GHENT UNIVERSITY - DEPARTMENT OF GEOLOGY – HYDROGEOLOGY AND APPLIED GEOLOGY

Hermans Thomas[1], Oware Erasmus[2], Caers Jef[3], Nguyen Frédéric[4]

[1] Ghent University [2] New York State University at Buffalo [3] Stanford University [4] Liège University

Abstract
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FACULTY OF SCIENCES

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

1. Introduction to the prediction-focused approach

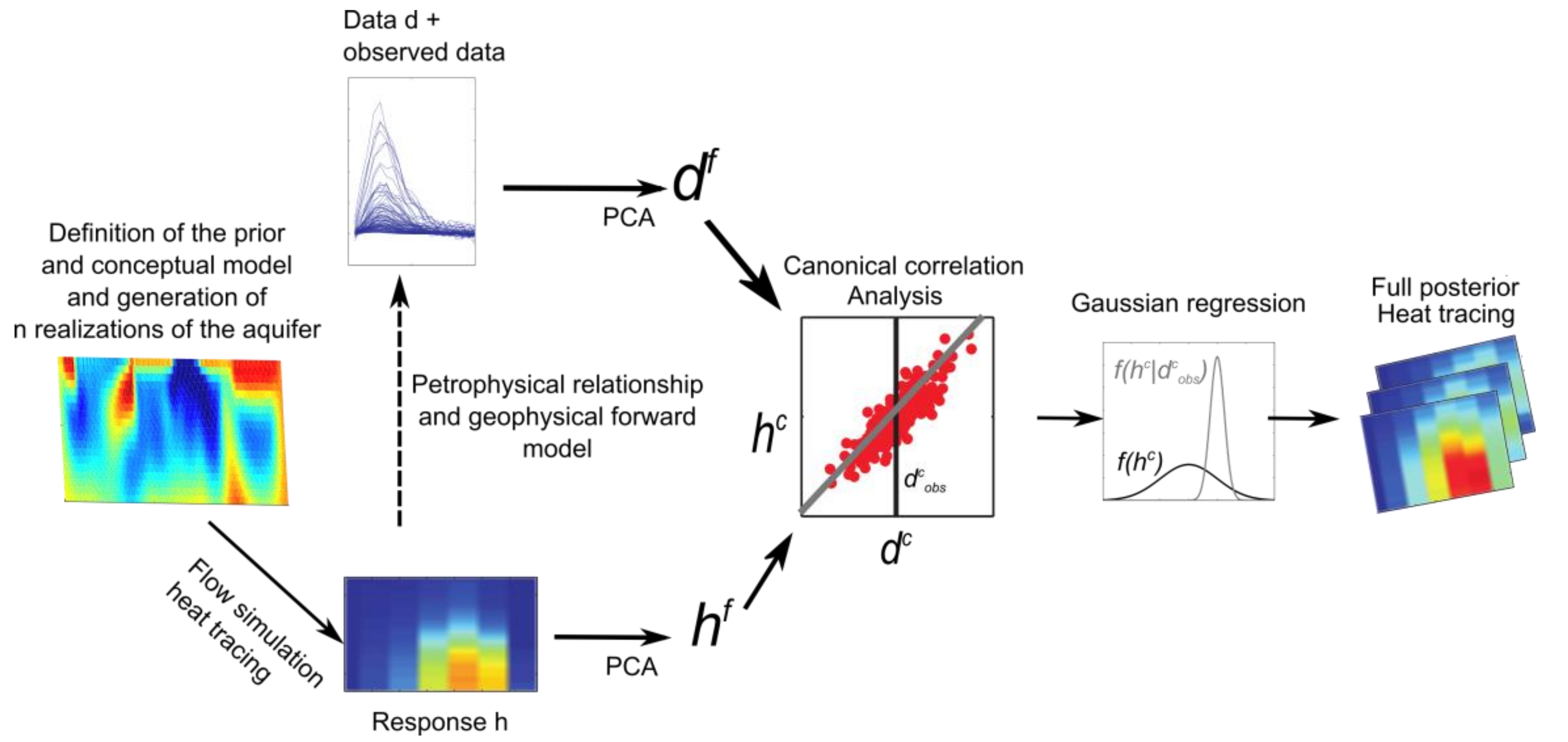

Fig. 1: Prediction-focused approach framework

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. 1):

1. Definition of the prior and generation of samples
2. Forward modeling of the prediction of interest and the data
3. Reduction of the dimension of the data and prediction variables (here with PCA)
4. Linearization of the relationship between reduced data and prediction (here with CCA)
5. Sampling of the posterior distribution in the low dimension space
6. Back-transformation in the original high dimension space

