Methods for Using Ground-Water Model Predictions to Guide Hydrogeologic Data Collection, with Application to the Death Valley Regional Ground-Water Flow System

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ABSTRACT

Calibrated models of ground-water systems can provide substantial information for guiding data collection. This work considers using such models to guide hydrogeologic data collection for improving model predictions, by identifying model parameters that are most important to the predictions. Identification of these important parameters can help guide collection of field data about parameter values and associated flow-system features that can lead to improved predictions. Methods for identifying parameters important to predictions include prediction scaled sensitivities (PSS), which account for uncertainty on individual parameters as well as prediction sensitivity to parameters, and a new "value of improved information" (VOII) method, which includes the effects of parameter correlation in addition to individual parameter uncertainty and prediction sensitivity. The PSS and VOII methods are demonstrated using a model of the Death Valley regional ground-water flow system. The predictions of interest are advective-transport paths originating at sites of past underground nuclear testing. Results show that for two paths evaluated, the most important parameters include a subset of five or six of the 23 defined model parameters. Some of the parameters identified as most important are associated with flow-system attributes that do not lie in the immediate vicinity of the paths. Results also indicate that the PSS and VOII methods can identify different important parameters. Because the methods emphasize somewhat different criteria for parameter importance, it is suggested that

parameters identified by both methods be carefully considered in subsequent data collection efforts aimed at improving model predictions.

INTRODUCTION

Ground-water models are often developed to obtain predictions of societal importance. Such predictions might be the response of an aquifer to future ground-water pumping, or the ground-water transport of contaminants from a source location. Because the ground-water flow system characteristics represented in such models are always unknown to some degree, model predictions are uncertain. To reduce this prediction uncertainty, it is necessary to improve the model so that it more accurately represents the flow system. However, ground-water models often represent extremely complex hydrologic and hydrogeologic conditions, and because field characterization of these conditions can be costly and time consuming, it is rarely feasible to improve the representation of all aspects of a simulated system. Thus, it is of interest to identify the particular attributes of a flow system that are most important to the relevant predictions, and to focus field characterization on these attributes.

In this paper, this problem is addressed by determining the model parameters that are most important to the predictions. Identification of these parameters can help guide collection of two types of hydrogeologic data that are likely to improve the predictions. First, information can be collected about the values of the important parameters. Field activities to obtain this type of data include, for example, hydraulic tests for estimating transmissivity and storativity values. Second, data can be collected about features of the flow system that are related to the important parameters, such as the geometry and internal variability of a hydrogeologic unit associated with a hydraulic-conductivity parameter. Field activities might include geologic and geophysical investigation and interpretation of the extent and thickness of the hydrogeologic unit. Relevance

of the proposed method to the second data type assumes a link between model parameter importance and flow-system feature importance. We recognize that the parameters identified as most important to the model predictions may not always correspond to the features of model construction that are most important to the model predictions, but it is expected that there will often be such a correspondence.

In the hydrologic literature, a number of procedures have been developed for improving model accuracy in the context of model predictions. One body of work focuses on collection of additional observations or targets used to calibrate a model, such as hydraulic heads, flows, and concentrations (e.g. Loaigica, 1989; Sun and Yeh, 1990; Wagner, 1995; Ely et al., 2000, Hill et al., 2001). Approaches more closely related to the work presented in this paper are those that address the collection of direct information about flow-system characteristics or about hydrogeologic property values, for the purpose of improving model predictions. These approaches can be divided into two broad groups. The first group includes methods for identifying important locations for additional aquifer property measurements (e.g. McLaughlin and Wood, 1988; McKinney and Loucks, 1992; and Sun and Yeh, 1992). In these studies, the simulated hydraulic-conductivity fields are estimated from point measurements by some variation of kriging. Inclusion of new hydraulic-conductivity measurements reduces the estimation variance of the kriged hydraulic-conductivity field, which in turn reduces prediction uncertainty.

Approaches in the second group are more closely related to the work presented in this paper. These methods evaluate model parameters in the context of model predictions, and have generally been applied to models in which a limited number of parameters are defined to represent a wide range of system characteristics on scales larger than that of a single model cell

or element. Most previous research on this topic uses techniques that consider the effects of both parameter uncertainty and prediction sensitivity on computed prediction uncertainty. An approach that has been applied to a wide range of hydrologic models is to rank the contribution of different model parameters to prediction uncertainty according to the relative size of certain terms of the first-order prediction uncertainty calculation (Walker, 1982; Melching et al., 1990; Indelman et al., 1996; and Hoybye, 1998). Alternatively, Monte Carlo simulation was used by Nichols and Freshley (1993) to conclude that a recharge parameter in an unsaturated flow model contributes most to uncertainty in predicted travel times. Hill et al. (1999) used composite scaled sensitivities, which measure the information provided by the observations about the parameters, together with prediction sensitivities to identify parameters most likely to contribute to prediction uncertainty. Levy et al. (1998) and Levy and Ludy (2000) used a Gauss-Hermite procedure to compute a measure of prediction sensitivity that implicitly considers parameter uncertainty, to assess the effects of different flow and transport model parameters on predictions of concentration and of wellhead protection areas.

In this paper, two methods are used to identify model parameters important to predictions. One method, prediction scaled sensitivities (PSS), is closely related to the approaches discussed above, and the other method, value of improved information, is a new technique. The PSS are similar to those used by Hill et al. (1999), but incorporate a different scaling, whereby information on parameter uncertainty is directly included in the calculated PSS. With this scaling, the PSS provide the same information contained in the terms of the first-order prediction uncertainty calculation that were used by Walker (1982), Melching et al. (1990), Indelman et al. (1996), and Hoybye (1998) to rank parameter contribution to prediction

uncertainty. The PSS are useful measures because conceptually they are fairly simple, and thus they can be interpreted in a straightforward manner.

A drawback of the PSS and of the related methods listed above is that they do not account for the effect of correlations between parameters. The correlation between a pair of parameters is a measure of the independence of the information provided about the parameters by the observations used for model calibration. Correlations near $|1.0|$ indicate that the calibration observations provide information towards estimating a combination of two parameter values, rather than the independent value of each parameter. These correlations are an important component of the total parameter uncertainty, and it is desirable for the information they contain to be included in measures of parameter importance to predictions.

Thus, we develop a new method, the value of improved information (VOII), that assesses the contribution of parameters to a prediction more completely than do PSS or other existing methods. The VOII approach takes advantage of the connection between parameter uncertainty, parameter correlation, and prediction uncertainty provided by the first-order equation for prediction uncertainty (e.g. Draper and Smith, 1998). The method calculates the reduction in prediction uncertainty that results from a reduction in the uncertainty of one or more parameters. The “value of information” concept was used by Reichard and Evans (1989) as a measure of the economic worth of ground-water monitoring for reducing the uncertainty in human exposure to contamination, and by Wagner (1999) as a measure of the reduced cost of ground-water management resulting from obtaining aquifer-state or aquifer-property measurements. In this work, the value of information concept is not used in an economic or ground-water management context, but rather as a measure of parameter importance to predictions. The term “value of

improved information” is used to distinguish potential new information about a parameter from available information about the parameter.

