall conceptual approach to uncertainty quantification and sensitivity analysis for the E-Area PA revision.
- Shipmon and Dyer (2017) summarize a sensitivity analysis of closure cap material property and design parameters that will impact infiltration rates predicted by the HELP model.

Conclusions and Recommendations

To facilitate uncertainty analysis during the next revision of the E-Area PA, a method has been developed to generate uncertainty distributions for intact- and subsided-area infiltration rates for the GoldSim probabilistic system model. The method combines sensitivity analysis of cover system infiltration rate using the HELP model with nonlinear regression of the resulting infiltration rate versus time profiles using Minitab® 17 to obtain a bounding set of log-logistic growth curves for pessimistic, best estimate, and optimistic cases. Specific recommendations are to:

- Conduct HELP model simulations of intact and subsided-area infiltration scenarios for both best-estimate and sensitivity-analysis cases to generate a reasonable and defensible distribution of infiltration rate versus time profiles.
- Identify three HELP infiltration profiles that represent the most pessimistic, best estimate, and most optimistic cases.
- Use Minitab® 17 or equivalent statistical software to fit the above three infiltration profiles to a four-parameter log-logistic growth curve.
- Add two additional cases (more pessimistic and more optimistic) via manual adjustment of the four fitting parameters to arrive at a set of five log-logistic growth curves that represents the uncertainty distribution for the closure-cap scenario of interest.

The scenarios and infiltration rates in this report are intended to illustrate the proposed method for managing uncertainty in infiltration rates in the E-Area PA system model. For this reason, all infiltration rates are preliminary and should not be used for final design and modeling purposes.

Discussion

HELP Model Sensitivity Analysis

Shipmon and Dyer (2017) used version 3.95D of the Hydrologic Evaluation of Landfill Performance (HELP v3.95D) model to conduct a sensitivity analysis of rainfall infiltration through the proposed intact E-Area LLWF closure cap. The objective of the analysis was to identify the cap design and material property parameters that most significantly impact intact infiltration rates over a 10,000-year simulation period. The results of the sensitivity analysis showed that saturated hydraulic conductivity (K_{sat}) for select cap layers, precipitation rate, surface vegetation type, and geomembrane layer defect density are dominant factors affecting intact infiltration rate. Interestingly, calculated intact infiltration rates were substantially influenced by changes in the saturated hydraulic conductivity of the Upper Foundation and Lateral Drainage layers. For example, an order-of-magnitude decrease in K_{sat} for the Upper Foundation layer lowered the maximum infiltration rate from a base-case 11 inches per year to only two inches per year. Conversely, an order-of-magnitude increase in K_{sat} led to an increase in infiltration rate from 11 to 15 inches per year.

Figure 1 and Figure 2 present the intact infiltration rate versus time profiles for the following sensitivity parameters evaluated by Shipmon and Dyer (2017):

- Closure cap slope (2% minimum, 3% base case, 5% maximum)
- Closure cap slope length (150 feet minimum, 400 ft base case, 600 feet maximum)
- Surface vegetation type, which affects evapotranspiration (bare ground, base-case grass, pine trees)
- Surface run-off factor (lesser run-off: CN=30; base-case run-off: CN=50; greater run-off: CN=70)
- Mean (μ) monthly precipitation ($\mu - 0.5\sigma$, μ , $\mu + 0.5\sigma$)
- Linear rate of increase (X) in number of geomembrane defects (0.5X, base-case X, 2X)

