# Wood River Valley Aquifer Model

# Version 1.1

# Uncertainty Analysis

Idaho Department of Water Resources
Allan Wylie

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## Abstract

The Idaho Department of Water Resources (IDWR) updated the Wood River Valley (WRV) Aquifer Model. 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 that calibrate the model lie within the valley. Thus, the model calibration is not unique. The user of the model should have an understanding of how a prediction can differ while moving amongst the suite of parameters that calibrate the model. A convenient way to investigate the variability of a model prediction is with a linear uncertainty analysis as proposed by Doherty and others (2010).

In all five test cases evaluated in this analysis, calibration of the WRV Aquifer Model reduced the 95% Confidence Interval (CI) for the prediction. The fact that calibration improves the predictive power of the model implies that the calibration dataset helped limit the more important parameters involved in evaluating the example scenarios. Predictive uncertainty for future versions of the WRV model can be further reduced by increasing the number of water-level observations. The increase in the number of water-level observations should be focused south of Bellevue because that is where the predictive uncertainties are highest. Reducing the noise in the reach gain calibration targets for Silver Creek and Willow Creek will also help reduce predictive uncertainty, perhaps by filtering or manually removing data during runoff.

## Introduction

This report documents an uncertainty analysis conducted with Wood River Valley (WRV) Aquifer Model Version 1.1 (Wylie and others, 2019). Figure 1 shows the location of the WRV within Idaho. WRV1.1 is an update to WRV1.0 (Fisher and others, 2016). WRV1.1 includes data collected between 1/1/2011 and 12/31/2014 along with the WRV1.0 calibration period of 1/1/1998 through 12/31/2010. Including the time span between 1/1/2011 and 12/31/2014 incorporates more groundwater level and streamflow data than were collected in the WRV than in any other four year span in the calibration period.

Some important modifications in WRV1.1 include changes to the way the Big Wood River is represented between Glendale Road and Wood River Ranch (Figure 1). In WRV1.0, when the water rights accounting indicated that the Big Wood River was dry below the diversion for the Bypass Canal near Glendale Road, the Big Wood River between Glendale Road and Wood River Ranch was assumed dry until the following November. Analysis of Landsat images indicated that this was not always a valid assumption. Thus, for WRV1.1 Landsat images were used to determine when the Big Wood River resumed flow between Glendale Road and Wood River Ranch. Moreover, when there is flow between Glendale Road and Wood River Ranch, the stage, or depth of water in the river, is more constant than the width of the river. In WRV1.1 this was accounted for by providing different riverbed conductance terms depending on the flow in the Big Wood River.

Typically, a model is developed because decisions are being contemplated and policy makers wish to evaluate the consequences of the decisions. The value of a model-based analysis is not only in its ability to help evaluate outcomes, but also in its ability to provide an examination of uncertainty surrounding the outcomes and the types of additional data that will minimize the uncertainties.

## 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”; which is 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 region of nearly equal objective function values rather than having a minimum at a single point. The parameter distributions describing the region typically calibrate the model nearly as well; therefore, the model calibration is not unique. Policy makers should have an understanding of how the non-uniqueness in parameters impacts model predictions. Thus, an effort should be made to explore