We next present the PSS and VOII methods and demonstrate their use for a steady-state, three-layer model of the Death Valley regional ground-water flow system (D’Agnese and others, 1997, 1999), located in southern Nevada and southeastern California (fig. 1). The flow model was calibrated using nonlinear regression. The predictions of interest are the simulated advective-transport paths from areas on the Nevada Test Site at which underground testing of nuclear devices has occurred.

METHODS

Prediction Scaled Sensitivities (PSS)

The scaled sensitivity of prediction z_ℓ to model parameter b_j is defined here as:

$$pss_{\ell j} = \left(\frac{\partial z_\ell}{\partial b_j} \right) \left(\frac{s_{b_j}}{100} \right) \left(\frac{1}{z_\ell} \right) \times 100 \quad (1)$$

where

z_ℓ is the ℓ^{th} predicted value;

b_j is the j^{th} parameter value of $\underline{b}$, the vector of NP parameter values;

NP is the number of defined model parameters;

$\frac{\partial z_\ell}{\partial b_j}$ is the sensitivity of prediction z_ℓ to parameter b_j ; and

s_{b_j} is the standard deviation of b_j .

The $pss_{\ell j}$ of equation (1) differs from the measure presented by Hill et al. (1999) and Hill (1998) in that the parameter standard deviation s_{b_j} is used for scaling, rather than the parameter value b_j .

With the scaling used here, $pss_{\ell j}$ approximately equal the percent change in predicted value z_ℓ caused by a change in parameter value b_j equal to one percent of its standard deviation.

Parameters with larger uncertainty and to which a given prediction is more sensitive will have larger values of $pss_{\ell j}$. Because of this relation, if the model represents the true system reasonably well, it is expected that improving model features associated with these parameters will result in a greater improvement in the accuracy of prediction z_ℓ than will model enhancements related to parameters with smaller $pss_{\ell j}$. Thus, parameters with larger $pss_{\ell j}$ are considered to be more important to prediction z_ℓ than are parameters with smaller $pss_{\ell j}$.

The interpretation of $pss_{\ell j}$ as the percent change in z_ℓ caused by a particular change in b_j is strictly true only if the model is linear. For linear models, the sensitivity $\partial z_\ell / \partial b_j$ is independent of the value of all parameters in $\underline{b}$. Commonly, simulation models are nonlinear, and for such models, $\partial z_\ell / \partial b_j$ is a function of $\underline{b}$. Using sensitivities to judge importance of parameters to predictions is reasonable for nonlinear models if $\partial z_\ell / \partial b_j$ is scaled such that it represents the change in predicted value caused by a small change in parameter value, and if the problem is linear enough that $\partial z_\ell / \partial b_j$ does not change radically for realistic values of $\underline{b}$. The quantity $s_{b_j} / 100$ that scales $\partial z_\ell / \partial b_j$ in equation (1) is expected to be small compared to b_j . If $s_{b_j} \gg b_j$, then, because of nonlinearity, the interpretation of $pss_{\ell j}$ as the percent change in z_ℓ caused by a one-percent change in s_{b_j} is not strictly true, but the measure can still be used to rank the relative importance of different parameters to prediction z_ℓ . An important advantage of scaling by s_{b_j} instead of by b_j , is that in some circumstances b_j equals zero, whereas s_{b_j} is unlikely to ever equal zero.

Value of Improved Information (VOII)

The VOII method is implemented by first computing prediction uncertainty using the calibrated model and existing independent information about parameter values, then recomputing prediction uncertainty under the assumption of reduced uncertainty in one or more parameter values.

Prediction Uncertainty

In this work, prediction uncertainty is quantified using prediction standard deviations calculated by a first-order linear statistical inference method (Dettinger and Wilson, 1981; Draper and Smith, 1998):

$$s_{z_\ell} = \left[(\underline{X}_Z \underline{C} \underline{X}_Z^T)_{\ell\ell} \right]^{1/2} \quad (2)$$

where

s_{z_ℓ} is the standard deviation of prediction z_ℓ ;

$\underline{X}_Z$ is the NZ by NP matrix of sensitivities of the predictions z_ℓ with respect to the model parameters b_j , with elements equal to $\partial z_\ell / \partial b_j$, calculated in this work using the sensitivity-equation method of MODFLOW-2000 (Hill et al., 2000);

NZ is the number of predictions;

NP is the number of defined model parameters;

$\underline{C}$ is a symmetric, NP by NP square parameter variance-covariance matrix;

T indicates the transpose of the matrix.

Matrix $\underline{C}$ is computed as:

$$\underline{C} = s^2 (\underline{X}^T \underline{\omega} \underline{X})^{-1} \quad (3)$$

where

s^2 is the calculated error variance from the calibrated model;

$$\underline{X} = \begin{bmatrix} \underline{X}_Y \\ \underline{I} \end{bmatrix}; \quad (4)$$

$$\underline{\omega} = \begin{bmatrix} \underline{V} & 0 \\ 0 & \underline{U} \end{bmatrix}; \quad (5)$$

$\underline{X}_Y$ is the ND by NP matrix of sensitivities of the simulated equivalents (y_i) of the ND calibration observations with respect to the NP model parameters, with elements equal to $\partial y_i / \partial b_j$, calculated in this work using the sensitivity-equation method of MODFLOW-2000 (Hill et al., 2000);

ND is the number of observations used in the calibration;

$\underline{I}$ is the NP by NP identity matrix;

$\underline{V}$ is the ND by ND matrix of weights on calibration observations, assumed to be diagonal here; and

$\underline{U}$ is the NP by NP matrix of weights on prior values for parameters, assumed to be diagonal here.

The prediction standard deviation s_{z_ℓ} is a function of (1) the uncertainty and correlation of all defined model parameters, as represented by the parameter variance-covariance matrix $\underline{C}$, and (2) the sensitivities of the predictions to these parameters. In calculating $\underline{C}$, the weights in $\underline{U}$ generally equal zero for parameters for which the calibration observations, such as measurements of hydraulic head and flow in a ground-water flow model, supply abundant information. For parameters supported better by independent information than by the calibration observations, non-zero prior weights should be specified in $\underline{U}$. These weights reflect the uncertainty in the independent information. By specifying prior weights in this manner, the variances for these parameters calculated using equation (3) reflect their actual level of uncertainty and correlation,

and the prediction uncertainty calculated using equation (2) reflects these realistic parameter uncertainties and correlations. The VOII method does not include performing regression with this prior imposed on these parameters; it is expected that doing so would result in estimates of these parameters that are very close to their prior values.

