Wood River Valley Aquifer Model

Version 1

Uncertainty Analysis

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Abstract

The Idaho Department of Water Resources (IDWR) and the U.S. Geological Survey developed a groundwater model of the Wood River Valley (WRV) aquifer system. The WRV aquifer extends from north of Ketchum, Idaho to Picabo, Idaho in the southeast and Stanton Crossing, Idaho in the southwest.

Models are calibrated by adjusting parameters to reduce the difference between model outputs and field observations. These discrepancies are contained in an "objective function"; defined as the weighted sum of squared differences between field observations and modeled values. Generally, the topology of an objective function for a groundwater model does not have a global low. Rather it contains a valley of nearly equal objective function values, and generally the parameter distributions describing the valley calibrate the model. Thus, the model calibration is not unique. The user of the model should have an understanding of how a prediction can differ along this valley in the objective function. An effective way to investigate the variability of a model prediction is with a linear uncertainty analysis as proposed by Doherty and others (2010).

In all cases, calibration of the WRV Aquifer Model reduced the standard deviation describing the predictive uncertainty for all the analyses conducted in this study. The fact that calibration improves the predictive power of the model implies that calibration was well posed and the model isn't being asked to predict something that it has no pertinent information to base the prediction on. Predictive uncertainty for future versions of the WRV model can be further reduced by collecting more water-levels in wells and quantifying the summer gains in the near Ketchum to Hailey reach of the Wood River.

Introduction

The Idaho Department of Water Resources (IDWR) and the U.S. Geological Survey recently developed a groundwater model of the Wood River Valley (WRV) aquifer. The WRV aquifer extends from north of Ketchum, Idaho to Picabo, Idaho in the southeast and Stanton Crossing, Idaho in the southwest (Figure 1). The WRV aquifer system consists of a single unconfined aquifer with an underlying confined aquifer in the southern end of the valley (Figure 2). Flow in the WRV aquifer is simulated using the computer program MODFLOW-USG (Panday and others, 2013). The transient flow model simulates groundwater flow between January 1995 and December 2010. The calibration period extends from January 1998 through December 2010. The model was calibrated using the parameter-estimation program PEST (Doherty, 2005). Details of the model are provided in Fisher and others (2016).

An understanding of a model's predictive uncertainty is essential when a model is one of the sources of information relied upon when making administrative decisions. Various procedures have been used to evaluate a model's predictive uncertainty ranging from a simple sensitivity analysis to a complex Monte Carlo analysis (Doherty and others, 2010). The IDWR chose to conduct a moderately complex linear analysis as outlined by Doherty and others (2010) to evaluate predictive uncertainty. The linear analysis also allows for a data worth evaluation, which can be used to refine plans for gathering additional data. The linear analysis assumes that the observation weights reflect measurement uncertainty. The observation weights used in the WRV aquifer model generally reflect measurement uncertainty, with the exception of the weights on some water-level observations. Out of 3,477 water-level observations utilized in model calibration, 2,027 were collected by The Nature Conservancy (TNC) using transducers installed in 10 wells during the last year of the calibration period. Thus, about 60% of the water-level observations were collected from 10 wells during 1/13 of the calibration period. To allow for equitable utilization of the other 40% of the water-level observations representing a more complete range of the calibration period, the weights on TNC water-level observations were reduced and do not reflect their measurement uncertainty.

The linear analysis also assumes that predictive uncertainty is normally distributed. A normal distribution follows a bell shaped curve, with equal areas above and below the mean. There are reasons to assume that predictive uncertainty is not normally distributed for all of the predictions that the WRV Aquifer Model will be asked to perform. For instance, it is possible that the predicted impact of pumping a well on a particular river reach could be close to zero. Because predictive uncertainty of the impact is assumed to be normally distributed, the computed 95% confidence interval (CI) of the impact could

include values less than zero, which is impossible. In spite of these shortcomings, the linear analysis provides a convenient means of evaluating predictive uncertainty and the more uncertain predictions will have larger predictive uncertainty standard deviations and consequently larger predicted 95% CI.

Methodology

Models are calibrated by adjusting parameters to reduce the difference between model output and field observations. With PEST (Doherty, 2005), these discrepancies are contained in an "objective function"; defined as the weighted sum-of-squared differences between field observations and modeled values. With groundwater models, the topology of the objective function typically contains a minimum that forms a valley of nearly equal objective function values rather than having a minimum at a single point. The parameter distributions describing the valley typically calibrate the model equally as well; therefore, the model calibration is not unique. Users of the WRV model should have an understanding of how a prediction can differ along this valley. A convenient way to investigate the variability in a model's prediction is with a linear uncertainty analysis, as proposed by Doherty and others (2010).

