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Abstract
H31B-1505

# GROUNDWATER TEMPERATURE ESTIMATION AND MODELING USING HYDROGEOPHYSICS

## 1. SUMMARY

Groundwater temperature may be of use as a state variable proxy for aquifer heat storage, highlighting preferential flow paths, or contaminant remediation monitoring. However, its estimation often relies on scarce temperature data collected in boreholes. Hydrogeophysical methods such as electrical resistivity tomography (ERT) and distributed temperature sensing (DTS) may provide more exhaustive spatial information of the bulk properties of interest than samples from boreholes. In this contribution, we use different field experiments under natural and forced flow conditions to review developments for the joint use of DTS and ERT to map and monitor the temperature distribution within aquifers, to characterize aquifers in terms of heterogeneity and to better understand processes. We show how temperature time-series measurements might be used to constraint the ERT inverse problem in space and time and how combined ERT-derived and DTS estimation of temperature may be used together with hydrogeological modeling to provide predictions of the groundwater temperature field.

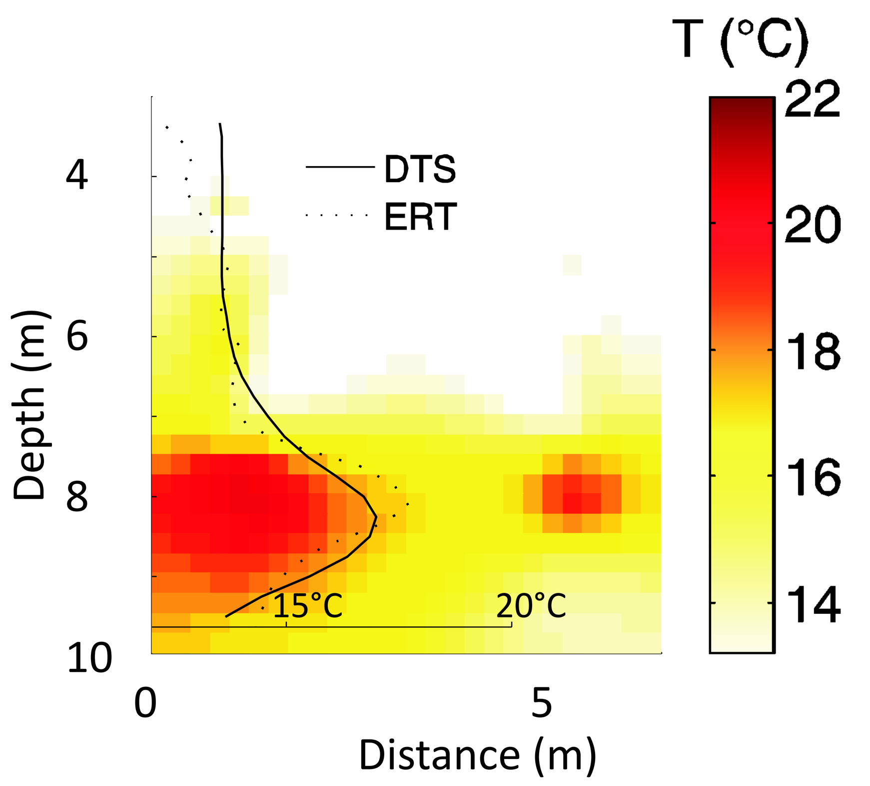
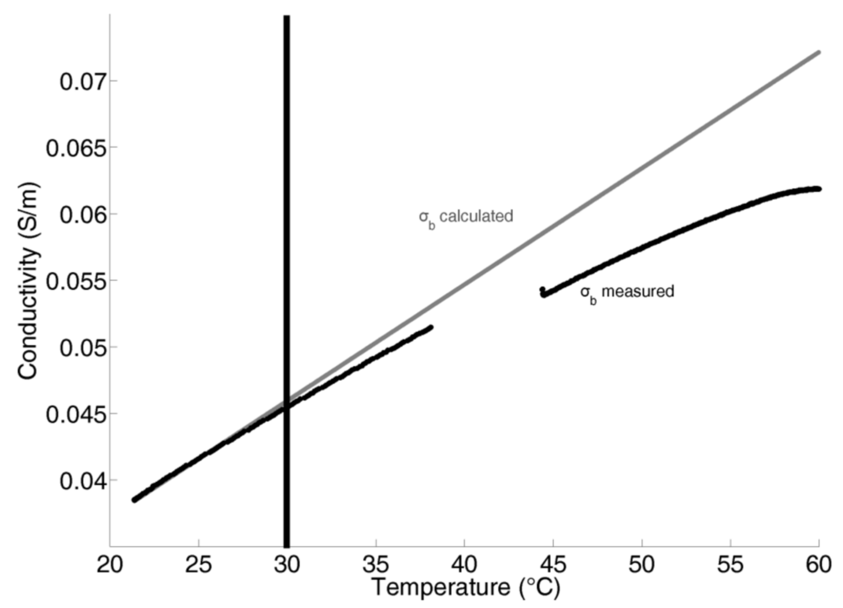