Equation 2 only propagates parameter value uncertainty to prediction uncertainty. Uncertainty in the model representation of the simulated system is accounted for only in the s^2 term, and thus is not explicitly considered through the sensitivities. However, in this work, the computed prediction standard deviations are not used to draw any conclusions about the magnitude of prediction uncertainty. Rather, as shown below, they are used to rank parameter importance by considering the reduction in prediction uncertainty that results from obtaining new information about a model parameter. As with PSS, equation (2) can be used as a basis for judging parameter importance if the model reasonably represents the true system and is sufficiently linear.

Implementing Improved Information

The prediction standard deviation produced with improved information on one or more parameters is calculated using a modified form of equation (2):

$$s_{z_\ell(\tilde{\underline{b}})} = \left[(\underline{X}_Z \underline{C}(\tilde{\underline{b}}) \underline{X}_Z^T)_{\ell\ell} \right]^{1/2} \quad (6)$$

where

$\tilde{\underline{b}}$ is a vector that identifies parameters with improved information;

$s_{z_\ell(\tilde{\underline{b}})}$ is the standard deviation of z_ℓ , calculated with improved information on parameters in $\tilde{\underline{b}}$;

and

$\underline{C}(\tilde{\underline{b}})$ is the symmetric, square NP by NP parameter variance-covariance matrix calculated with improved information on parameters listed in $\tilde{\underline{b}}$:

$$\underline{C}(\tilde{\underline{b}}) = s^2 (\underline{X}^T \underline{\omega}(\tilde{\underline{b}}) \underline{X})^{-1} \quad (7)$$

where

s^2 is the same as in equation (3);

$$\underline{\omega}(\tilde{\underline{b}}) = \begin{bmatrix} V & 0 \\ 0 & \underline{U}(\tilde{\underline{b}}) \end{bmatrix} \quad (8)$$

and

$\underline{U}(\tilde{\underline{b}})$ is a diagonal NP by NP matrix of weights on prior information, in which the weights for parameters in $\tilde{\underline{b}}$ are larger than their corresponding weights in $\underline{U}$, and the weights for all other parameters are equal to their values in $\underline{U}$.

Improved information on parameters is implemented by specifying larger prior weights.

Conceptually, a larger weight on a prior parameter value represents the increased certainty in the prior value that might result from collection of additional field data. With this specification of prior, the variances of parameters that have improved information are smaller in $\underline{C}(\tilde{\underline{b}})$ than in $\underline{C}$.

Because of parameter correlations, parameters that are not included in $\tilde{\underline{b}}$, but that are correlated with parameters in $\tilde{\underline{b}}$, will also tend to have smaller variances in $\underline{C}(\tilde{\underline{b}})$ compared to those in $\underline{C}$, and covariance terms of $\underline{C}(\tilde{\underline{b}})$ can differ from those in $\underline{C}$. The effect of parameter correlations is discussed in more detail below. Primarily because of the reductions in parameter variances,

$s_{z_\ell}(\tilde{\underline{b}})$ will generally be smaller than s_{z_ℓ} .

The scaled difference between $s_{z_\ell}(\tilde{\underline{b}})$ and s_{z_ℓ} is used as a measure of the value of improved information:

$$voii_{\ell}(\tilde{\underline{b}}) = 100 \times \left(1 - \frac{s_{z_\ell}(\tilde{\underline{b}})}{s_{z_\ell}} \right) \quad (9)$$

where $voii_{\ell}(\tilde{\underline{b}})$ is the percent reduction in the standard deviation of prediction z_{ℓ} that results from having improved information on parameters in $\tilde{\underline{b}}$. The statistic $voii_{\ell}(\tilde{\underline{b}})$ depends only on weights and sensitivities because s^2 cancels out in the division of equation (9). To rank the importance of individual parameters to prediction z_{ℓ} , $voii_{\ell}(\tilde{\underline{b}})$ is calculated NP times, each time with improved information on one parameter. During the j^{th} calculation, vector $\tilde{\underline{b}}$ contains the single parameter b_j . The parameter associated with the largest value of $voii_{\ell}(\tilde{\underline{b}})$ ranks as most important to prediction z_{ℓ} .

To implement improved information on each model parameter in a consistent manner, we use a criterion that is based on the calculated parameter standard deviations. In the absence of improved information, the standard deviation of parameter b_j is:

$$s_{b_j} = [(\underline{C})_{jj}]^{1/2} \quad (10)$$

where $(\underline{C})_{jj}$ is the variance of b_j , and is the j^{th} diagonal element of $\underline{C}$ (equation 3). The standard deviation of b_j calculated with improved information is:

$$s_{b_j}(\tilde{\underline{b}}) = [(\underline{C}(\tilde{\underline{b}}))_{jj}]^{1/2} \quad (11)$$

To specify improved information for parameter b_j , we set $\tilde{\underline{b}} = [b_j]$ and stipulate that $s_{b_j}(\tilde{\underline{b}})$ be a required percentage smaller than s_{b_j} . A trial-and-error procedure is then used to determine the weight on the prior for parameter b_j that produces the required reduction in s_{b_j} . In this work, a 10 percent reduction is used for all VOII calculations. Specifying a prior weight that achieves this reduction is intended to reflect a situation in which improved, but imperfect, field data has been obtained about a parameter value or a flow-system feature.

Effect of Parameter Correlations on Identifying Sets of Important Parameters

The effect of parameter correlations can complicate the assessment of parameters important to the predictions by the VOII method. The correlation between two parameters b_i and b_j , calculated as $(\underline{C})_{ij} / [(\underline{C})_{ii}]^{1/2} [(\underline{C})_{jj}]^{1/2}$, is a measure of the independence of the information provided about b_i and b_j by the available calibration observations. Because of these correlations, specifying improved information for an individual parameter b_j will not only result in a value of $(\underline{C}_{(\tilde{b})})_{jj}$ that is smaller than $(\underline{C})_{jj}$, but may also result in other terms of $\underline{C}_{(\tilde{b})}$ that are different from the corresponding terms in $\underline{C}$. In particular, when improved information is specified on b_j , as the absolute value of the correlation between parameters b_j and b_i increases, $(\underline{C}_{(\tilde{b})})_{ii}$ becomes increasingly smaller than $(\underline{C})_{ii}$.

This effect of the correlations on calculated parameter variances can strongly influence which parameters are important to a prediction. As shown in equations (2) and (6), prediction uncertainty is a function of the product of parameter uncertainty and prediction sensitivities. Thus, if prediction z_r is highly sensitive to parameter b_j , then reducing the uncertainty of b_j will likely reduce the uncertainty of prediction z_r . If parameter b_i is highly correlated with parameter b_j , then specifying improved information on b_i will reduce the uncertainty of b_j . In this situation, improved information on b_i is also likely to reduce the uncertainty of prediction z_r , even if prediction z_r is not highly sensitive to parameter b_i .