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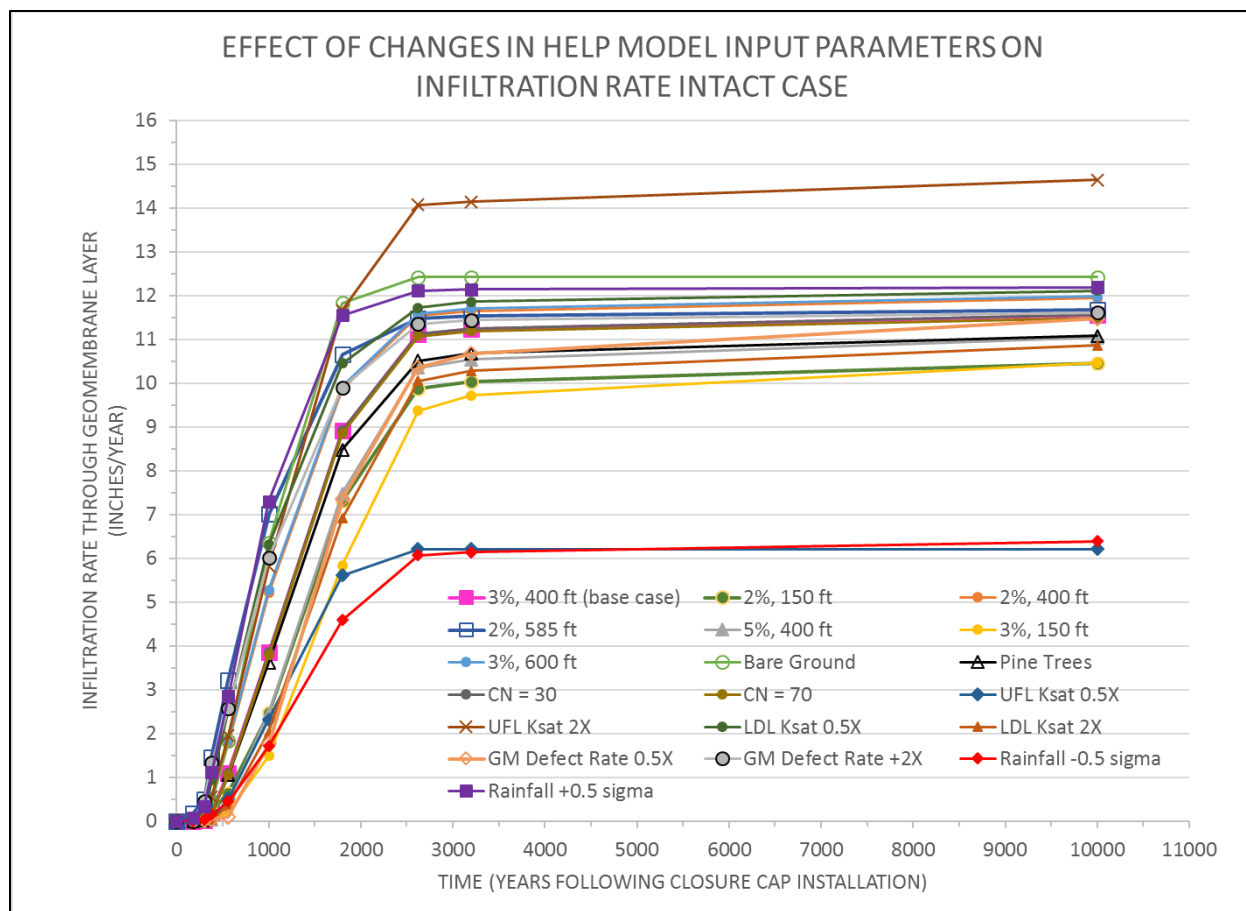


Figure 1. Effect of Changes in HELP Model Input Parameters on Intact Infiltration Rates (linear-linear plot)

- Saturated hydraulic conductivity of upper foundation layer ($0.5K_{sat}$, base-case K_{sat} , $2K_{sat}$)
- Saturated hydraulic conductivity of lateral drainage layer ($0.5K_{sat}$, base-case K_{sat} , $2K_{sat}$)

Shipmon and Dyer (2017) provide a much more detailed description of the parameter values used in the HELP model simulations for each sensitivity case.

Log-Logistic Growth Curve

A four-parameter log-logistic growth curve or Fisk distribution is commonly used by hydrologists to represent stream flow and precipitation, which are both characterized by a rate that increases initially and then decreases with time. The functional form of a four-parameter log-logistic growth curve is given by:

$$\text{Infiltration Rate (in/yr)} = \theta_1 + \left(\frac{\theta_2 - \theta_1}{1 + e^{(\theta_4 \cdot \ln(t/\theta_3))}} \right) \quad (1)$$