Image: ERT-derived temperature tomography highlighting preferential flow paths and superposed direct temperature measurements with fiber optics

## 2. FLUID TEMPERATURE AS A PROXY FOR HYDROGEOPHYSICS

If a properly calibrated DTS reading provides direct measurements of the groundwater temperature in the well, ERT requires one to determine the fractional change per degree Celsius. One advantage of this petrophysical relationship is its relative simplicity: the fractional change is often found to be around 0.02 per °C, and represents mainly the variation of electrical resistivity due to the viscosity effect. However, in presence of chemical and kinetics effects, the variation may also depend on the duration of the test and may neglect reactions occurring between the pore water and the solid matrix. Such effects are not expected to be important for low temperature systems (<30 °C), at least for short experiments (figure 1).




EQ1: $$\frac{\sigma_{f,T}}{\sigma_{f,T_{ref}}} = m_{f,T_{ref}}(T - T_{ref}) + 1$$

$\sigma_{f,T}$ is the fluid electrical conductivity at temperature T (in °C), $\sigma_{f,Tref}$ is the fluid electrical resistivity at the temperature of reference (typically 25°C), and $m_{f,Tref}$ is the linear temperature dependence of electrical conductivity with (°C$^{-1}$).

Fig. 1: The calculated conductivity (equation 1) is not coherent with the measured conductivity due to chemical reactions in the sample. The missing data correspond to a bad electrical contact on the measuring device. [1]

## 3. RECENT DEVELOPMENTS AND RESULTS OF HEAT TRACER

In [2], we propose a geostatistical constraint (figure 2), namely the model parameter change covariance matrix, as regularization operator for the time-lapse ERT inverse problem (equation 2). The method is applied to field data from a heat tracing experiment where the comparison with direct measurements shows a strong improvement on the breakthrough curves retrieved by ERT (figure 3).

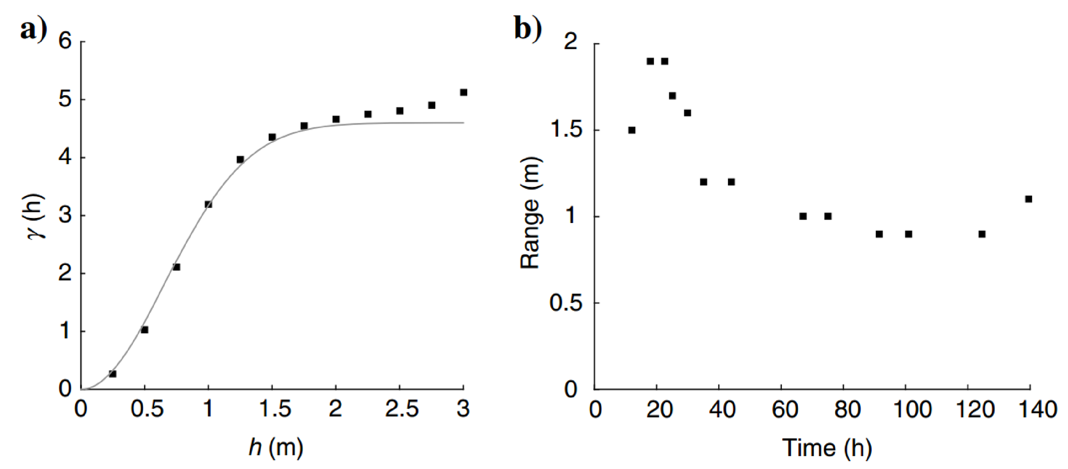



Fig. 2: a) The experimental variogram for the time step 30h after beginning of injection and its description by a Gaussian model. b) The range of the fitted variogram model evolves with time.