Parameter correlations can produce situations in which the set of MP parameters (where $1 < MP < NP$) with the highest individual $voii_{\ell(\tilde{b})}$ values is not identical to the set of MP parameters that are most important when improved information on multiple parameters is considered. Thus, it is important to consider the effect of improved information on multiple

parameters. To determine a set of *MP* parameters that is most important to prediction z_i by the VOII method, the following procedure is used:

- (1) Form all possible sets of *MP* parameters from the set of *NP* defined parameters.
- (2) For each set of *MP* parameters, specify improved information on each parameter in the set ($\tilde{b}$ contains *MP* parameters), and calculate $voii_{\ell}(\tilde{b})$.
- (3) The largest value of $voii_{\ell}(\tilde{b})$ is associated with the set of *MP* parameters that is most important to prediction z_i .

USING ADVECTIVE-TRANSPORT PREDICTIONS TO GUIDE HYDROGEOLOGIC DATA COLLECTION FOR A MODEL OF THE DEATH VALLEY REGIONAL FLOW SYSTEM

To demonstrate and compare the PSS and VOII methods, the three-layer model of the Death Valley regional flow system (DVRFS) is used (D'Agnese et al., 1997, 1999). Although a refined model is under construction, this preliminary model of the flow system is sufficiently complicated to demonstrate the strengths and weaknesses of the methods considered.

The Death Valley Regional Ground-Water Flow System and The Three-Layer Model

From the 1960's until 1992, underground testing of nuclear devices was conducted at the Nevada Test Site (NTS) in southern Nevada, USA (Fig. 1). The majority of the tests occurred at locations on Yucca Flat and Pahute Mesa. In addition, Yucca Mountain, located near the NTS, is being studied as a potential site for a high-level radioactive waste repository. Possible transport from the underground test sites and from Yucca Mountain is of concern, prompting the U.S. Department of Energy to investigate the underlying DVRFS.

The DVRFS encompasses nearly 80,000 km² and extends from west of Las Vegas, Nevada, to Death Valley National Park, California. Ground-water levels in the region range from

more than 1,500 m above to 86 m below sea level. The regional hydrology is the result of both arid climatic conditions and complex geology. Ground-water flow generally is dominated by interbasin flow and can be conceptualized as having two main components: a series of relatively shallow and localized flow paths that are superimposed on deeper regional flow paths (Figure 1). A significant component of the regional flow is through a thick sequence of Paleozoic carbonate rock that generally occurs at depth. Structural features, such as faults and fractures, probably control regional flow. Water recharges the system mostly as infiltration of precipitation in highlands such as the Spring Mountains and Pahute Mesa. Water discharges from the system as evapotranspiration by plants, evaporation from playa surfaces, and flow to springs and wells. The flow system is hydrogeologically complex and very heterogeneous, with possible local values of hydraulic conductivity ranging over 14 orders of magnitude and hydraulic gradients ranging from nearly zero to more than 2 percent.

The DVRFS was evaluated by D'Agnese and others (1997, 1999) using a three-dimensional, steady-state, finite-difference flow model, which is used in this work. The flow-model grid has 163 rows, 153 columns, and 3 layers. The grid cells are oriented north-south and are of uniform size, with side dimensions of 1,500 m. The three layers span depths below the estimated water table of 0-500 m, 500-1,250 m, and 1,250-2,750 m. In the model, 23 parameters are defined to represent physical quantities such as hydraulic conductivity, vertical anisotropy, recharge, evapotranspiration, the hydraulic connection of the springs to subsurface sources, and pumpage (table 1). Zonation is used to represent the hydraulic conductivity (fig. 2) and areal recharge (fig. 3) distributions. Four of the hydraulic-conductivity zones each represent a variety of rock types thought to have high (zone K1), moderate (K2), low (K3), and very low (K4) hydraulic-conductivity values. The remaining five hydraulic-conductivity zones represent

specific hydrogeologic features located in model layers 2 and 3. Recharge zones represent areas of zero (zone Rch0), low (Rch1), moderate (Rch2), and high (Rch3) recharge.

The DVRFS model was calibrated by nonlinear regression using the inverse ground-water flow model MODFLOWP (Hill, 1992); for the work presented in this paper, the model was converted to MODFLOW-2000 (Harbaugh, et. al., 2000; Hill et. al., 2000). During model calibration, 501 hydraulic-head observations and 16 spring-flow observations were used, and nine of the 23 parameter values were estimated. The remaining 14 parameter values were specified because these parameters were generally not well supported by the observations used in the regression (D'Agnese et al., 1999, figure 12). Evaluation of the calibrated model (D'Agnese et al., 1997, p. 117) indicated that the model reasonably represents the flow system and that all parameter estimates are within expected ranges, but that there is some evidence of model bias.

In the analysis of prediction uncertainty, it is important to include the uncertainty of all defined model parameters. This was achieved by including all 23 of the defined parameters in the calculations for both the PSS and VOII methods. In implementing the VOII method, prior information was used for parameters not estimated during calibration, as discussed above in the Prediction Uncertainty section. Prior weights were assigned on the basis of the available, often scarce, information about the quantities involved. The parameter standard deviations used to compute these weights are given in Table 1.

Advective-Transport Predictions

The predictions of greatest interest in the DVRFS model are the transport of existing or potential contaminants that originate at the water table directly beneath the underground testing areas and Yucca Mountain. In this work, advective transport is used as a surrogate for contaminant transport because advection is the transport process most dominated by the regional-

scale processes represented by the three-layer DVRFS model. Because of the large cell sizes in the regional model it is impossible to represent accurately small-scale features that affect other transport processes such as hydrodynamic dispersion or diffusion of solute into the rock matrix.

We consider the transport paths from one representative underground testing site on Yucca Flat and one representative site on Pahute Mesa (fig. 1). The advective paths originating at these sites are calculated using a particle-tracking method that differs slightly (Anderman and Hill, 2001) from the method used in MODPATH (Pollock, 1994). We consider the first 10,500 m of advective transport from the locations of interest, which is the distance across about 7 finite-difference grid cells. This distance is long enough to span several cells and thus demonstrate the PSS and VOII methods, but short enough to avoid large discrepancies between predicted and true paths, which are likely to increase as the path length increases. To compute the particle trajectory, total particle displacement is decomposed into displacements in the three spatial dimensions of the DVRFS model: east-west (E-W), north-south (N-S), and vertical. Thus, at any point along a path, there are three advective-transport predictions z_i : the total distance traveled in the E-W, N-S, and vertical directions. The 10,500 m predicted advective paths from the underground testing sites on Yucca Flat and Pahute Mesa are shown in Figures 2 and 3. The PSS and VOII methods are applied to the last point on each path.