Conducting a linear predictive uncertainty analysis with PEST involves the following steps:

1. Identify the prediction(s) and the steps necessary to analyze the prediction(s).
2. Prepare the model files necessary to run the prediction(s).
3. Make a copy of the PEST control file that contains all of the field observations, as well as all of the adjustable parameters set at their calibrated values with their bounds set to logical limits.
4. Replace the word 'regularization' with the word 'estimation' on the third line of the PEST control file.
5. Increase the number of observations by the number of prediction(s).
6. Increase the number of observation groups by one (1) because PEST will now be required to monitor each prediction.
7. Add 'predict' to the list of observation groups.
8. Increase the number of instruction files by the number of prediction(s).
9. Change NOPTMAX on line 9 to -1 or -2. A value of -1 or -2 tells PEST to calculate the Jacobian matrix.
10. Add an observation representing each prediction to the observation section and set the weight to zero.
11. Change the model command line to reflect the name of the batch file used to run the model and prediction(s).

12. Add the name of the new instruction file(s) and the output file(s) that need to be read to the PEST control file.

During a linear predictive uncertainty analysis, PEST will: A) change each of the adjustable parameters sequentially, B) assemble the input files for the WRV model, C) run the WRV model, D) compare model output with field observations, and E) build a Jacobian matrix containing information on how changes in each adjustable parameter impact the modeled match for every field observation, including all predictions.

Once the Jacobian matrix is constructed, it can be used to predict the topology of the objective function. This includes projecting how the selected predictions change within the set of parameter values yielding an acceptable calibration.

Three different types of analysis were conducted as part of this study: 1) a single cell steady state analysis where stress was applied in one model cell at steady state, 2) a more regional analysis where stress was applied in a block of cells, five cells on a side, and 3) a transient analysis where stress was applied continuously at one cell and the impact was observed after 10 months. All analyses involved injecting water at the five example locations shown in Figure 2 and analyzing the percentage of the impact exiting the model in a nearby reach of a river or stream. Water was injected into layer 3 for Examples 1 through 3 and layer 1 for Examples 4 and 5.

Results

Table 1 summarizes the results of these analyses, presenting the results in terms of the standard deviation of the percentage of the impact exiting the model through the target river or stream reach, assuming the uncertainty distribution is normal. In all cases, calibration reduces the standard deviation for the predictive uncertainty. The fact that calibration improves the predictive power of the model implies that calibration was well posed and the model isn't being asked to predict something that it has no pertinent information to base the prediction on. In some cases we may wish that the calibrated standard deviations were smaller, such as the transient cases for Examples 1 and 2. These standard deviations may be high because there aren't enough water-levels collected at regular intervals in model layer 3. If so, this can only be remedied by gathering more data and then recalibrating the model.

Table 1. Uncalibrated and calibrated standard deviations for the 15 different analyses.

Analysis	Target Reach	Uncalibrated 1 Cell	Calibrated 1 Cell	Uncalibrated 5x5 Cell	Calibrated 5x5 Cell	Uncalibrated Transient	Calibrated Transient
Example 1	Silver Creek	107.66%	3.98%	108.28%	4.23%	168.27%	12.59%
Example 2	Silver Creek	65.81%	5.09%	69.13%	4.77%	95.54%	12.85%
Example 3	Wood R Hai-StanX	71.63%	2.77%	79.56%	6.60%	86.45%	6.17%
Example 4	Wood R Hai-StanX	278.79%	4.39%	277.56%	4.47%	53.03%	5.04%
Example 5	Wood R Nr Ket-Hai	14.31%	3.52%	15.28%	2.39%	31.17%	2.37%

Table 2 provides more details for the scenarios presented above. The column labeled "Prediction 1 cell" in Table 2 shows the percentage of the impact introduced at the Example Site exiting the model via the target reach. For instance, Example 1 in Table 2 indicates that the WRV Aquifer Model predicts that about 58% of the impact injected at the model cell in layer three at the Example 1 site will exit the model in Silver Creek. The column labeled "CI 95 1 cell" contains the estimated double sided 95% CI, approximated as ± two standard deviations. Staying with Example 1, the prediction is 58% ± 8%. The "Prediction 5x5 cell" column shows the percentage of the impact introduced in a block of cells, five cells on a side, centered on the respective example location. The "CI 95 5x5 cells" column contains the double sided 95% CI for the 5x5 analyses. The column labeled "Prediction Transient" shows the percentage of the impact introduced at the Example Site exiting the model via the target reach within 10 months. The "CI 95 Transient" column contains the calculated double sided 95% CI for the prediction. Note that both the steady state analyses for Example 1 show a prediction of about 58% ±8% of the steady state impact leaves the model in Silver Creek while the transient prediction is about 55% ±25%. The uncertainty in the transient and steady state predictions overlap, thus, the possibility that the transient prediction at 10 months could be the same as the steady state prediction cannot be dismissed.