EQ2: $$\phi_{diff}(\Delta\mathbf{m}) = \left\| W_d \left[ (\mathbf{d} - \mathbf{d_0}) - (f(\mathbf{m}) - f(\mathbf{m_0})) \right] \right\|^2 + \lambda \left\| C_{\Delta\mathbf{m}}^{-0.5} \Delta\mathbf{m} \right\|^2$$

$\Delta\mathbf{m}$ is the change in resistivity between the background model $\mathbf{m_0}$ and the monitored model $\mathbf{m}$. $\mathbf{d}$ and $\mathbf{d_0}$ are the corresponding resistance data weighted by $W_d$ and $f$ is the forward operator. $\lambda$ is the regularization parameter, $C_{\Delta\mathbf{m}}$ is the model parameter change covariance matrix computed from the variogram (figure 2).

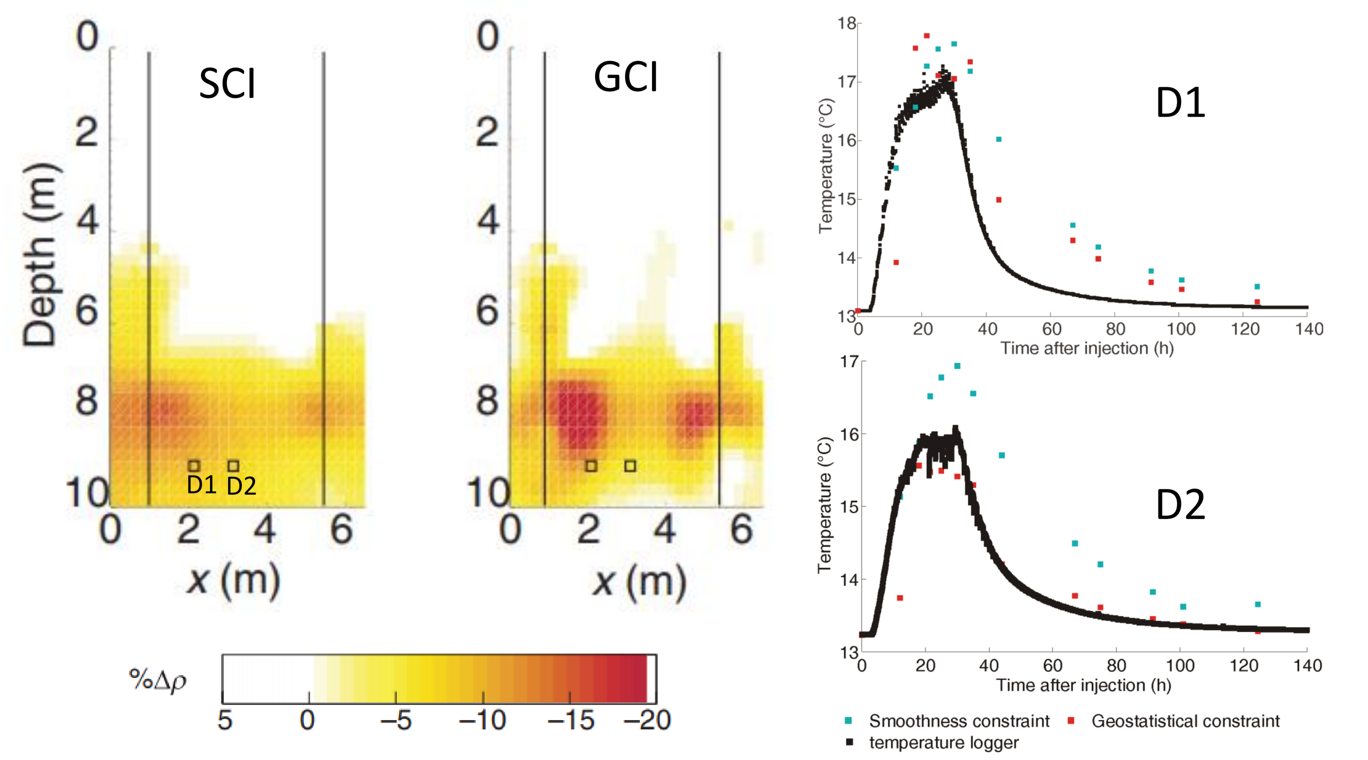