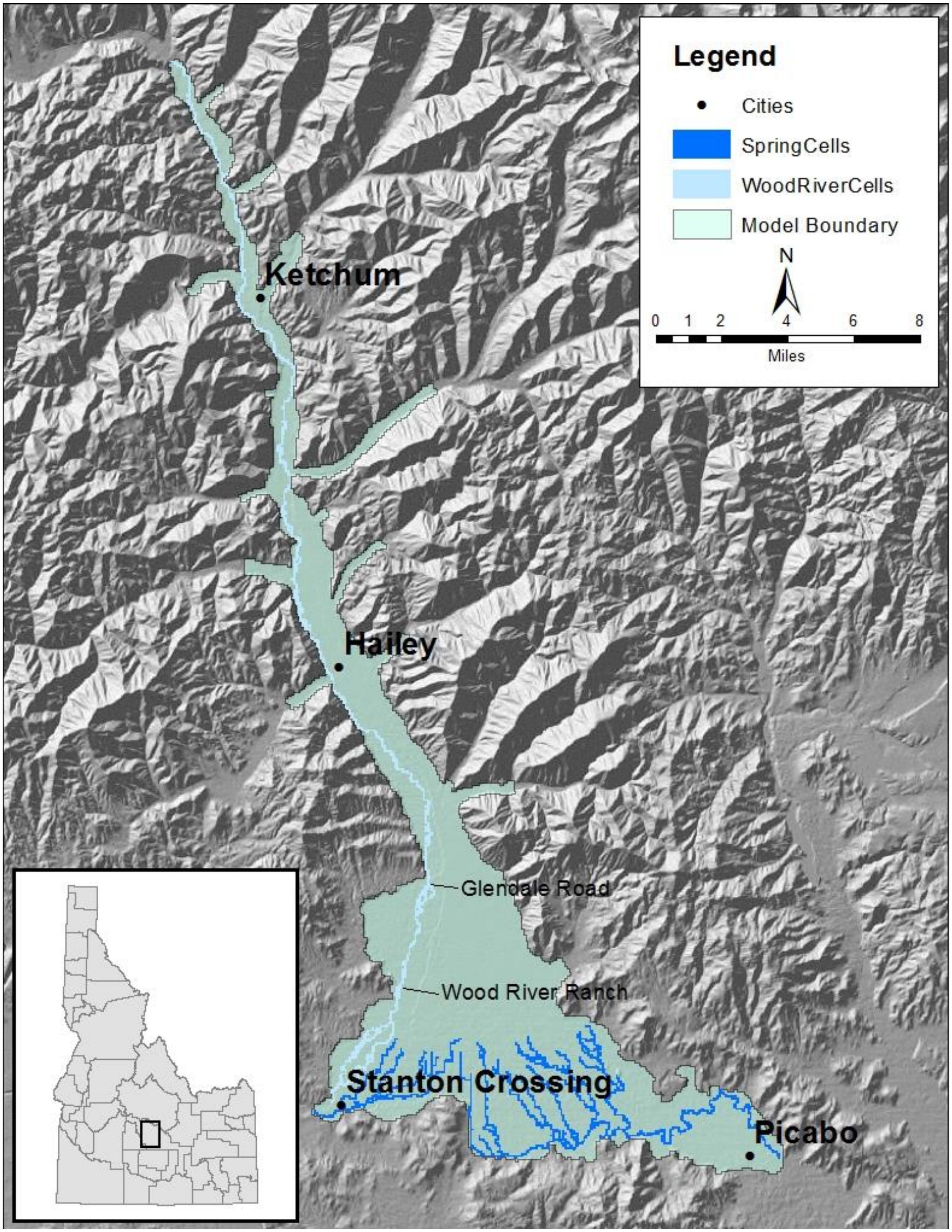



Figure 1. Extent of the Wood River Valley Aquifer Model.

how predictions can differ within this region. 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 infer the topology of the objective function. In the WRV01 uncertainty analysis Wylie (2016) explored three different types of analysis at five different locations. Wylie and others (2019) concluded that because of the annual variability in the length of the

Big Wood River in hydraulic communication with the aquifer below Glendale Road, a steady state version of the WRV1.1 should not be developed. Therefore, this analysis explores only transient analyses at the five example locations shown in Figure 2. Each analysis involves injecting water into the aquifer at a single model cell for 10 months and then determining how much water is recovered in a nearby river reach. Thus, each example analysis involves running the model twice. The model is run once to establish a baseline with that particular parameter distribution, and a second time incorporating the example scenario with the same parameter distribution and then differencing the results.

## Results

Table 1 summarizes the results of the analysis at the five example locations, presenting the results in terms of the 95% CI, assuming the uncertainty distribution is normal. Table 1 shows the 95% CI for the percentage of injected water recovered in the target reach after 10 months of injection. For instance, at the Example 1 site shown in Figure 2, if an analytical solution were used to make the calculation, the analysis could be off by ±51% (the "Uncalibrated" column in Table 1). If WRV1.1 was used, the analysis could be off by ±22% (the "Calibrated" column in Table 1). If WRV1.0 was used, the analysis could be off by ±25% (the "WRV1.0" column in Table 1). In all cases, calibration reduces the 95% CI and in all cases WRV1.1 has a lower, or about the same predictive uncertainty as WRV1.0. The fact that calibration improves the predictive power of the model implies that the calibration dataset contains information that can be used to lower predictive uncertainty. The fact that WRV1.1 has a lower, in most cases, predictive uncertainty than WRV1.0 shows that the data gathered between 1/1/2011 and 12/31/2014 is the type that will reduce predictive uncertainty for these analyses.

Table 1. Uncalibrated, calibrated, and WRV1.0 95% confidence intervals for the 5 example analyses.

| Analysis | Target Reach | Uncalibrated | Calibrated | WRV1.0 |
|---|---|---|---|---|
| Example 1 | Silver Creek Abv Sportsman's Access | 51% | 22% | 25% |
| Example 2 | Silver Creek Abv Sportsman's Access | 46% | 22% | 26% |
| Example 3 | Wood R Hailey - Stanton Crossing | 30% | 15% | 21% |
| Example 4 | Wood R Hailey - Stanton Crossing | 21% | 11% | 11% |
| Example 5 | Wood R nr Ketchum - Hailey | 7.6% | 0.54% | 4.7% |