We apply PFA to derive the posterior distribution of temperature using time-lapse ERT data

2. Experimental set-up and noise analysis

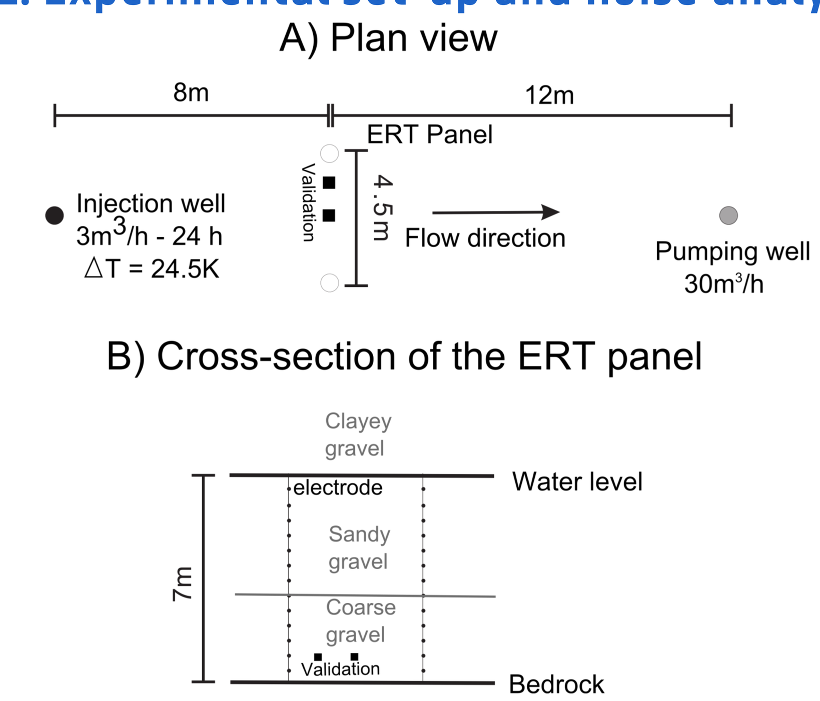

Fig. 2: Experimental set-up

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 h) is extracted and transformed into resistivity variations to simulate change in resistance data d [2].

To account for noise in the data [3] we generate noise-free data set 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