As indicated above, use of the PSS and VOII methods to evaluate parameter importance is appropriate if the model is sufficiently linear with respect to the prediction sensitivities. To test the linearity, sensitivities of predicted advective transport at the Yucca Flat and Pahute Mesa sites were computed for parameter values that differ by ten percent of s_{b_j} (equation 10) from those shown in Table 1. The pss_{ij} calculated at the alternative parameter values mostly differed by no more than a few tens of percent from those calculated using the parameter values of Table

1. Most importantly, the relative magnitudes of the prediction sensitivities to the different parameters are generally the same when calculated at the alternative values. This result suggests that the DVRFS model appears to be adequately linear so that use of the PSS and VOII methods is appropriate.

Prediction Scaled Sensitivities

The PSS for the Yucca Flat site (fig. 4a,b) suggest that K5 (very high K of NE/SW structural zones) and Rch0 (zero recharge) rank as the most important parameters to the 10,500m advective-transport distance. In both the E-W and N-S directions, K5 has the largest pss_{ij} . Increasing the value of K5 by one percent of its standard deviation would change the distance traveled in the E-W direction by about 0.5 percent and the distance traveled in the N-S direction by about 0.7 percent (fig. 4a). Advective transport in the E-W and N-S directions is also fairly sensitive to K1 (high K) and K3 (low K), compared to the sensitivities to most other model parameters. In the vertical direction, advective transport is significantly more sensitive to Rch0 than to any other model parameter (fig. 4b). Increasing Rch0 by 1 percent of its standard deviation would change the distance traveled in the vertical direction by about 13 percent.

The PSS for the Pahute Mesa site show that Rch2 (moderate recharge), K2 (moderate K), and Rch1 (low recharge) rank as most important to the advective path in, respectively, the E-W, N-S, and vertical directions (fig. 4c). In the E-W and N-S directions, several other parameters also have relatively large values of pss_{ij} , whereas in the vertical direction, the pss_{ij} for Rch1 and Rch2 are significantly larger than those for all other model parameters.

Value of Improved Information

Value of Improved Information on Individual Parameters

Application of the VOII method for individual parameters to the Yucca Flat site shows that reducing the standard deviation of K1 (high K) by 10 percent produces the greatest decrease in the uncertainty of both the E-W and the N-S transport components (fig. 5a). Reducing the uncertainty of K2 (moderate K), K3 (low K), or Rch3 (high recharge) also decreases prediction uncertainty in the E-W and N-S directions substantially more than does reducing the uncertainty of most other parameters. For the vertical component of transport, the VOII results suggest that Rch0 (zero recharge) is the only important parameter (fig. 5b). Reducing its standard deviation by 10 percent produces a 10 percent reduction in the prediction standard deviation in this direction. Decreasing any other parameter standard deviation by 10 percent reduces the prediction uncertainty by less than 0.6 percent.

The VOII results for the Pahute Mesa path (fig. 5c) indicate that K3 and K2 rank as most important to the components of advective transport in, respectively, the E-W and N-S directions. Reducing the standard deviation of either of these parameters by 10 percent decreases prediction uncertainty by 9 to 10 percent in the applicable transport direction. For the vertical direction, Rch1 (low recharge) is much more important to predicted advective transport than any other parameter, though it is not as dominant as Rch0 is for vertical transport from the Yucca Flat site.

Effect of Correlations on Results for Individual Parameters

Comparison of the results in figures 4 and 5 clearly shows that the parameters identified as important to a prediction can differ among the PSS and VOII methods. For example, the pss_{ij} indicate that predicted advective transport from the Yucca Flat site in the E-W and N-S directions is relatively insensitive to Rch3 (fig. 4a). However, the $voii_{\ell(\tilde{b})}$ indicate that Rch3 is

important to advective transport in these directions (fig. 5a). These different rankings by the two methods are an example of how parameter correlations affect the VOII results.

The explanation of this effect is facilitated by understanding the details of the computation of s_{z_ℓ} (and, analogously, $s_{z_\ell}(\tilde{b})$). The matrix multiplication for calculating s_{z_ℓ}

(equation 2) expands to a summation of terms of the form $\frac{\partial z_\ell}{\partial b_j} C(b_j, b_i) \frac{\partial z_\ell}{\partial b_i}$. If $j=i$, $C(b_j, b_j)$ is

the variance of b_j , and if $j \neq i$, $C(b_j, b_i)$ is the covariance of parameters b_j and b_i . In the following

discussion, the term $\frac{\partial z_\ell}{\partial b_j} C(b_j, b_j) \frac{\partial z_\ell}{\partial b_j}$ is referred to as the variance term for parameter b_j , and

the term $\frac{\partial z_\ell}{\partial b_j} C(b_j, b_i) \frac{\partial z_\ell}{\partial b_i}$ is referred to as the covariance term for parameters b_j and b_i .

For the Yucca Flat path, the difference in the ranking of Rch3 by the PSS and VOII methods can be explained by the large correlations between Rch3 and K1 and between Rch3 and K3 (table 2), in combination with the relatively large sensitivities of advective transport in the E-W and N-S directions to K1 and K3 (fig. 4a). Because of the large parameter correlations, specifying improved information on Rch3 will not only reduce the calculated variance of Rch3, but will also significantly reduce the variances of K1 and K3. Thus, the variance terms for K1 and K3 in $s_{z_\ell}(\tilde{b})$ are much smaller than the corresponding terms of s_{z_ℓ} ; these differences cause the large reductions in E-W and N-S prediction uncertainty when improved information is specified for Rch3.

For the Pahute Mesa path, parameters such as ETM (maximum evapotranspiration factor) and Q1 (pumpage multiplier) have very small pss_{ij} in the E-W and N-S directions (fig. 4c), yet rank as relatively important by the VOII method (fig. 5c). Parameters ETM and Q1 are each

highly correlated with K1, K2, K3, and Rch3 (table 2), which have relatively large pss_{ij} for the E-W and/or the N-S component of advective transport (fig. 4c). Thus, reducing the uncertainty of ETM or Q1 decreases the variance terms for K1, K2, K3, and Rch3, which results in the large values of $voii_{\ell(\tilde{b})}$ for parameters ETM and Q1.

The effects of parameter correlations on the VOII results have an important consequence regarding the cost-effectiveness of hydrogeologic data collection. For example, the preceding discussion illustrates that primarily because of the correlation between Rch3 and K1 or K3, reducing the uncertainty of Rch3 produces a significant reduction in the uncertainty of the predicted E-W and N-S transport components at the Yucca Flat path. Thus, for purposes of improving predicted advective transport at the Yucca Flat site, field data could be collected about Rch3 instead of about K1 or K3. Collecting data about a recharge rate or the geographic extent of a recharge zone is likely to be less expensive than collecting subsurface information about a hydraulic-conductivity value or hydrogeologic unit.