Table 2. Linear uncertainty analysis conducted with WRV Aquifer Model. Prediction represents percentage of impact introduced at the example site that was realized at the target reach.

Analysis	Target Reach	Prediction 1 cell	CI 95 1 cell	Prediction 5x5 cell	CI 95 5x5 cell	Prediction Transient	CI 95 Transient
Example 1	Silver Creek	58.15%	7.96%	58.15%	8.45%	54.95%	25.17%
Example 2	Silver Creek	97.23%	10.18%	97.19%	9.53%	97.16%	25.71%
Example 3	Wood R Hai-StanX	86.65%	5.54%	86.64%	13.20%	76.53%	12.34%
Example 4	Wood R Hai-StanX	60.99%	8.78%	60.99%	8.95%	8.10%	10.08%
Example 5	Wood R Nr Ket-Hai	99.99%	7.04%	99.99%	4.78%	97.50%	4.74%

Example 1

The Example 1 location is adjacent to the Wood River with the stress introduced in layer three below the aquitard (Figure 3 inset). The 95% CI for Example 1 increased from ±7.96% when the stress was introduced at a single cell to ±8.45% when the stress was introduced in a 5x5 block of cells (Table 2). This change in the CI is assumed to be within the confidence limits of the analysis and negligible.

Table 2 shows that the 95% CI for the transient analysis is larger than either of the steady state analyses for Example 1. This fact is emphasized visually in Figure 3. Figure 3 illustrates the increase in the standard deviation of predictive uncertainty if a particular observation group was removed as a calibration target[1]. The observation groups consist of observation wells (Obs Wells), geolocated wells (Geo Wells), driller located wells (Drl Wells), Sun Valley Wells, Nature Conservancy Wells, Wood River gains between the north edge of the model and Hailey[2] (nr Ketchum-Hailey), Wood River gains between Hailey and Stanton Crossing (Hailey-Stanton X), Willow Creek gains (Willow Cr), Silver Creek gains below Sportsman Access (Silver Blw), Silver Creek gains above Sportsman Access (Silver Abv), subreach gains (Subreach), and subsurface discharges from the model (outflow). The various observation groups are described in more detail by Fisher and others (2016). The height of the bars in both Figure 3a and 3b represents the increase in the standard deviation of predictive uncertainty if that observation group were removed. In both steady state analyses, the observation wells, the geolocated wells and the Willow Creek gains are the most critical data (Figure 3a), while in the transient analysis, the observation wells and the Willow Creek gains and gains in the near Ketchum to Hailey reach of the Wood River are the most critical (Figure 3b). Collecting more water-level observations in layers one, two, and three would likely lower the predictive uncertainty at this location. Collecting sufficient data to calculate the summer reach gains in the near Ketchum to Hailey reach of the Wood River would likely also lower the predictive uncertainty.

Example 2

The aquifer system at the Example 2 location is modeled as basalt in layers two and three with no aquitard in between and the stress is introduced in layer three (Figure 4 inset). In the steady state analyses the 95% CI decreased from about ±10.18% for the single cell scenario to about ±9.53% for the 5x5 block of cells (Table 2), which is assumed to be within the confidence limits of the analysis. Figure 4a

[1] Standard deviations are not additive. The square of the standard deviations (i.e. the variance) is additive.
[2] These gains lack summer time observations because tributary inflow is assumed to exist for at least part of the summer, but was not measured.

is a bar chart showing the predicted impact on the uncertainty standard deviation for the two steady state analyses if one of the observation groups was removed. Figure 4b adds the transient analysis results. Note that for both of the steady state analyses the observation wells, Willow Creek gains and geolocated wells appear to be especially important calibration targets. The observation wells and the near Ketchum to Hailey and Willow Creek reach gains are the more important observations for the transient analysis. It appears that more water-level data and summer reach gains for the near Ketchum to Hailey reach gains will reduce predictive uncertainty. The water-level data are used to inform the model how the aquifer responds seasonally and from year to year to cyclic and long-term changes in water use.