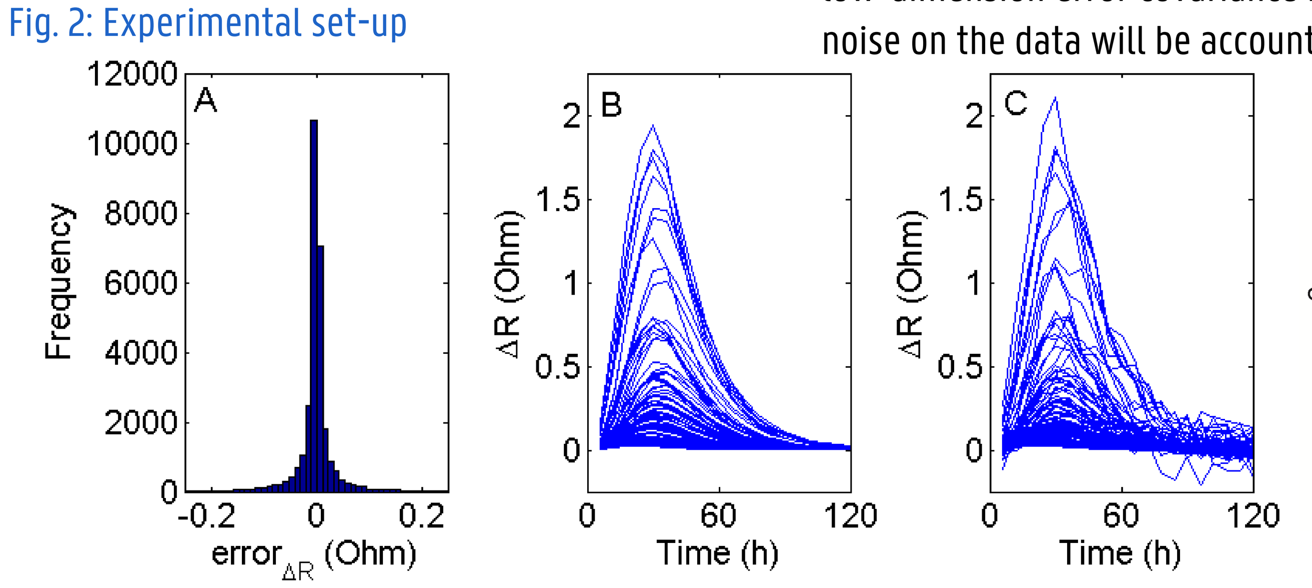

Fig. 3: Noise model (A), noise-free (B) and noisy (C) data sets

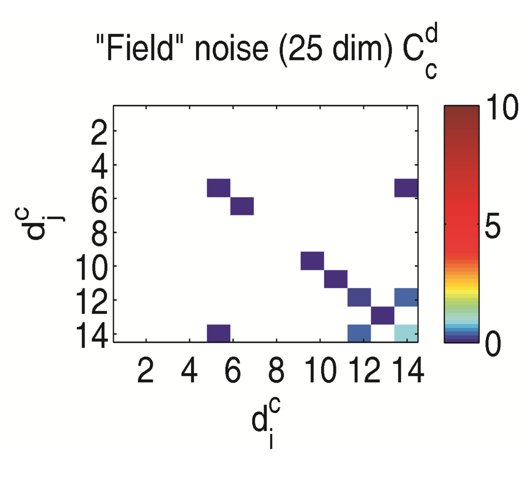

Fig. 4: Covariance matrix in CCA

3. Synthetic Examples

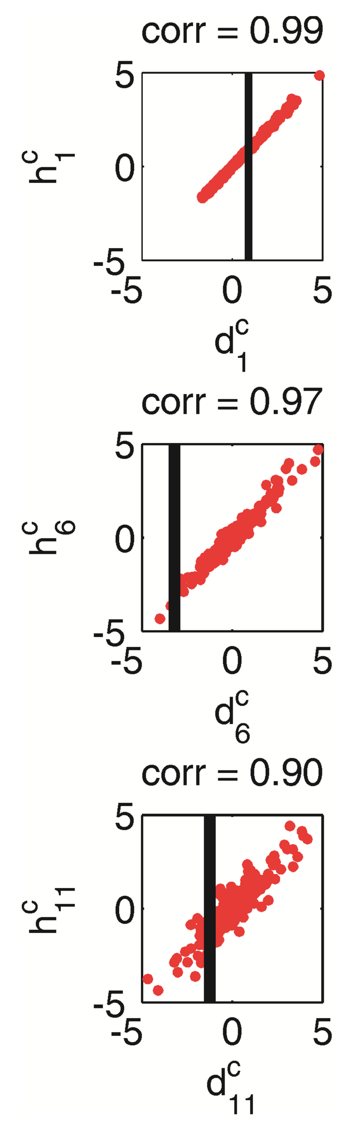

Fig. 5: 3 of the 14 dimensions in CCA

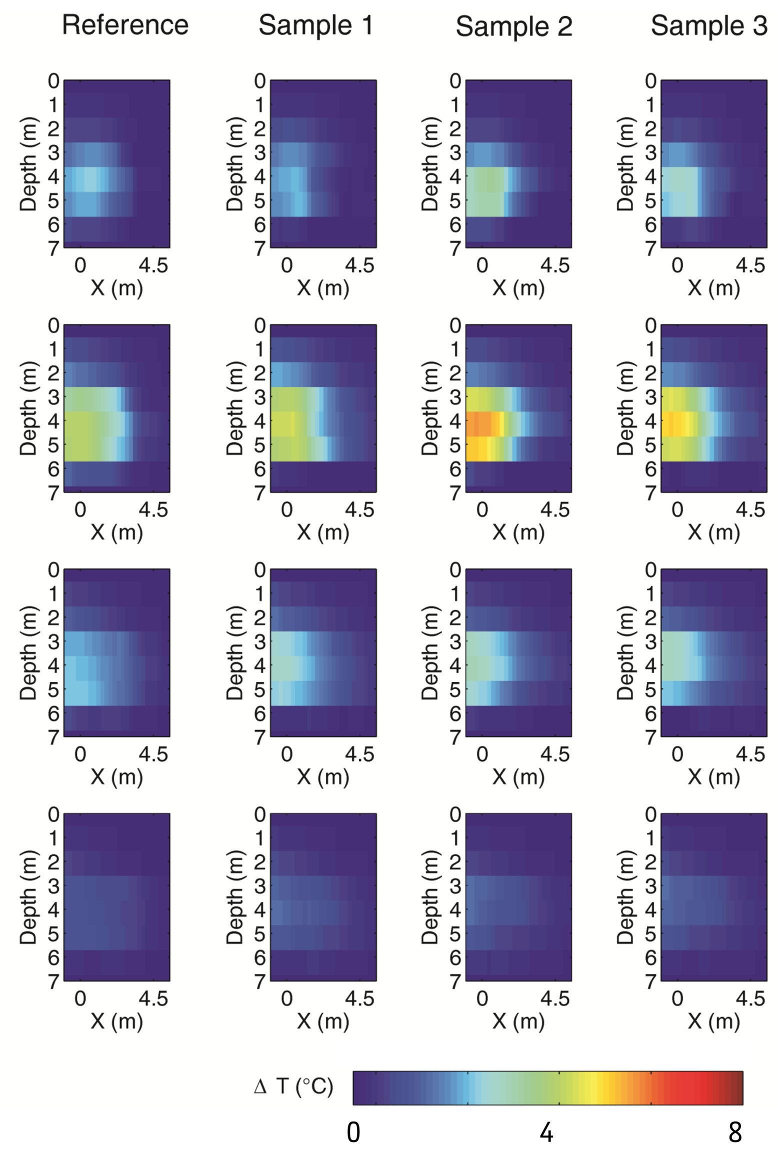

Fig. 6: Reference model and 3 sample sof the posterior distribution

In the synthetic example, we keep 25 dimensions in the data and 14 in the prediction after PCA. CCA enables us to derive 14 independent linear relationships between those reduced dimensions (Fig. 5). We choose one of the synthetic model as the reference and try to estimate the temperature distribution given the corresponding data (black lines, Fig. 5) and the prior models (red points on Fig. 5).