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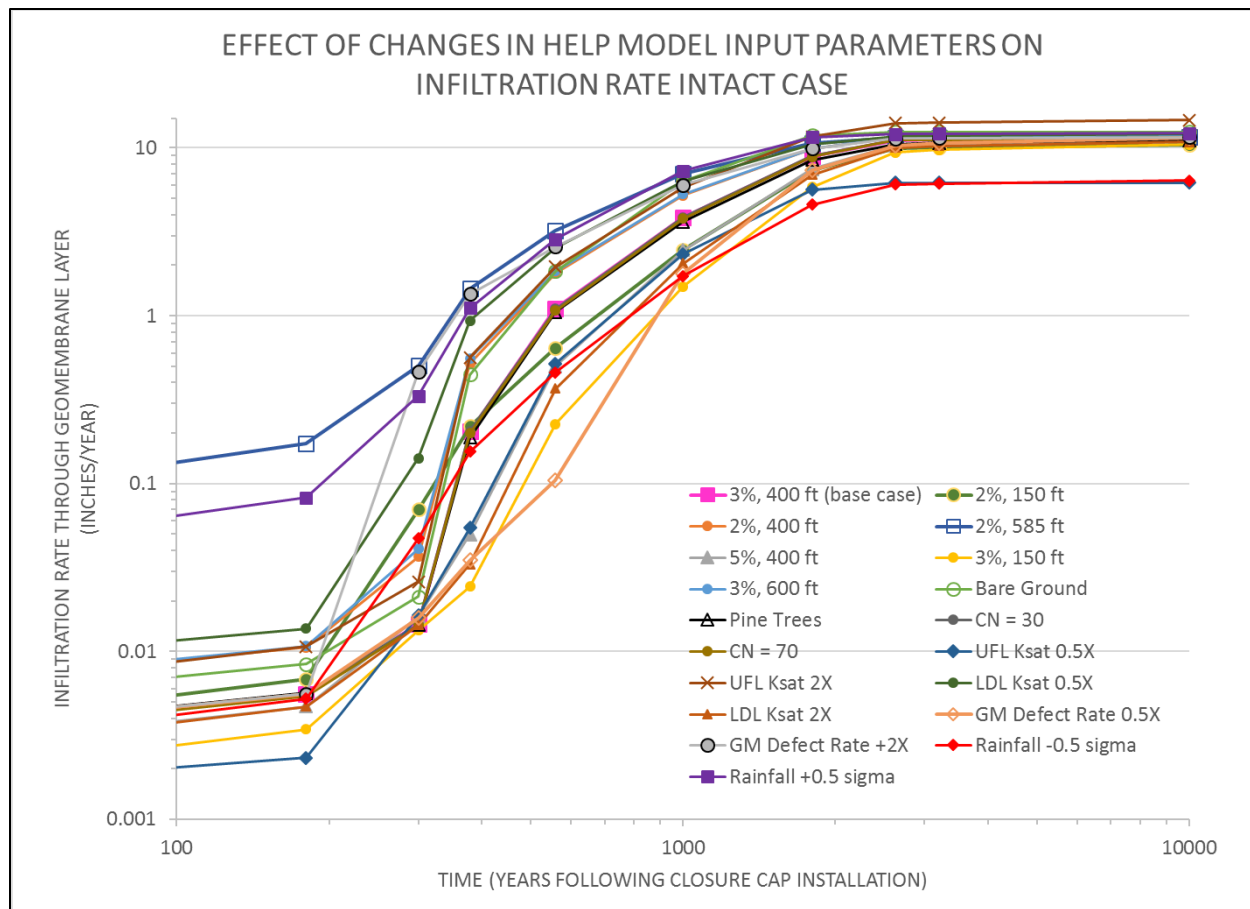


Figure 2. Effect of Changes in HELP Model Input Parameters on Intact Infiltration Rates (log-log plot)

where t equals time in years, and θ_1 , θ_2 , θ_3 , and θ_4 are the four fitting parameters. Figure 3 shows a generalized depiction of a log-logistic growth curve.

The log-logistic growth curve is also quite effective at capturing the sigmoidal shape of the infiltration rate versus time profiles generated by the HELP model as part of the closure cap degradation analysis. The cover system degradation analysis considers: loss of permeability in lateral drainage layers due to “silting in,” erosion of surface layer(s), subsidence of the cap due to waste compaction, and degradation of the geomembrane and geosynthetic clay liners due to oxidation, tears, and tree-root penetration over 10,000 years.

The purpose of this memorandum is to build upon the sensitivity analysis results above and generate a set of five log-logistic growth curves that represents a reasonable and defensible uncertainty distribution for each intact and subsided closure-cap scenario of interest. The five log-logistic curves for a scenario seek to capture the most pessimistic, more pessimistic, best estimate, more optimistic, and most optimistic infiltration rates over the initial 1,000 years of most importance in the PA. By way of example, visual inspection of Figure 2 indicates that the cases