Fig. 3: Comparison of the smoothness constraint (SCI) and geostatistical inversion (GCI) results at 35h during a heat tracing experiment and with direct measurements of the temperature loggers at positions D1 and D2.

## 5. 4D MONITORING OF HEAT STORAGE AND MODELING

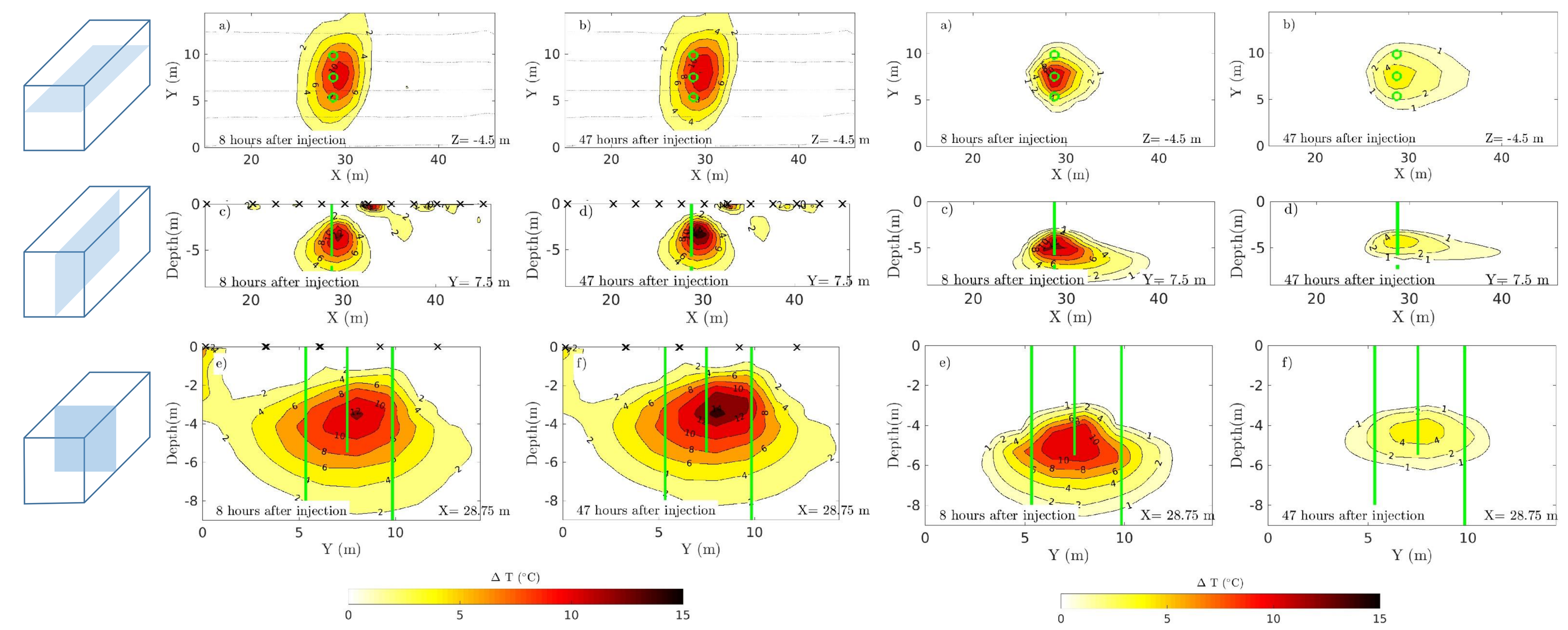



Fig. 4: Left: ERT-derived temperature changes 8 h and 47 h after the injection started. The green circles and lines represent the injection and measurement boreholes. The black dotted lines and crosses correspond to the electrodes. Regularization tends to over-smooth the images. Right: HydroGeoSphere model of the experiment. [3]