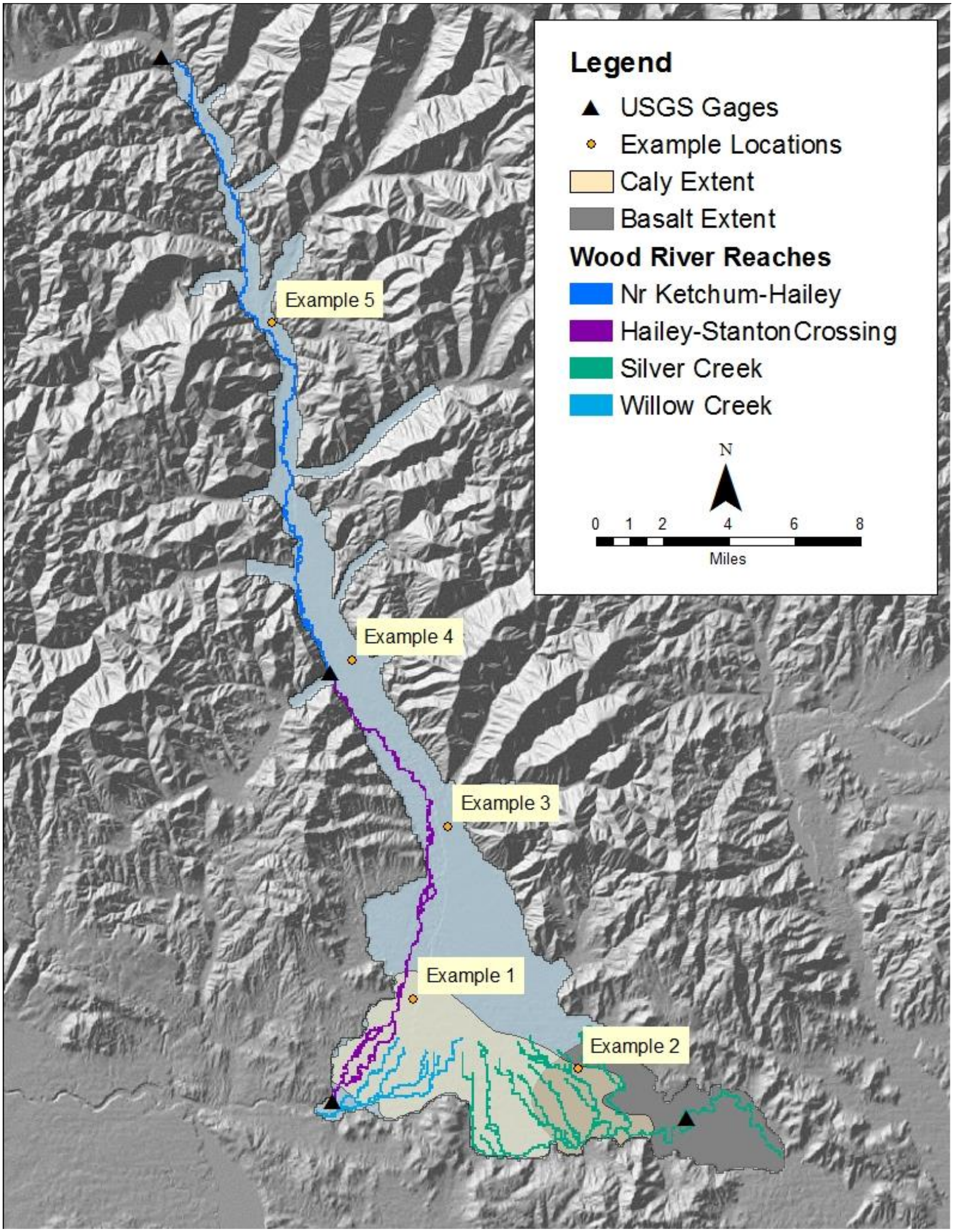



Figure 2. Example prediction locations and target river reaches.

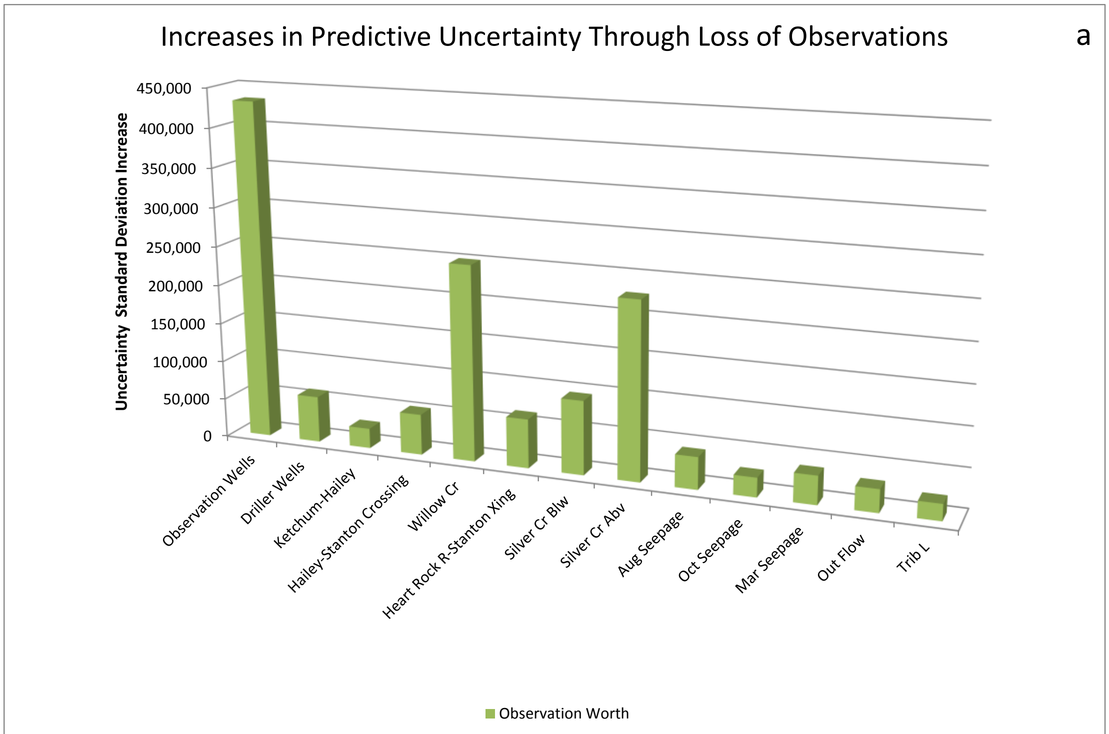
### Example 1

The Example 1 location is adjacent to the Big Wood River along the western edge of the Bellevue triangle. The stress was introduced in layer three below the clay layer or aquitard and the gains were observed in Silver Creek upstream from the Sportsman's Access gage (Figure 2). The exact extent of the aquitard is unknown and is adjustable during model calibration (Wylie and others, 2019). The 95% CI for Example 1 decreased from ±51% of the recovered volume to ±22% of the recovered volume with model calibration, over a 50% reduction in predictive uncertainty (Table 1). This reduction in the CI indicates that the calibration dataset provides information that the model is able to effectively use to limit the key parameters used in this analysis.