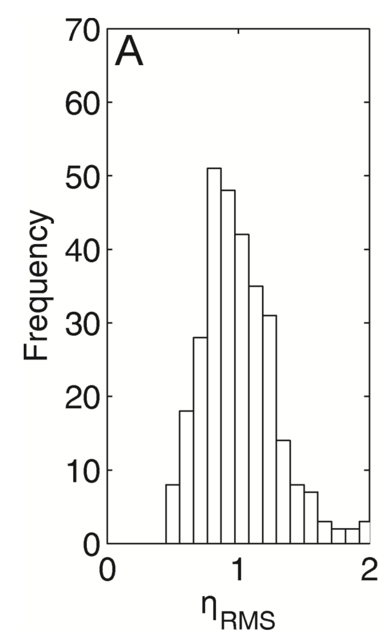

Fig. 8: Error weighted RMS of the posterior samples

By Gaussian regression, we can sample the posterior distribution of the predictions and back-transform it in the original space, giving us the posterior distribution of temperature.(Fig. 6) . The samples show that the spatial distribution is well resolved but that uncertainty on the maximum temperature exists.

The analysis of the mean temperature in the panel (Fig. 7) further shows that the method accurately estimate the temporal behavior of the tracer and that the temperature range is correctly estimated. A clear reduction of uncertainty is observed between the prior (grey curves, Fig. 7) and posterior (blue curves, Fig. 7), confirming that ERT contains crucial information to derive the spatio-temporal behavior of the tracer