Example 3

The Example 3 location is south of Bellevue where the aquifer material is expected to be sand and gravel with no aquitard (Figure 5 inset) with the stress introduced in layer three. The 95% CI increases from about ±5.54% for the single cell scenario to about ±13.2% for the 5x5 block of cells, a significant increase (Table 2). Figure 5a is a bar chart showing the impact on the predictive uncertainty standard deviation for the two steady state analyses if one of the observation groups was removed. The most critical observation groups are the observation wells and Willow Creek for the single cell analysis and the observation wells and the Nature Conservancy Wells for the 5x5 cell steady state analysis. Figure 5b includes the results from the transient analysis where the most critical observation groups are the observation wells, the near Ketchum to Hailey gains and the Willow Creek gains.

A unique characteristic with the Example 3 site is that it is adjacent to a transition between hydraulically connected and perched stretches of the Wood River. Down river from the Example 3 site, the Wood River is perched to a point near the Example 1 site (Figure 2). The water table drops off quickly south of the Example 3 site as shown by the closely spaced contour lines in Figure 2. Injecting water in the 5x5 block of cells at the Example 3 site impacts the stretch of hydraulically connected river more than injecting in a single cell, and perhaps the uncertainty in the length of hydraulically connected river cells results in the jump from a ±5.54% CI for the 1 Cell analysis to the ±13.2% CI for the 5x5 cell analysis.

Example 4

The Example 4 location is south of Hailey where the aquifer material is expected to be sand and gravel with no aquitard and the stress is introduced in layer one (Figure 6 inset). The 95% CI for the single cell analysis is ±8.78% and ±8.95% for the 5x5 cell analysis (Table 2), which is assumed to be a negligible

difference. Figure 6a is a bar chart showing the impact on the predictive-uncertainty standard deviation if one of the observation groups were removed for the steady state analyses. The observation wells, geolocated wells and the gains in the near Ketchum-to-Hailey gains are the most critical observation groups. For the transient analysis (Figure 6b), after the water-level data from the observation wells, the Willow Creek and the near Ketchum-to-Hailey gains are the most critical. It is interesting that the Willow Creek gains are more important than the near Ketchum-to-Hailey gains. Perhaps this is because the near Ketchum-to-Hailey gains are missing data during the summer months leading to a decreased impact on the transient analysis.

Example 5

The Example 5 location is south of Ketchum (Figure 7 inset) where the aquifer material is expected to be sand and gravel with no aquitard and the stress is introduced in layer one. The steady state analysis for this scenario is simple, with nearly 100% of the stress introduced at the Example 5 site exiting the model in the Ketchum-to-Hailey reach (Figure 2). The steady state 95% CI for the single cell analysis is ±7.04% and the 95% CI for the 5x5 block of cells is ±4.74% (Table 2). The difference between the single cell CI and the CI for the 5x5 block of cells is meaningful, indicating that if the stress is imposed in a larger footprint the predictive uncertainty is smaller. The transient analysis is more complex and asks how much of the impact will exit the model via the near Ketchum-Hailey reach after 10 months. The transient analysis for this scenario benefits from model calibration more than the steady state analysis (Table 1). Figure 7a is a bar chart showing the impact on the predictive uncertainty standard deviation if one of the observation groups were removed. Predictably the critical groups are the Sun Valley Wells, the observation wells and the near Ketchum to Hailey gains. Surprisingly, in the transient analysis, the primary observation groups are the Sun Valley Wells, the Observation wells, and Willow Creek. Perhaps the near Ketchum-to-Hailey gains are not as important as expected for the transient analysis because of the missing data during the summer months.

Conclusions

All scenarios showed that model calibration reduced predictive uncertainty when compared to an analytical solution (Table 1), demonstrating that data used in the calibration process were relevant to the scenarios evaluated in this study. The five example analysis included a variety of the hydrogeologic conditions found within the WRV Aquifer Model, including situations involving the confined aquifer, the basalt aquifer, the unconfined aquifer, and a location near the transition point between the two major river reaches (Figure 2). Because all five analyses showed that the WRV Aquifer Model was an

improvement over an analytical solution and the example locations included a variety of the hydrologic conditions, the WRV Aquifer Model is an improvement over an analytical solution.

All scenarios indicated that water-levels collected in wells were key observations. These are the data that inform the model how the aquifer is responding to seasonal changes, changes in agricultural practices, and population shifts. In order to reduce the predictive uncertainty in future calibrations of the WRV Aquifer Model, more observation-well data need to be collected at regular intervals in a manner that will document how the aquifer responds to these impacts.

The near Ketchum-to Hailey gains are missing summer data and the summer data will likely reduce the predictive uncertainty in the transient analyses. Data should be gathered that could be used to fill this gap.

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