Figure 3a illustrates the increase in the standard deviations for predictive uncertainty if a particular observation group was removed from the calibration data set. The observation groups consist of Observation Wells, Driller Wells, Big Wood River gains between the north edge of the model and Hailey (Ketchum-Hailey), Big Wood River gains between Hailey and Stanton Crossing (Hailey-Stanton Crossing), Willow Creek gains (Willow Cr), Big Wood River gains between Heart Rock Ranch and Stanton Crossing (Heart Rock R-Stanton Xing), Silver Creek gains below Sportsman Access (Silver Blw), Silver Creek gains above Sportsman Access (Silver Abv), August 2012 seepage study (Aug Seepage), October 2012 seepage study (Oct Seepage), March 2013 seepage study (Mar Seepage), subsurface discharges from the model (Out Flow), and calibration targets intended to keep the water table below land surface in the tributary canyons lacking observation wells (Trib L). The various observation groups are described in more detail by Wylie and others (2019). The height of the bars in Figure 3a represents the increase in the standard deviation for the analysis at this particular location if that observation group were removed. The observation wells, Willow Creek gains, and Silver Creek gains above the Sportsman's Access gage are most critical for constraining the uncertainty at the Example 1 site.

The graph in Figure 3b shows the reduction in predictive uncertainty obtained through model calibration. The parameter groups are drain conductance (Drain Cond), layer 1 hydraulic conductivity (L1 K), layer 2 hydraulic conductivity (L2 K), layer 3 hydraulic conductivity (L3 K), vertical conductance (Vert Cond), layer 1 specific yield (L1 S), layer 2 storage (L2 S), layer 3 storage (L3 S), riverbed conductance (Riv Cond), irrigation entity efficiency (Irr Eff), underflow from tributary streams east of the Big Wood River (E Trib), underflow from tributary streams west of the Big Wood River (W Trib), and parameters that shape tributary underflow (U_Flw). The graph in Figure 3b shows that calibration reduces predictive uncertainty primarily by constraining, or limiting, layer one and layer two hydraulic conductivity, riverbed conductance, and layer 2 storage coefficient.

The above analysis suggests increasing the number of observation wells and reducing the noise in the reach-gain observations for Silver Creek and Willow Creek will reduce the predictive uncertainty for analysis similar to Example 1.



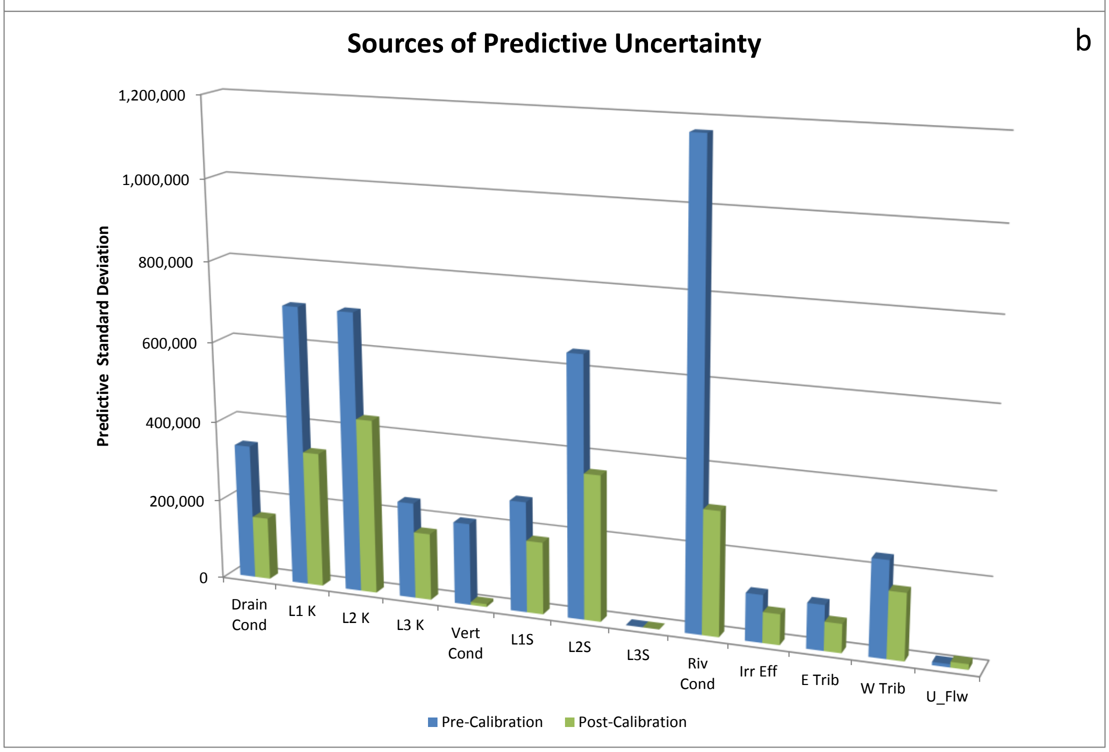




Figure 3. Contributions to predictive uncertainty standard deviation for Example 1.

## Example 2

The aquifer system at the Example 2 location is modeled as containing a sand and gravel aquifer in layer one, clay in layer two, and basalt in layer three. The stress is introduced in layer three and river gains are monitored in Silver Creek above Sportsman's Access gage (Figure2). The 95% CI for the Example 2 analysis decreased from ±46% of the recovered volume for the uncalibrated analysis to ±22% of the recovered volume with model calibration (Table 1). This indicates that the calibration data contain relevant observations. Figure 4a shows that the most important types of calibration data for the Example 2 analysis are water-levels collected in observation wells, the gains in Silver Creek above the Sportsman's Access gage, and the gains in Willow Creek.