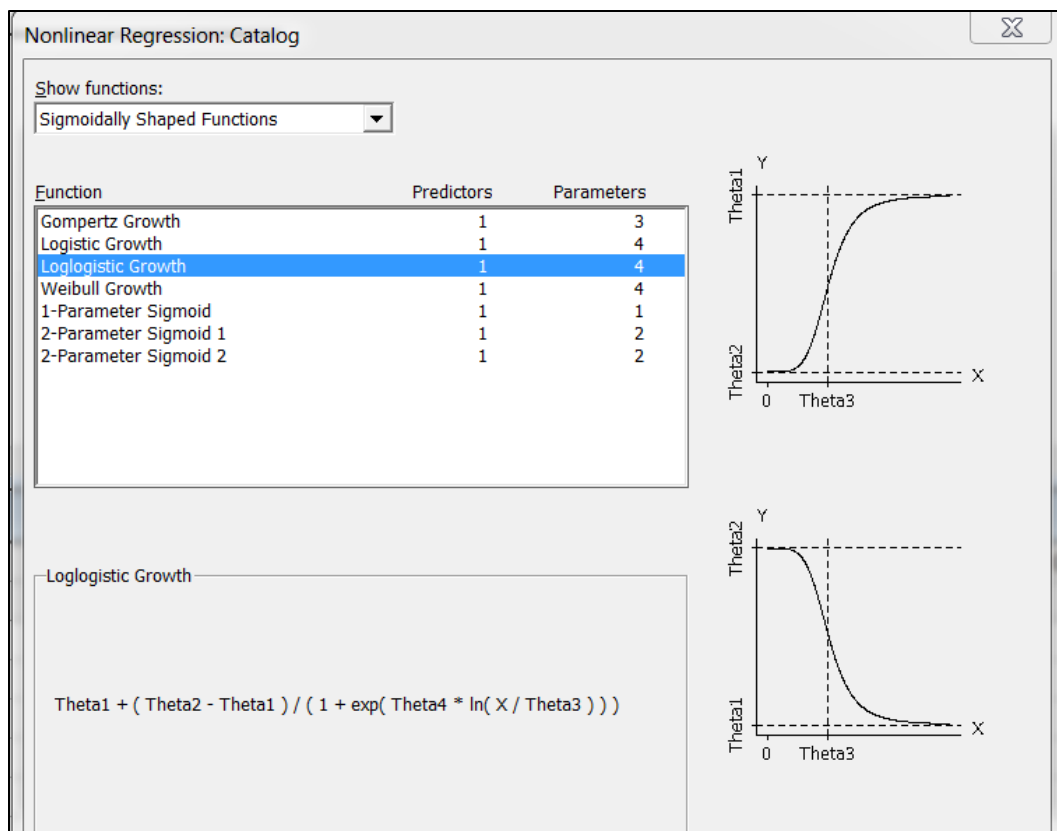


Figure 3. Log-Logistic Growth Curve from Minitab® 17 Nonlinear Regression Catalog

below represent a reasonable uncertainty distribution for the intact scenario during the first 1,000 years following closure cap installation:

- Most pessimistic: 2% slope, 585-foot slope length
- Best estimate: 3% slope and 400-foot slope length
- Most optimistic: 3% slope, 150-foot slope length

The method used to arrive at an uncertainty distribution for the intact infiltration case includes two steps:

1. Nonlinear regression of HELP model infiltration data for the most pessimistic, best estimate, and most optimistic cases in Figure 2 using Minitab® 17 to generate the log-logistic growth curves (Figure 4 through Figure 6) and associated regression parameters (Table 1).
2. Manual adjustment of the theta parameters, using the values listed in Table 1 for the most pessimistic, best estimate, and most optimistic cases as guidance, to arrive at log-logistic growth curves for the more pessimistic and more optimistic cases shaded in light blue.

The method assumes (1) a log-triangular uncertainty distribution for infiltration rate (I), i.e., log I has a triangular distribution, (2) the triangular distribution for log I is symmetric, and (3) a modified one-dimensional Latin

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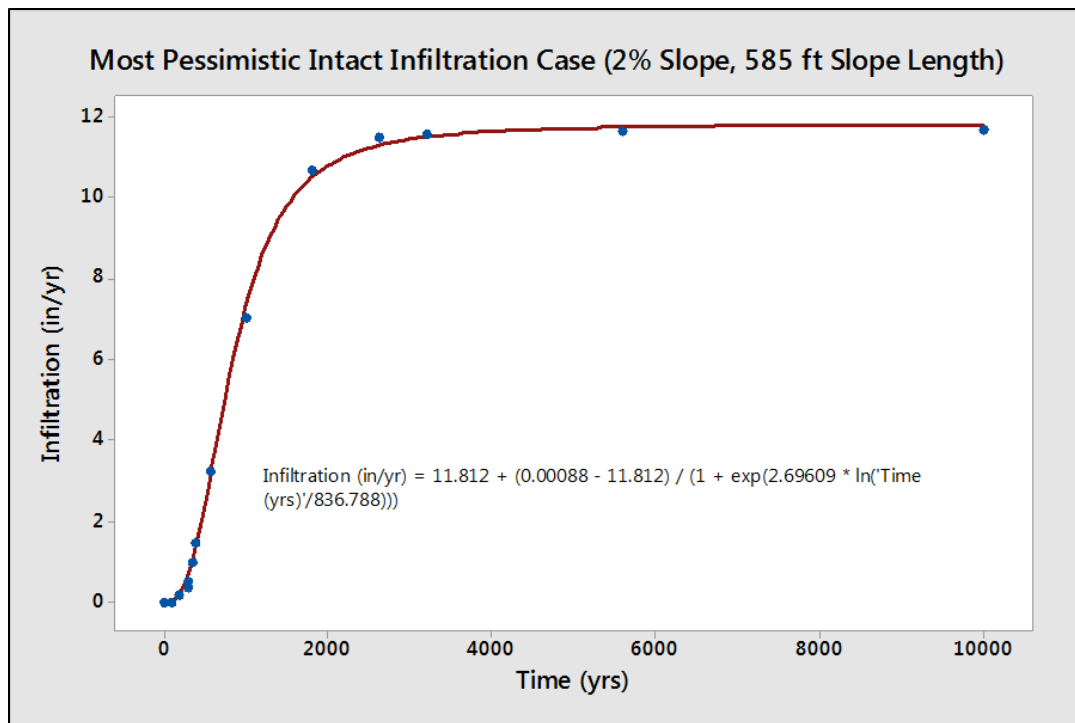