Improved Information on Multiple Parameters

The VOII method is also applied to determine the sets of two or three parameters that together are most important to the advective-transport predictions. Specifying improved information on all possible combinations of two DVRFS model parameters (fig. 6a) shows that improving both K1 and Rch3 produces the largest decrease in prediction uncertainty in the E-W direction at the Yucca Flat site. In the N-S direction, improving K1 and K5 together yields the largest uncertainty reduction. By the analysis of individual parameters, K1 and Rch3 rank as most important in both the E-W and N-S directions (figure 5a). Thus, in the N-S direction, the two parameters that together rank highest are not identical to the two that individually rank highest. When three parameters are considered, the combination of K1, K3, and K5 produce the

largest reduction in prediction uncertainty in the E-W direction, and K1, K5, and Rch3 rank highest in the N-S direction (fig. 6a). There is one parameter within each of these sets (K3 and Rch3) that is not in the set of three highest-ranking parameters resulting from application of the method to individual parameters (fig. 5a).

In both the E-W and N-S directions, the value of $voii_{\ell(\tilde{b})}$ for improved information on two parameters is substantially larger than that for only one parameter, and the value of $voii_{\ell(\tilde{b})}$ for three parameters is much larger than that for two parameters (fig. 6a). These results suggest that it would be beneficial to obtain information about all three parameters identified as most important to advective transport in these directions. In contrast, in the vertical direction, improving two or three parameters produces only a minor increase in $voii_{\ell(\tilde{b})}$, compared to the value calculated when only one parameter is improved. This result indicates that a point of diminishing return is reached, in terms of the reduction in prediction uncertainty produced by improved information on multiple parameters. The results for this transport component suggest that improved information on Rch0 alone should be collected, and that very little benefit, from the perspective of improving the advective-transport predictions, would be gained by obtaining additional information about K4 (very low K) or Aniv3 (vertical anisotropy).

For the Pahute Mesa site, simultaneous improvement of all possible combinations of two parameters shows that the parameter pairs most important to the E-W, N-S, and vertical components of advective transport are, respectively, K1-K3, K2-Rch3, and Rch1-Rch3 (fig. 6b). For all transport directions, improved information on three parameters produces a significantly larger value of $voii_{\ell(\tilde{b})}$ than that for two parameters. When the results for all three components of transport are considered, the combined set of most important parameters identified by

considering improved information on three parameters is the same as that identified by considering improved information on two parameters. In practice, use of these results depends on whether transport in all or only selected directions is considered to be important.

Summary of Parameters Identified as Important to Advective-Transport Predictions

Table 3 summarizes the parameters that are identified by the PSS and VOII methods as important to predicted advective transport from the Yucca Flat and Pahute Mesa sites. The PSS results emphasize parameters to which the predictions are most sensitive, while the VOII results include the important effects of parameter correlations. Both these criteria are valuable for assessing parameter importance, and thus parameters that rank highly by both measures are included in the final set considered most important to a prediction. The PSS results are compiled using the three highest-ranking parameters in each direction, except where only one or two parameters have significantly greater pss_{ij} than all other parameters. The VOII results for 1, 2, and 3 parameters are compiled from, respectively, the highest ranking 1, 2, or 3 parameters in each direction, except for the vertical transport component at the Yucca Flat site, where improved information on 2 or 3 parameters produces results similar to those for individual parameters (fig. 6a).

DISCUSSION

Application of the PSS and VOII methods to the DVRFS model suggests that the parameters most important to the Yucca Flat and Pahute Mesa predicted advective-transport paths include four of nine hydraulic-conductivity parameters (K1, K2, K3, and K5) and all four recharge parameters (Rch0, Rch1, Rch2, and Rch3) (Table 3). We next evaluate these results in the context of two important issues: (1) the relation of the identified parameters to the predicted paths, and (2) the use of these results to guide hydrogeologic data collection.

Relation of Identified Important Parameters and Predicted Advective-Transport Paths

It is important to consider how the VOII and PSS results relate to the simulated flow-system dynamics. As a first step, consider the location of the identified important parameters within the DVRFS model, in relation to the advective paths to which they are important. The Yucca Flat path remains in hydraulic-conductivity zone K1 (high K) during the first 10,500 m of travel and recharge zone Rch0 (zero recharge) overlies all cells along the path (figs. 2 and 3). Thus, it is not surprising that K1 and Rch0 are among the most important parameters to advective transport (table 3). In fact, the PSS and VOII results both suggest that Rch0 is the sole parameter important to the vertical advective-transport component (figs. 4b, 5b, and 6a). A positive value of Rch0 is the only influence that can cause the path to move below the water table, by the particle tracking algorithm used (Anderman and Hill, 2001). Substantial evidence supports the Rch0 value of 0.0 in many areas represented by the three-layer DVRFS model, including Yucca Flat, as evidenced by the small standard deviation used to compute the weight for the prior information on Rch0 (Table 1). The PSS and VOII results emphasize the importance of this characteristic of the system to predicted advective transport at this site.

Parameters K5 (very high K of NE/SW structural zones), Rch3 (high recharge), and K3 (low K) also rank as important to the predicted Yucca Flat path (table 3). These parameters represent aspects of the flow system that lie outside the path trajectory. Parameter K5, which has the largest pss_{ij} in the E-W and N-S directions (fig. 4a), is associated with the hydraulic-conductivity zone located in model layer 2 directly beneath the path. This highly transmissive feature has a large influence on simulated flow directions in all layers beneath Yucca Flat. Recharge zone Rch3 is located about 23,000 m (about 15 grid cell lengths) upgradient of the path origin (fig. 3). Zones Rch1 and Rch2 lie closer to the path, but they are not identified among the most important parameters to predicted advective transport. The greater importance of Rch3 is

likely because its recharge rate (expressed as percent of precipitation) is larger than that of Rch1 or Rch2 (Table 1), and thus it is a more significant stress in the simulated flow system. The hydrogeologic reason for the importance of K3 is somewhat less obvious; large patches of zone K3 are located in layer 1 about 8,500 to 10,000 m to the sides of the Yucca Flat path (fig. 2).

The most important parameters to advective transport from the Pahute Mesa site (table 3) are mostly associated with hydraulic-conductivity or recharge zones along the path. This advective path lies in hydraulic-conductivity zones K2 (moderate K) and K3 (low K) (fig. 2), and in a short segment of zone K1 (high K) in layer 2. Zones Rch1 (low recharge) and Rch2 (moderate recharge) overlie most of the path trajectory (fig. 3). Rch3 (high recharge) is the only identified important parameter that lies outside of the path trajectory, and is located about 9,000 m (6 grid cell lengths) upgradient of the path (fig. 3). As was discussed for the Yucca Flat path, the importance of this parameter is likely because of its high recharge rate.