The graph in Figure 4b shows that calibration reduces predictive uncertainty primarily by constraining riverbed conductance, layer one and layer two hydraulic conductivity, and layer two storage coefficient.

The above analysis suggests increasing the number of water-level observations and reducing the noise in the reach-gain measurements for Silver Creek and Willow Creek will further reduce the predictive uncertainty for predictions similar to Example 2.

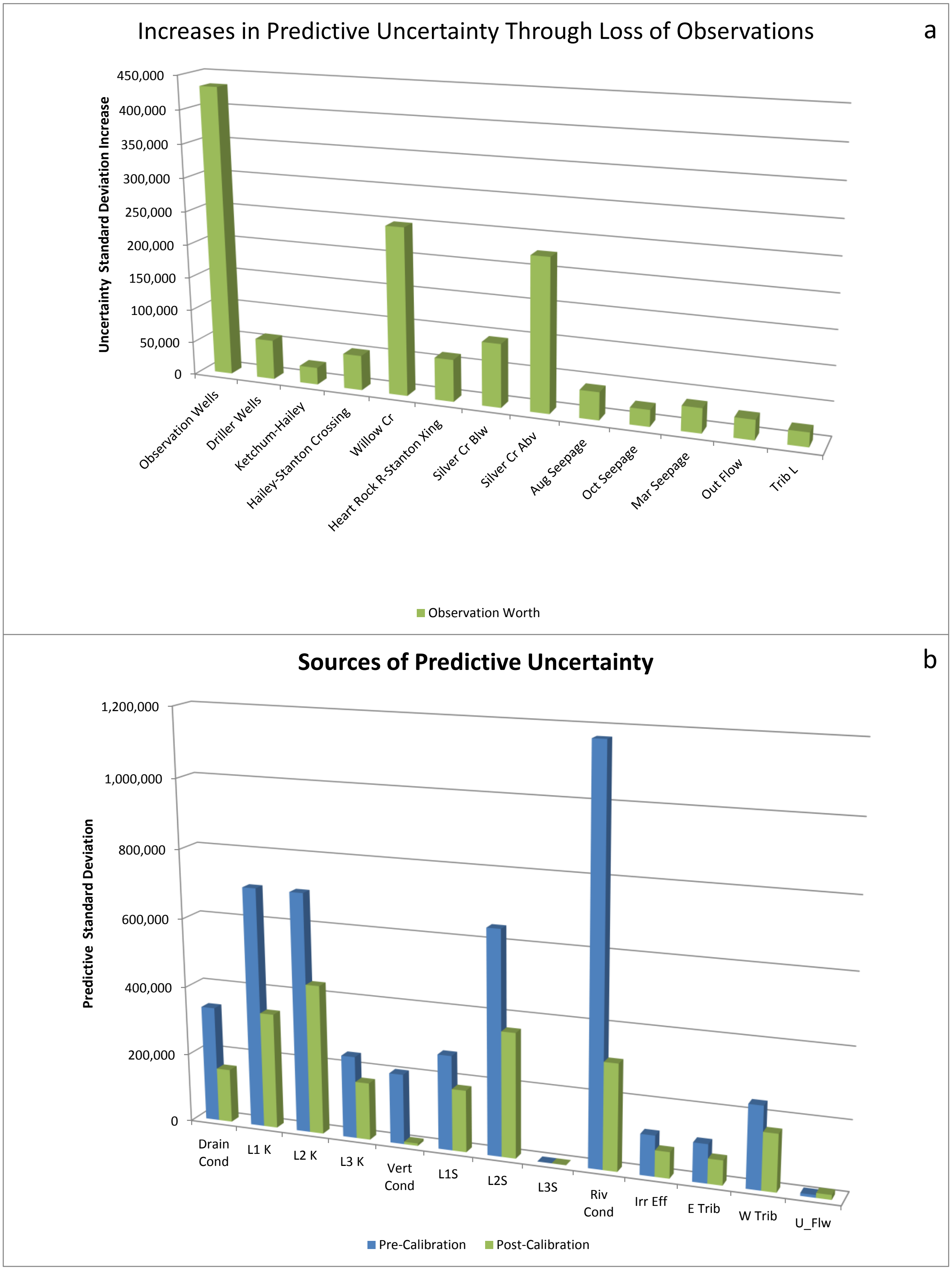



Figure 4. Contributions to predictive uncertainty standard deviation for Example 2.

## 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 2). The stress was introduced in layer three and the river gains were monitored in the Hailey to Stanton Crossing reach of the Big Wood River. The 95% CI for the Example 3 analysis decreased from ±30% of the recovered volume for the uncalibrated analysis to ±15% of the recovered volume with model calibration (Table 1). This indicates that the calibration data provides information that limits parameter uncertainty. Figure 5a shows that the three main types of data that reduce predictive uncertainty for the Example 3 analysis are water-levels collected in observation wells, the gains in Silver Creek above the Sportsman's Access gage, and the gains in Willow Creek.

The graph in Figure 5b shows that calibration reduces predictive uncertainty primarily by constraining riverbed conductance, layer one hydraulic conductivity, and layer two storage coefficient.

The above analysis suggests increasing the number of observation wells and reducing the noise in the reach-gain observations for Silver Creek and Willow Creek will reduce the predictive uncertainty for predictions similar to Example 3.

