Abstract

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HYDROGEOPHYSICAL INVERSION USING THE PREDICTION-FOCUSED APPROACH: METHODOLOGY AND APPLICATION

1. Introduction to the prediction-focused approach

The objective of prediction-focused approaches (PFAs) is to find a direct relationship between data and predictions (1). PFAs rely on a realistic prior distribution of subsurface realizations, accounting for any uncertain component, to derive this relationship by forward modeling of both data and predictions. The method can be divided into 6 main steps (Fig. 13)

1. Definition of the prior and generation of samples
2. Forward modeling of the prediction of interest and the data

2. Experimental setup and noise analysis

A) Plan view

The objective of the study is to derive the temperature distribution during a heat tracing experiment using cross-borehole resistance data (Fig. 2). The alluvial aquifer is modeled using 500 geostatistical realizations and the heat tracing experiment is simulated using HydroGeoSphere for each one. The temperature distribution (prediction) is extracted and transformed into resistivity variations to simulate change in resistance data (2).

To account for noise in the data (3) we generate noise-free data sets and estimate with Monte Carlo simulations (Fig. 3) how the noise is propagated in the low dimension space. We limit our analysis to dimensions weakly affected by noise and compute the low-dimension error covariance matrix (Fig. 4) to ensure that the noise on the data will be accounted for in the prediction.

B) Cross-section of the ERT panel

3. Synthetic examples

The observed behavior of the plume, limited to the bottom part of the aquifer, is coherent with the presence of a clean gravel layer just above the bedrock. The division of the plume in two is likely related to the presence of a clay lens upstream from the ERT panel. Both behavior are confirmed by direct measurements and classical inversion approaches.

Finally, we validate the temperature distribution by comparison with two temperature loggers located at 9 meter depth in the panel (Fig. 2). The posterior samples (grey curves, Fig. 10) encompass the observed curve (red curve, Fig. 10). The difference between the mean of the posterior (blue curve, Fig. 10) and the true temperature is similar to the discrepancies obtained with 2 standard inversion methods (4).

4. Field application

We simulate the data corresponding to the posterior samples and observe that they are fitted within the error level (Fig. 8), although no forward modeling is performed for prediction.

For the field application, we generate 500 realizations of the alluvial aquifers using sequential Gaussian simulations. In addition to spatial uncertainty, seven parameters are considered uncertain: the mean and variance of hydraulic conductivity, the porosity, the range, anisotropy and orientation of the variogram model. Finally, uncertainty in the boundary conditions of the flow model is integrated by imposing an uncertain natural gradient in the aquifer.

We analyze the 6 first ERT time-steps corresponding to the increasing part of the breakthrough curve. We keep 12 dimensions in the data and 8 in the predictions, representing 99% and 90% of the variance respectively.

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Three selected samples (Fig. 9) show again that the spatial distribution of temperature changes is well resolved and that most uncertainty is linked to the maximum temperature.

Conclusion

In this contribution, we demonstrate the ability of prediction-focused approaches to derive the temperature distribution in an alluvial aquifer during a heat tracing experiment monitored by ERT. Both synthetic and field case show that a proper noise analysis and dimension reduction allow to generate the posterior distribution without any explicit inversion. Compared to standard methods, this approach allows to generate more geologically realistic samples, avoiding smoothing due to regularization and to assess uncertainty by generating many possible solutions consistent with the data. The approach only requires independent forward runs and can be parallelized. We think that such an approach has a huge potential for hydrogeophysical predictions, but more generally to any prediction problems in Earth Sciences.

References


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