Figure 4. Log-Logistic Fit of HELP Model Results for 2% Slope and 585-Foot Slope Length

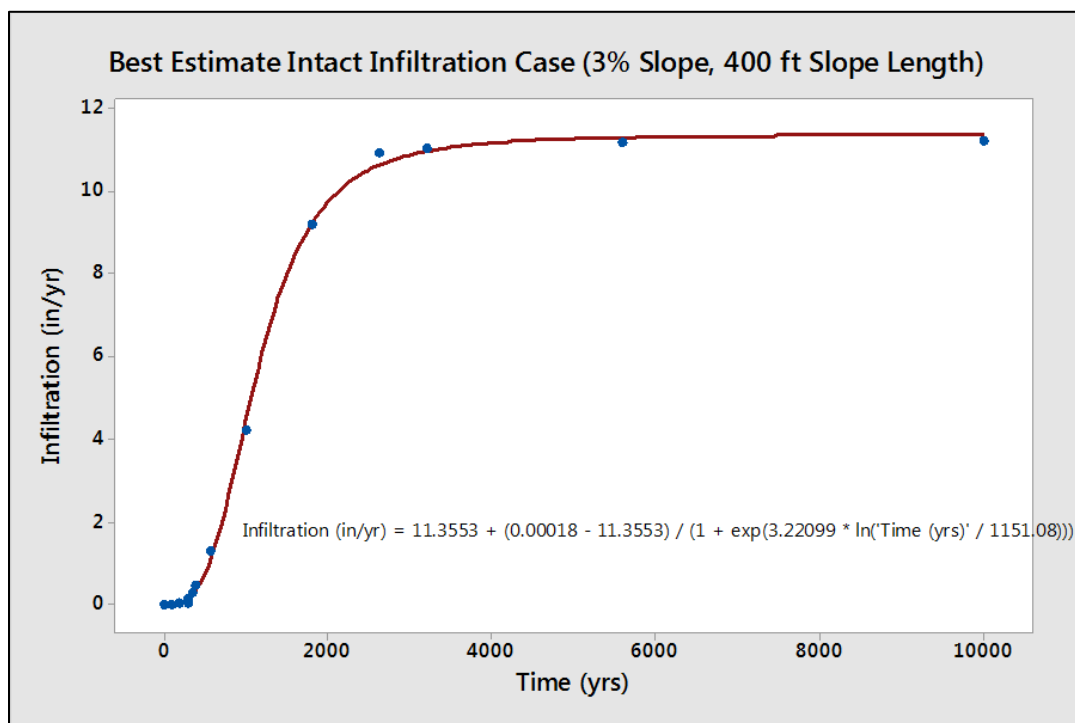


Figure 5. Log-Logistic Fit of HELP Model Results for 3% Slope and 400-Foot Slope Length

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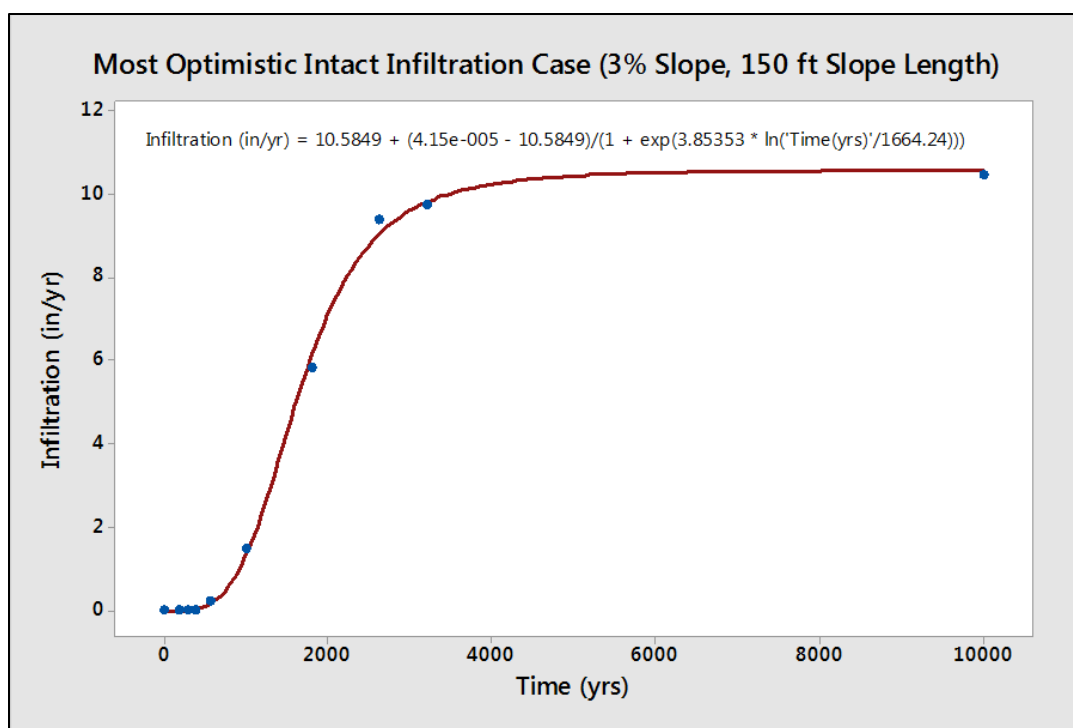