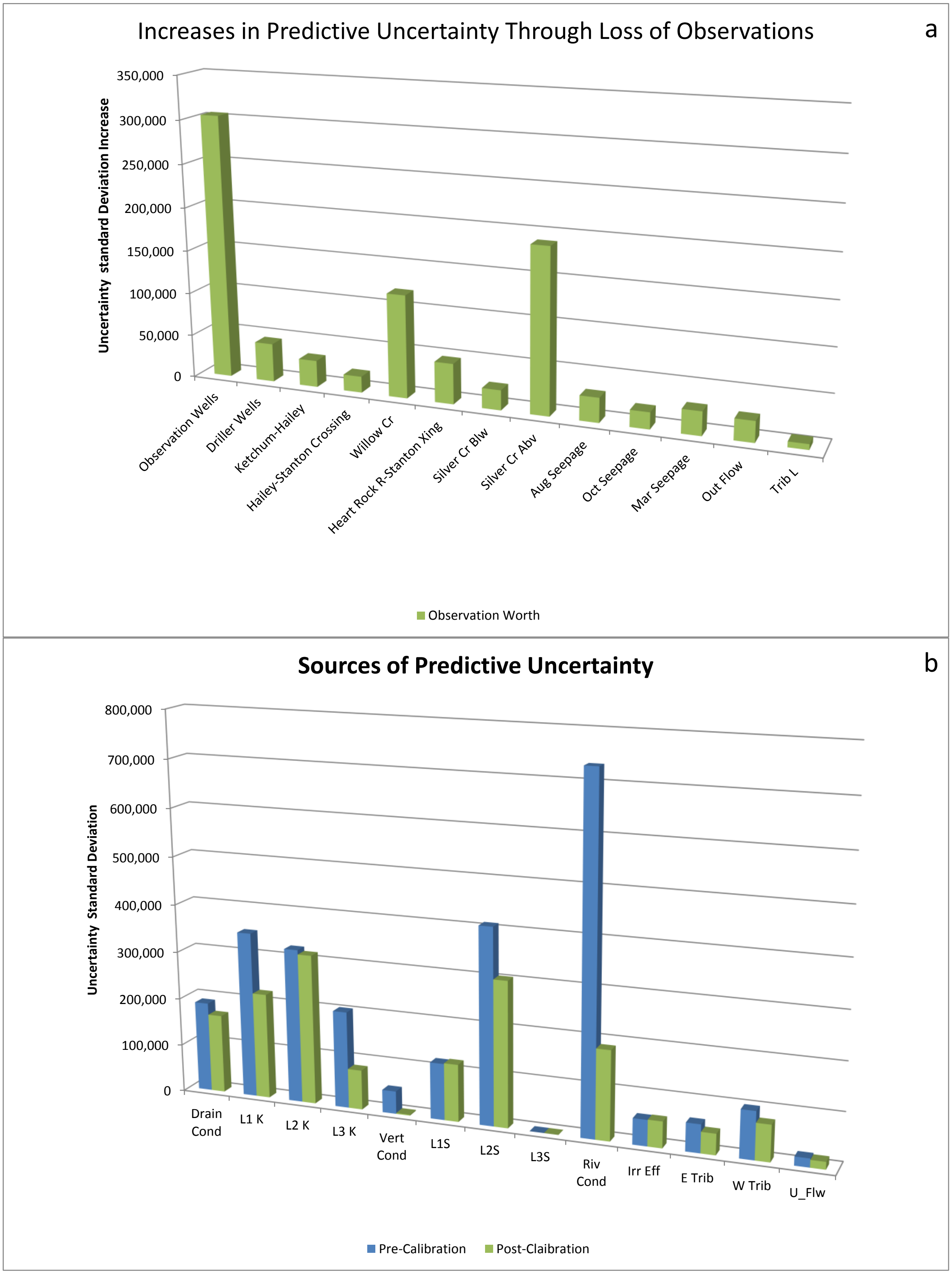



Figure 5. Contributions to predictive uncertainty standard deviation for Example 3.

### Example 4

The Example 4 location is east of Hailey where the aquifer material is expected to be sand and gravel with no aquitard. The stress was introduced in layer one and the river gains were monitored in the Hailey to Stanton Crossing reach of the Big Wood River (Figure 2). The 95% CI for the Example 4 analysis decreased from ±21% of the recovered volume for the uncalibrated analysis to ±11% of the recovered volume with model calibration (Table 1). This indicates that the calibration data provides information that reduces predictive uncertainty. Figure 6a shows that the three most important types of data for the Example 4 analysis are water-levels collected in observation wells, the gains in Silver Creek above the Sportsman's Access gage, and the gains in Willow Creek.

The graph in Figure 6b shows that calibration reduces predictive uncertainty primarily by constraining riverbed conductance and hydraulic conductivity in layer one.

The above analysis suggests increasing the number of observation wells and reducing the noise in the reach-gain observations for Silver Creek and Willow Creek will reduce the predictive uncertainty for predictions similar to Example 4.