Using the Results to Guide Hydrogeologic Data Collection

It is also important to assess the PSS and VOII results in the context of the overall goal of this work, which is to guide the collection of hydrogeologic data for reducing prediction uncertainty (increasing prediction reliability). In practice, there are several steps involved in achieving improved prediction reliability as a result of identifying parameters most important to the predictions. First, field studies are focused on collecting data about aspects of the groundwater flow system that are represented by the parameters identified as most important. The new field data are incorporated into the model, and the updated model is recalibrated using regression methods. Finally, updated model predictions are made. We next examine some details of how field characterization might be translated into improved prediction reliability.

Collecting Hydrogeologic Data about the Flow-System Representation

One approach to field characterization is to collect information about the representation (e.g. physical structure, geometry, location, etc.) of a flow-system feature associated with a model parameter identified as important to a prediction. For example, consider field characterization of hydrogeologic units associated with the hydraulic-conductivity parameters identified as important to the DVRFS model advective-transport predictions. Field work might involve detailed geologic or geophysical investigation of these units to better delineate their boundaries or their internal variation. This effort would then lead to modifying the model representation of these units, followed by recalibration of the updated model. The updated model is expected to be more accurate by virtue of the improved representation of the hydrogeologic units. Furthermore, because the hydraulic-head and flow data used to calibrate the DVRFS model support estimation of all hydraulic-conductivity parameters important to the predictions (tables 1 and 3), the estimates of these parameters are also expected to be more accurate. Because of the increased accuracy of model features related to the hydraulic-conductivity parameters identified as important to the predictions, it is expected that the predictions will be more reliable.

However, the prediction uncertainty calculated by equation (2), which is a function of parameter uncertainty and prediction sensitivities, will not necessarily decrease. Parameter uncertainty is a function of the calibration data sensitivities $\underline{X}_Y$ and the calculated error variance s^2 , which represents model fit (eqn. 3). The sensitivities may change due to the different representation of the hydrogeologic units, but they will not necessarily be smaller. Because of improved model accuracy, the model fit may improve, but a decrease in s^2 is not guaranteed. Therefore, field characterization to improve the model representation of a flow-system feature is likely to result in more accurate predictions, but may not improve the quantitative measures of prediction reliability considered in this work.

Collecting Hydrogeologic Data about a Parameter Value

Alternatively, field characterization can focus on obtaining information about a model parameter value, instead of about the representation of the associated flow-system feature. For the hydraulic-conductivity parameters identified as important to the DVRFS advective-transport predictions, this approach might lead to conducting aquifer tests to obtain field estimates of hydraulic conductivities. Because the calibration observations support estimation of these parameters, the field estimates can be used as independent checks on the reasonableness of the optimal parameter estimates obtained during calibration (Hill, 1998). If the optimal estimates are consistent with the new aquifer test data, then it is expected that the confidence in these estimates will increase. However, there will be no quantitative change in the parameter or prediction uncertainty. If any optimal parameter estimates are unreasonable compared to the aquifer test data, then the conceptual model needs to be re-evaluated, possibly leading to additional field characterization of the flow system. As discussed above, incorporating these data into the model is expected to improve model accuracy, leading to more reliable predictions, but may not reduce the calculated prediction standard deviations.

Additional data about a parameter value might also be used when the calibration observations do not support estimation of the parameter. For the DVRFS model, Rch0 and Rch1 are identified as important to the advective-transport predictions but were not estimated during model calibration (tables 1 and 3). Thus, new data such as independent estimates of these recharge rates would best be used to improve the specified value of the parameter in the model, followed by model recalibration to estimate other parameters. Because of the improved specified value, the recalibrated model and the predictions may be more accurate.

New parameter value information can also be used in the calculation of prediction uncertainty by equation (2). As discussed in the Methods section, prior information on parameters and associated weighting can be specified during this calculation, so that realistic parameter uncertainty is propagated to prediction uncertainty. New field data about a parameter value can be used to increase the weight associated with the prior information for the parameter, which will always quantitatively decrease prediction uncertainty.

CONCLUSIONS

In this paper, methods were developed for identifying model parameters that are most important to model predictions. These methods include prediction scaled sensitivities (PSS), which as scaled here include the effects of uncertainty on individual parameters, and value of improved information (VOII), which includes the effects of parameter correlation in addition to individual parameter uncertainty and prediction sensitivity. Applying these methods can help direct field work towards collection of hydrogeologic data that will be beneficial to improving prediction reliability. Given that field characterization of hydrogeologic conditions can be costly and time consuming, application of these methods to ground-water systems can facilitate making the best use of limited resources available for field investigations. The effects of parameter correlations on the VOII results can be used to further improve the cost-effectiveness of data collection.

The PSS and VOII methods were applied to a three-layer model of the Death Valley regional ground-water flow system (DVRFS), to identify a set of model parameters that are most important to predicted advective-transport paths from beneath Yucca Flat and Pahute Mesa, locations where underground nuclear testing occurred. The two methods identify similar, but not identical, sets of parameters that rank as most important to each predicted path. Because the methods emphasize somewhat different criteria for determining parameter importance,

parameters that rank highly by both methods are included in the final set of parameters that are considered most important to the two predicted paths. For the Yucca Flat path, this set includes parameters associated with the hydraulic-conductivity and recharge zones that lie along the path, as well as parameters associated with flow-system features that lie outside the path trajectory. For the Pahute Mesa path, most of the most important parameters lie along the path.

A key premise of this work is that identification of model parameters important to the predictions can ultimately lead to an increase in prediction reliability, through field characterization of the flow-system features associated with the identified parameters and inclusion of the new data in the model. An evaluation of how this might be achieved showed that the improvement in prediction reliability may be qualitative. This qualitative improvement results from an expected increase in model accuracy resulting from improved representation of model features on the basis of the new field information, followed by recalibration of the updated model. The qualitative nature of the improvement does not diminish the benefit of the additional data. Rather, it reflects the fact that equation (2) used in this work for calculating prediction uncertainty explicitly considers only uncertainty in parameter values, and thus reducing the uncertainty in the representation of a flow-system feature cannot be quantitatively translated to a decrease in prediction uncertainty.

It is important to recognize that the utility and validity of the PSS and VOII methods, and of their use for guiding hydrogeologic data collection, depend on the validity of the model to which the methods are applied. In the model of the hydrogeologically complex DVRFS, the representation of flow-system features is obviously somewhat uncertain. However, the sophisticated and consistent use of geologic and hydrogeologic information in the development of this model, together with a thorough evaluation which concluded that the model reasonably

represents the flow system (D'Agnese et al., 1997), lends credence to the results obtained from application of the PSS and VOII methods.