Figure 6. Log-Logistic Fit of HELP Model Results for 3% Slope and 150-Foot Slope Length

hypercube sampling (LHS) technique with five (5) samples. In traditional one-dimensional LHS, the cumulative distribution function (CDF) is divided into an equal number of partitioned regions (N); one sample point is then randomly selected from each of the N partitioned regions. For the modified LHS technique proposed here, the five samples are not randomly selected from each CDF partition, but are instead positioned at the midpoint of each equally sized partitioned region as shown in Figure 7. The five non-random samples correspond to the following uncertainty cases: most optimistic (CDF = 0.1), more optimistic (CDF = 0.3), best estimate (CDF = 0.5), more pessimistic (CDF = 0.7), and most pessimistic (CDF = 0.9). In Figure 7, variable x represents one of the four theta fitting parameters (θ_1 , θ_2 , θ_3 , and θ_4) in the log-logistic function whose value is equal to zero for the best-estimate case and is normalized to -1 and +1 for the most optimistic and most pessimistic cases, respectively. The more optimistic and more pessimistic cases are situated at -0.41 and +0.41, respectively, which is -41% and +41% of the distance between the best estimate and the most optimistic and most pessimistic cases, respectively.

Figure 8 and Figure 9 are linear-linear and log-log plots, respectively, displaying the five log-logistic growth curves included in Table 1. This set of five infiltration rate versus time profiles depicts the reasonable and defensible uncertainty distribution for the F-Area Tank Farm intact closure-cap scenario considered by Shipmon and Dyer (2017).

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Table 1. Best-Fit Log-Logistic Growth Curve Parameters and Predicted Infiltration Rates for Intact Uncertainty Cases

	Theta Parameters for Log-Logistic Growth Curve				
	Most Pessimistic	More Pessimistic	Best Estimate	More Optimistic	Most Optimistic
θ_1	11.812	11.542547	11.3553	11.039436	10.5849
θ_2	0.00088	0.000467	0.00018	0.0001232	4.15E-05
θ_3	836.788	1022.22028	1151.08	1361.4756	1664.24
θ_4	2.69609	3.005781	3.22099	3.4803314	3.85353

	Infiltration Rate (inches/year)				
Time	Most Pessimistic	More Pessimistic	Best Estimate	More Optimistic	Most Optimistic
0	0.00088	0.000467	0.00018	0.0001232	4.15E-05
100	0.0392	0.0111	0.004517	0.00137	0.0002498
180	0.1855	0.0625	0.0289	0.0098	0.0020
290	0.6425	0.2563	0.1325	0.0506	0.0126
300	0.7002	0.2831	0.1476	0.0569	0.0144
340	0.9582	0.4076	0.2194	0.0877	0.0233
380	1.2573	0.5614	0.3112	0.1286	0.0356
560	2.9887	1.6253	1.0155	0.4797	0.1569
1000	7.2983	5.5810	4.4128	2.8114	1.3036
1800	10.4829	9.7608	9.1804	8.0088	6.0861
2623	11.2932	10.9009	10.6080	10.0171	9.0221
3200	11.5028	11.1805	10.9488	10.5029	9.7962
5600	11.7422	11.4734	11.2862	10.9596	10.4872
10000	11.7973	11.5304	11.3446	11.0288	10.5744

Regression parameters for the more pessimistic and optimistic cases are located -41% and +41% of the distance between the best estimate and the most optimistic and pessimistic cases, respectively, as shown in Figure 7.