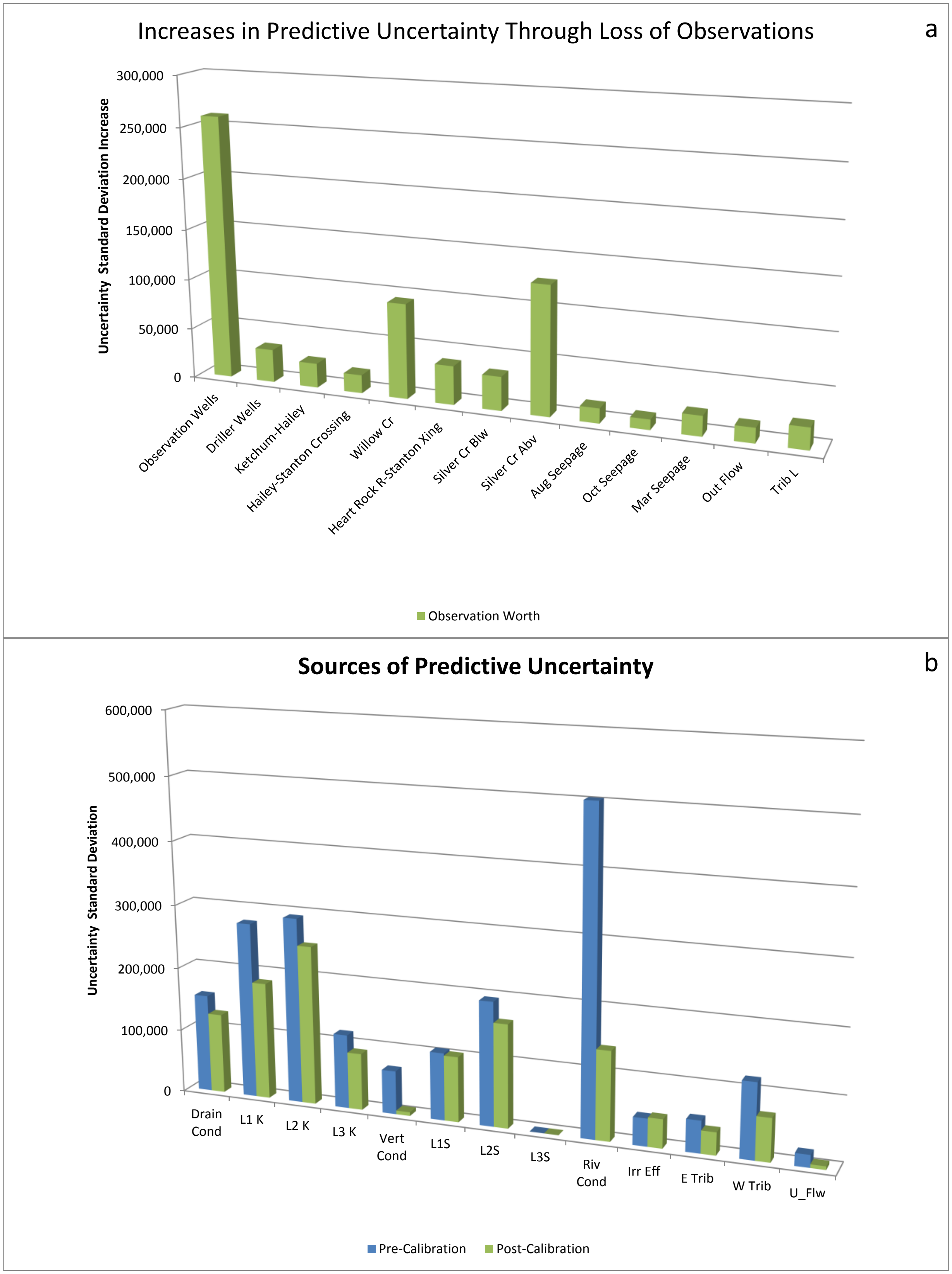



Figure 6. Contributions to predictive uncertainty standard deviation for Example 4.

## Example 5

The Example 5 location is south of Ketchum where the aquifer material is expected to be sand and gravel. The stress was introduced in layer one and the river gains were monitored in the Near Ketchum to Hailey reach of the Big Wood River (Figure 2). The 95% CI for the Example 5 analysis decreased from ±7.6% of the recovered volume for the uncalibrated analysis to ±0.54% of the recovered volume with model calibration (Table 1). The low uncalibrated predictive uncertainty indicates that the analysis is relatively straight forward, and the reduction in predictive uncertainty with calibration indicates that the calibration data are relevant with respect to this prediction. Figure 7a shows that the primary types of data that reduce the predictive uncertainty for the Example 5 analysis are water-levels collected in observation wells, the gains in Willow Creek, gains in the Ketchum-Hailey reach of the Big Wood River, and the gains from the August, October, and March seepage runs.

The graph in Figure 7b shows that calibration reduces predictive uncertainty primarily by constraining layer one hydraulic conductivity and riverbed conductance.

It is unrealistic to expect to reduce the predictive uncertainty relative to the Example 5 analysis.