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Table 1. Parameter data for the three-layer DVRFS model. Parameter names in bold indicate parameters estimated by the regression procedure used to calibrate the model (D'Agnese et. al., 1997; 1999).

Parameter name	Units	Description	Parameter value	Standard deviation used to compute prior weight ¹
K1	m/d	High hydraulic conductivity	0.275	--
K2	m/d	Moderate hydraulic conductivity	0.443×10^{-1}	--
K3	m/d	Low hydraulic conductivity	0.562×10^{-2}	--
K4	m/d	Very low hydraulic conductivity	0.856×10^{-4}	--
K5	m/d	Hydraulic conductivity of NE/SW trending structural zones (very high hydraulic conductivity)	21.2	--
K6	m/d	Hydraulic conductivity of Eleana Formation	1.0×10^{-6}	2.3
K7	m/d	Hydraulic conductivity of NE/SW trending faults	1.0×10^{-4}	2.3
K8	m/d	Hydraulic conductivity of Central Desert Range	0.065	2.3
K9	m/d	Hydraulic conductivity of South Funeral Mountains	0.159	--
ANIV1	--	Vertical anisotropy of model layers 1 and 2	1	1.2
ANIV3	--	Vertical anisotropy of model layer 3	164	--
RCH0	percent of precipitation	Area of no recharge potential	0	0.0025
RCH1	percent of precipitation	Area of low recharge potential	1	0.005
RCH2	percent of precipitation	Area of moderate recharge potential	3.02	--
RCH3	percent of precipitation	Area of high recharge potential	22.7	--
ETM	multiplier	Maximum evapotranspiration rate factor	1	0.375
GHBa	m ² /d	Spring conductance for Ash Meadows	100	1.15
GHBg	m ² /d	Spring conductance for Grapevine Springs	11	0.98
GHB0	m ² /d	Spring conductance for Oasis Valley	2	0.58
GHBf	m ² /d	Spring conductance for Furnace Creek	5	0.58
GHBt	m ² /d	Spring conductance for Tecopa	.1	1.15
Q1	--	Ground-water pumpage multiplier for Pahrump Valley	1	0.125
Q2	--	Ground-water pumpage multiplier for locations outside Pahrump Valley	0.25	0.188

¹Prior weight $(\underline{U})_{jj}$ (equation 5) is computed as the inverse of the squared standard deviation.

For all K, ANIV, and GHB parameters, the standard deviation relates to the natural logarithm of the parameter.

Table 2. Correlations between selected pairs of the DVRFS model parameters.

Parameter Pair	Correlation
K1 , Rch3	0.96
K3 , Rch3	0.94
K1 , ETM	0.95
K2 , ETM	0.90
K3 , ETM	0.92
Rch3 , ETM	0.93
K1 , Q1	0.93
K2 , Q1	0.94
K3 , Q1	0.92
Rch3 , Q1	0.94

Table 3. Summary of parameters important to predicted advective transport at the Yucca Flat and Pahute Mesa sites by the prediction scaled sensitivity (PSS) (eq. 1, fig. 4) and value of improved information (VOII) (eq. 9, figs. 5-6) methods.

Method	Yucca Flat Site		Pahute Mesa Site	
	Hydraulic-Conductivity Parameters	Recharge Parameters	Hydraulic-Conductivity Parameters	Recharge Parameters
PSS ¹	K1, K3, K5	Rch0	K2, K3	Rch1, Rch2, Rch3
VOII on 1 parameter ²	K1	Rch0	K2, K3	Rch1
VOII on 2 parameters ³	K1, K5	Rch0, Rch3	K1, K2, K3	Rch1, Rch3
VOII on 3 parameters ³	K1, K3, K5	Rch0, Rch3	K1, K2, K3	Rch1, Rch3
All	K1, K3, K5	Rch0, Rch3 ⁴	K1 ⁴ , K2, K3	Rch1, Rch2 ⁵ , Rch3

- Parameters listed include up to 3 highest-ranking parameters from each of 3 transport directions; fewer are listed if 1 or 2 parameters have significantly larger pss_{ij} than all other parameters.
- Parameters listed include the highest-ranking parameter in each of 3 transport directions.
- Parameters listed include the highest-ranking 2 or 3 parameters in each of 3 transport directions; fewer are listed if improving more than 1 parameter did not significantly reduce prediction uncertainty.
- Parameter that would have been excluded from the set of important parameters if only PSS had been used.
- Parameter that would have been excluded from the set of important parameters if only VOII had been used.

Figure Captions

Figure 1. Location of the three-layer model of the Death Valley regional ground-water flow system (DVRFS). White arrows show dominant regional flow directions. (Figure modified from D'Agnese et al., 1997, figures 1 and 30.)

Figure 2. Hydraulic conductivity zonation in layer 1 of the 3-layer DVRFS model (and location of the patch of zone K5 in layer 2 that underlies Yucca Flat), and the representative 10,500 m advective transport paths at the Pahute Mesa and Yucca Flat sites. The path origins are indicated by the filled circles. The dashed segment of the Pahute Mesa path shows where the path travels through layer 2 of the model.

Figure 3. Areal recharge zonation in the 3-layer DVRFS model, and the representative 10,500 m advective transport paths at the Pahute Mesa and Yucca Flat sites. The path origins are indicated by the filled circles. The dashed segment of the Pahute Mesa path shows where the path travels through layer 2 of the model.

Figure 4. Absolute value of prediction scaled sensitivities (pss_{ij}), defined as the percent change in predicted value z_i produced by a one percent change in the standard deviation of parameter b_j , calculated for each DVRFS model parameter at an advective transport distance from (a, b) the Yucca Flat site and (c) the Pahute Mesa site.

Figure 5. Results of applying the VOII method for individual parameters. Bars show the percent decrease in prediction standard deviation produced by specifying improved information on each DVRFS model parameter, for a predicted advective transport distance of 10,500 m from (a, b) the Yucca Flat site origin and (c) the Pahute Mesa site origin.

Figure 6. Results of applying the VOII method for multiple parameters. Bars show the percent decrease in prediction standard deviation produced by specifying improved information on sets of 2 or 3 DVRFS model parameters (results for 1 parameter also shown for comparison), for a predicted advective transport distance of 10,500 m from (a) the Yucca Flat site origin and (b) the Pahute Mesa site origin. Parameter sets listed are those that produce the largest $voii_{\ell(\tilde{b})}$ value among all possible parameter sets of the same size. Parameter labels R0, R1, R3, and A3 denote, respectively, parameters Rch0, Rch1, Rch3, and Aniv3 (see table 1).