## 5. PFA FOR HYDROGEOPHYSICAL INTEGRATION (SEE ALSO H31B-1509)

The objective of prediction-focused approaches (PFAs) in our case is to find a direct relationship between data (resistances) and predictions (temperature) [4,5] without inverting the data to avoid any regularization bias. To do so, PFAs rely on a realistic prior distribution of subsurface realizations, accounting for any uncertain component, to derive the relationship between data and predictions (figure 5).

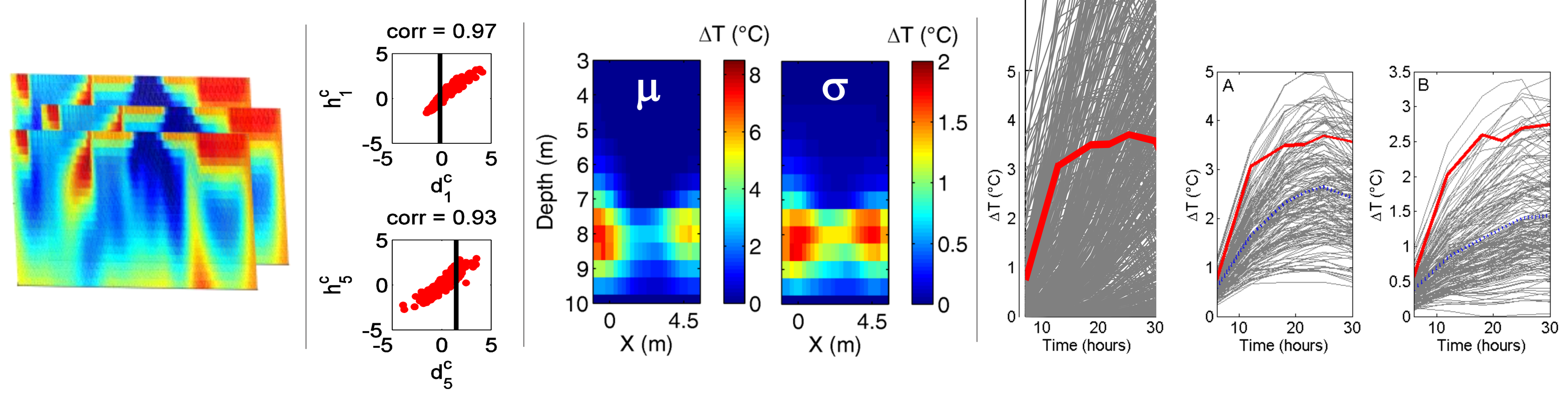



Fig. 5: PFA from left to right : N realizations of the aquifer and hydrogeophysical modeling | PCA-CCA to derive the relationship data **d** and prediction **h** in a reduced space (ᶜ) | sampling of the posterior (mean, standard deviation, compare to fig.3) | validation of the prior and posterior distribution with the **mean** with direct measurement (red) in the unreduced space.

## Conclusion

We demonstrate that electrical resistivity tomography derived temperature fields can be used for aquifer characterization and monitoring using heat injection in both forced and natural conditions in 2D and 3D. We improved the deterministic imaging of the heat plume with inversion honoring the observed temporal variation of geostatistics. To further avoid the bias introduced by regularization, we proposed a prediction focused approach to generate more realistic geological scenario, to integrate hydrogeophysical data and to assess uncertainty.

### Contact and information

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Measurements taken at the site of Hermalle-Sous-Argenteau (Belgium)
http://hplus.ore.fr/en/enigma/data-hermalle
ERT inversion performed with CRTomo qnd EIDORS, hydrothermo modelling performed with HydroGeoSphere:

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