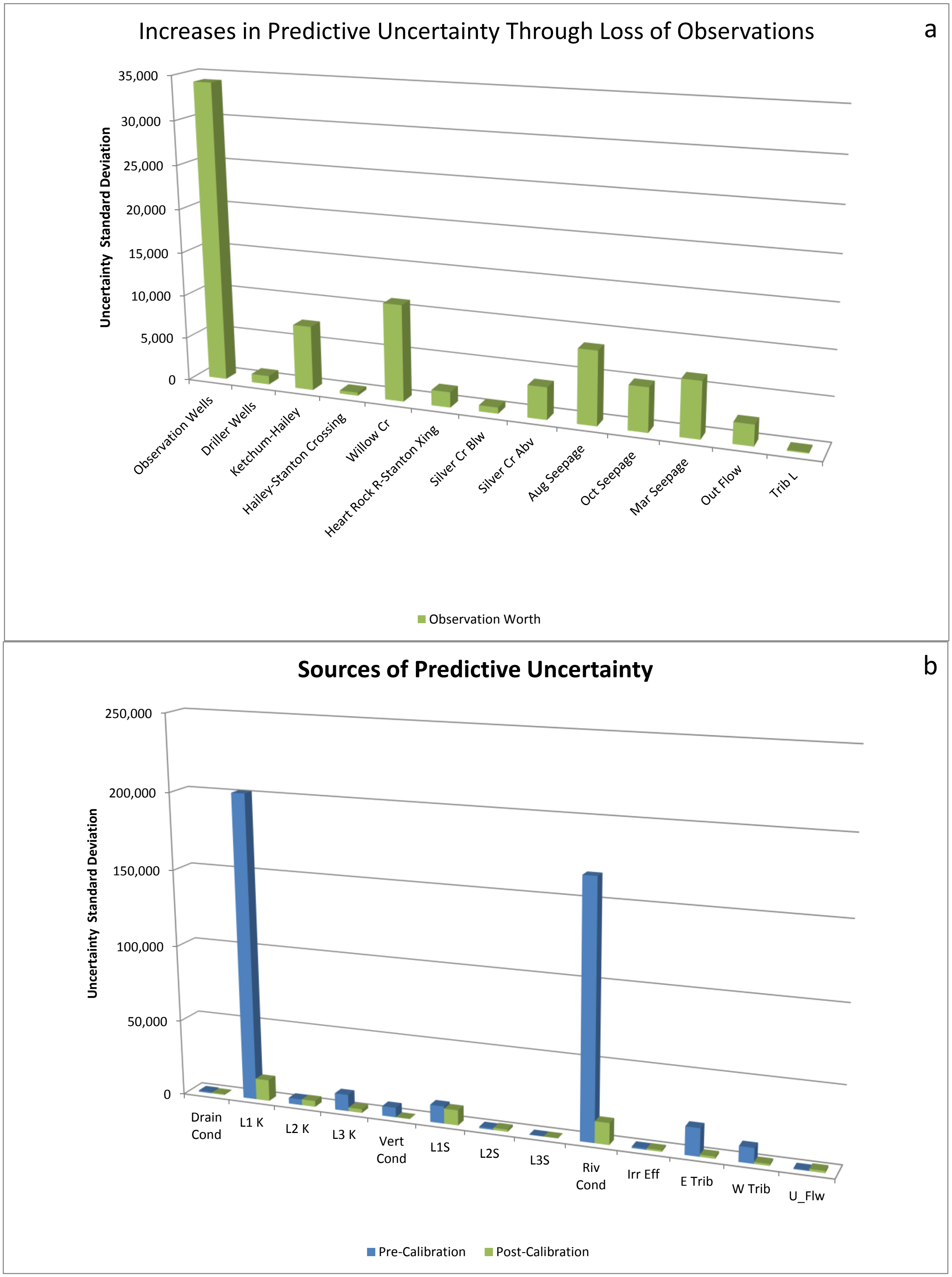



Figure 7. Contributions to predictive uncertainty standard deviation for Example 5.

## Conclusions

The five scenarios evaluated in this analysis encompassed 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 between the two major river reaches in the Big Wood River. The stresses were applied at the same locations and using the same procedure as for the WRV1.0 transient uncertainty analysis (Wylie, 2016). Because all five analyses showed that the WRV1.1 Model reduced predictive uncertainty when compared to an analytical solution (uncalibrated analysis) and reduced predictive uncertainty or, in the case of Example 4, held it about the same when compared to the WRV1.0 Model, and the example locations included a variety of hydrogeologic conditions, the WRV1.1 Model is considered the best available science.

All scenarios indicated that water-levels collected in observation wells were key. These are the data that inform the model how the aquifer is responding to seasonal changes in water supply, changes in agricultural practices over time, and population shifts. In order to reduce the predictive uncertainty in future versions 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. Because the Example locations with the greatest predictive uncertainty are south of Bellevue, the increase in the number of wells should be focused south of Bellevue.

All scenarios indicated that reach gain calculations in Silver Creek and Willow Creek are important in reducing predictive uncertainty. Perhaps filtering Silver Creek and Willow Creek calibration targets with a Butterworth filter (Doherty, 2008) would improve the calibration targets. Perhaps both filtered and unfiltered reach gain calibration targets should be considered. Another approach might be to reduce the weights on the gains during spring flows since they may be impacted by overland flow, ungagged tributary stream contributions, and gage error.

## References


Bartolino, J.R. 2014. Stream Seepage and Groundwater Levels, Wood River Valley, South-Central Idaho, 2012-13. USGS Scientific Investigations Report 2014-5151.

Butterworth, S. 1930. On the Theory of Filter Amplifiers. Experimental Wireless and the Wireless Engineer, V 7 pp. 536-541.

Doherty, J.E., 2008. PEST Surface Water Utilities. Watermark Numerical Computing and University of Idaho. Brisbane, Australia.

Doherty, J.E., 2005. Model-Independent Parameter Estimation-User Manual. Watermark Numerical Computing, Brisbane, Australia, 5th ed.

Doherty, J.E., R.J. Hunt, and M.J. Tonkin. 2010. Approaches to Highly Parameterized Inversion: A Guide to Using PEST for Model-Parameter and Predictive-Uncertainty Analysis. USGS Scientific Investigation Report 2010-5211 p. 71.

Fisher J,C., J.R. Bartolino, A.H. Wylie, J. Sukow, and M. McVay. 2016. Groundwater-Flow Model for the Wood River Valley Aquifer System, South-Central Idaho. USGS Scientific Investigation Report 2016.

Panday, Sorb, C.D. Langevin, R.G Niswonger, M. Ibraki, and J.D. Hughes, 2013. MODFLOW-USG Version1: An Unstructured Grid Version of MODFLOW for Simulating Groundwater Flow and Tightly Coupled Processes using a Control Volume Finite-Difference Formulation. USGS Techniques and Methods, Book 6, Chap. A45.

Wylie, A., 2016. Wood River Valley Aquifer Model Version 1 Uncertainty Analysis. Idaho Department of Water Resources Open File Report.

Wylie, A., J. Sukow, M McVay, J. Bartolino, 2019. Groundwater-Flow Model for the Wood River Valley Aquifer System, Version 1.1