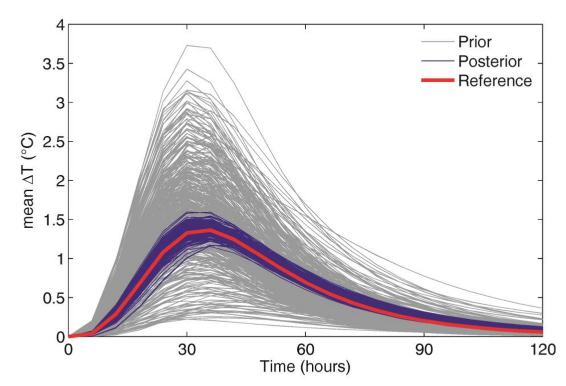

Fig. 7: Prior and posterior distribution of the mean temperature

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

Contact

thomas.hermans@ugent.be
www.ugent.be

4. Field application

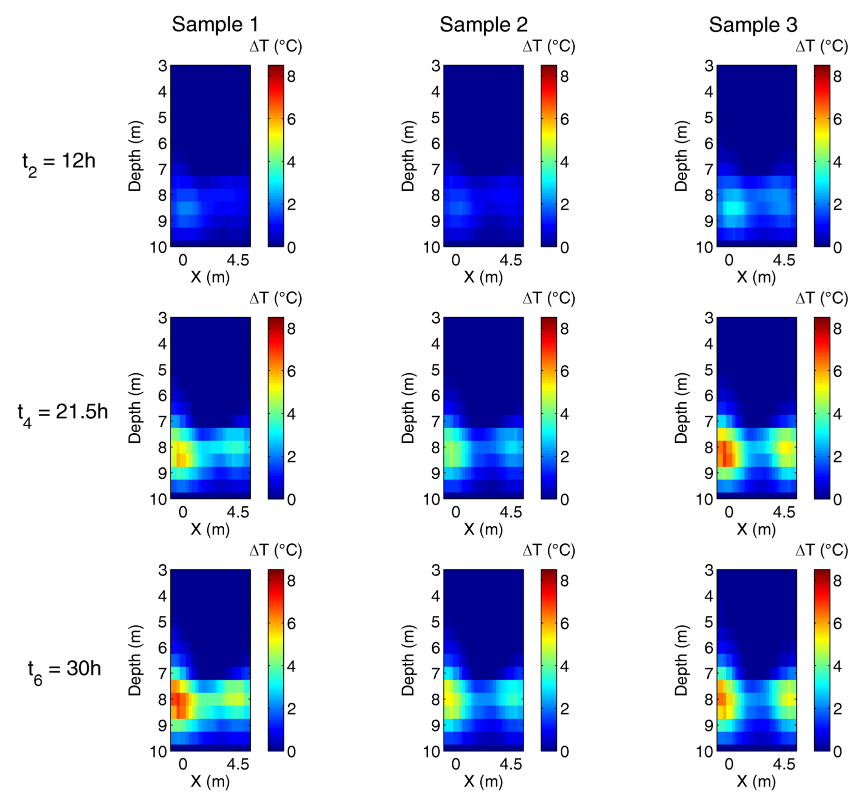

Fig. 9: 3 samples of the posterior distribution for the field experiment

For the field application, we generate 500 realizations of the alluvial aquifers using sequential Gaussian simulations. In addition to spatial uncertainty, seven paramaters 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 curves. We keep 12 dimensions in the data and 8 in the predictions, representing 99% and 90% of the variance respectively.

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.

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].

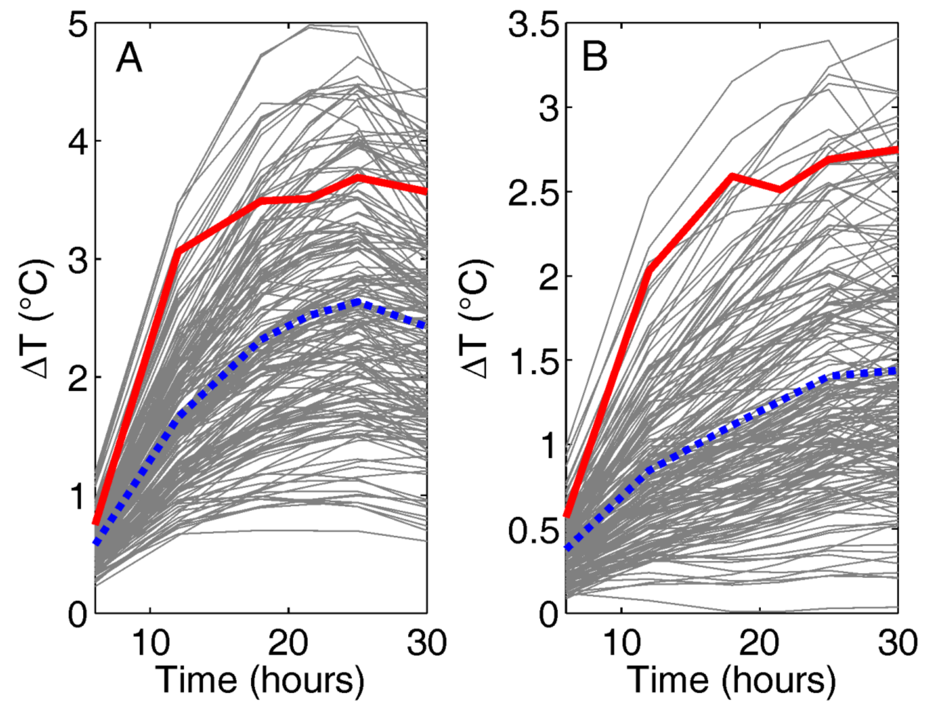

Fig. 10: Validation of the temperature distribution using direct temperature measurements

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 cases 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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