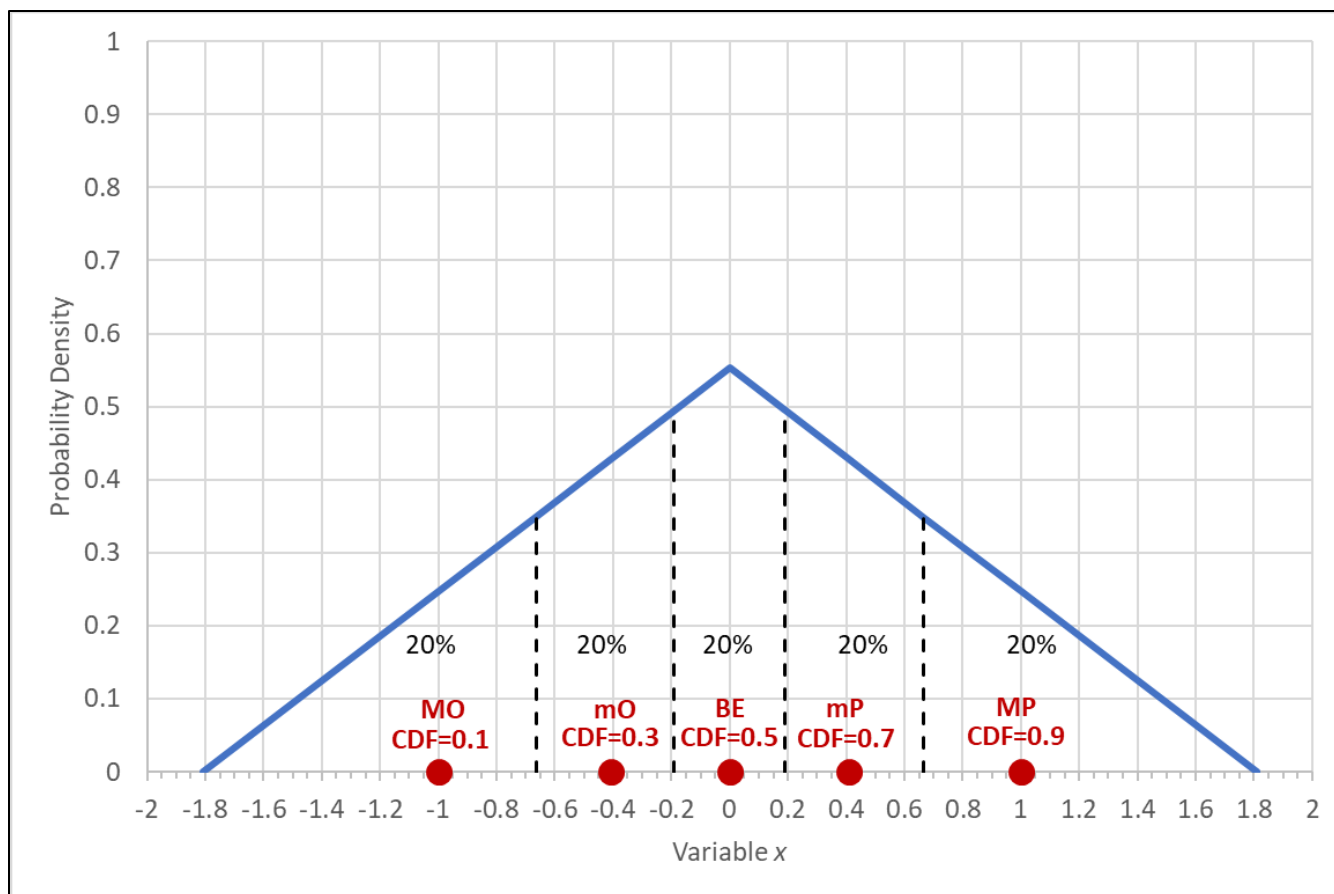


Figure 7. Representative Symmetric Probability Density Function for a Modified One-Dimensional Latin Hypercube Sampling Technique with Five Non-Random Samples (partitioned regions indicated by dashed vertical lines each represent 20% of the total area under the PDF; CDF = cumulative distribution function; MO = most optimistic; mO = more optimistic; BE = best estimate; mP = more pessimistic; MP = most pessimistic)

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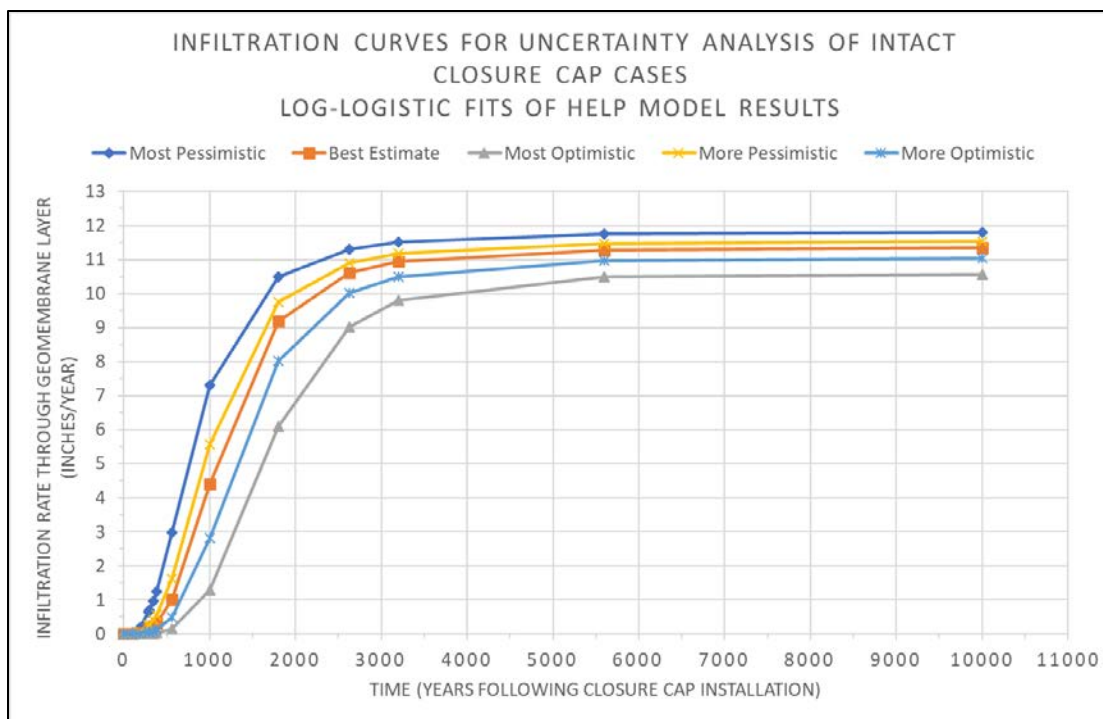


