INVERSE MODELING FOR ESTIMATING PARAMETERS OF GROUNDWATER MODELS WITH UNCERTAIN FORCING DATA

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The presence of uncertainty and possibly bias in groundwater model input and output measurements coupled with parameter uncertainty can lead to biased model parameter estimates and predictions when regression based inverse modeling techniques are used. This study first quantifies the bias in groundwater model parameterization and prediction due to errors in irrigation pumping data. Next, the study presents an alternate inverse modeling technique for robust parameter estimation when pumping and other forcing data are uncertain. The approach uses the generalized least squares method, with the weight in the objective function depending on the level of pumping uncertainty and adjusted iteratively during the parameter estimation process. We have conducted both analytical and numerical experiments using agricultural irrigation data from the Republican River Basin in Nebraska to evaluate the performance of the new method compared to the conventional least square method for different error structures of the data. Results from the conventional least squares calibration method illustrate the presence of statistically significant bias in parameters and model predictions that persists despite calibrating the model in a stochastic manner using Monte Carlo realizations of the irrigation pumping data and against different calibration data and sample sizes. By directly accounting for model input and output data uncertainty with inverse modeling, the new method is able to effectively minimize bias without increasing computational requirements of the calibration process.