Figure 8. Proposed Intact Infiltration Rate Profiles for Uncertainty Analysis (linear-linear plot)

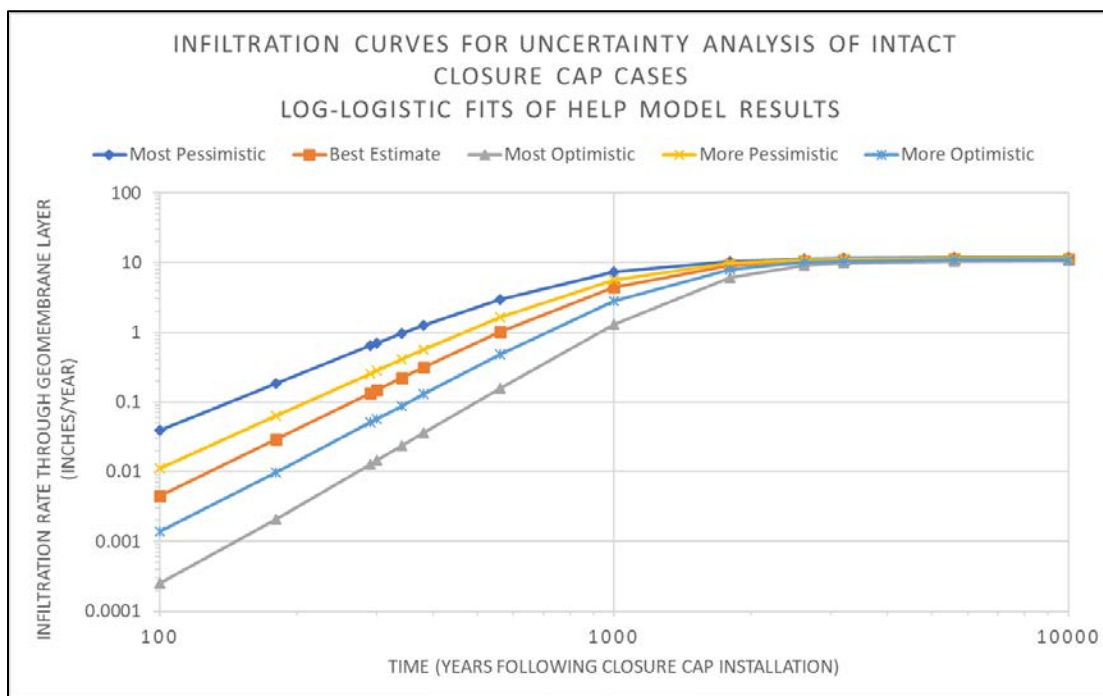


Figure 9. Proposed Intact Infiltration Rate Profiles for Uncertainty Analysis (log-log plot)

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References

Dyer, J. A. (2017a) Conceptual Modeling Framework for E-Area PA HELP Infiltration Model Simulations. SRNL-STI-2017-00678. Savannah River National Laboratory, Aiken, SC.

Dyer, J. A. (2017b) E-Area Low-Level Waste Facility Vadose Zone Model: Confirmation of Water Mass Balance for Subsidence Scenarios. SRNL-STI-2017-00728. Savannah River National Laboratory, Aiken, SC.

Dyer, J. A., and Flach, G. P. (2017) E-Area LLWF Vadose Zone Model: Probabilistic Model for Estimating Subsided-Area Infiltration Rates. SRNL-STI-2017-00729. Savannah River National Laboratory, Aiken, SC.

Flach, G. P. (2017) Overall Conceptual Approach to Uncertainty Quantification and Sensitivity Analysis for the E-Area PA Revision. SRNL-STI-2017-00062. Savannah River National Laboratory, Aiken, SC.

Shipmon, J. C., and Dyer, J. A. (2017) Analysis of Factors that Influence Infiltration Rates using the HELP Model. SRNL-STI-2017-00506. Savannah River National Laboratory, Aiken, SC.

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