# Direct prediction of temperature from time-lapse ERT using Bayesian Evidential Learning : extension to a 4D experiment

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**Abstract**

The use of geophysical methods to characterize subsurface properties has significantly grown in the last decade. Although geophysics can bring relevant spatial and temporal information on subsurface processes, the quantitative interpretation and integration in models remain difficult. Indeed, standard deterministic solutions suffer from (excessive) smoothing and spatially variable resolution, whereas joint or coupled inversions remain difficult to apply in complex cases. Hermans et al. (2016) proved using cross-borehole ERT that physical properties distribution could be directly retrieved from data using Bayesian Evidential Learning (BEL). BEL uses a series of prior models to derive a direct relationship between data and forecast in a reduced dimension space. This can be challenging when the prediction becomes more complex with higher dimensions. In this contribution, we extend the work of Hermans et al. (2016) to a full 4D experiment (3D + time). We demonstrate that the shape and amplitude of the temperature plume can be retrieved, with uncertainty quantification, during a push-pull experiment using surface ERT. We analyze the robustness of the solution using a synthetic benchmark. The results indicate that the median of the posterior is very close to the true temperature distribution. The relative error increases at the edge of the temperature plume where the change of temperature is limited. This is related to the limited resolution of geophysics and the process of dimension reduction. We also investigate how discrete cosine transform can improve the dimension reduction process without altering the final prediction. Finally, we show that BEL is able to retrieve the spatio-temporal variability of the plume, while the smoothness constraint inversion fails to accurately image the corresponding contrast, largely underestimating the amplitude of the temperature change. BEL is therefore a well-suited framework for the interpretation of 4D geophysical data avoiding the drawbacks of standard deterministic solutions. Hermans, T., Oware, E., & Caers, J. (2016). Direct prediction of spatially and temporally varying physical properties from time-lapse electrical resistance data. Water Resources Research, 52, 7262-7283.

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## 1. Introduction to Bayesian Evidential Learning

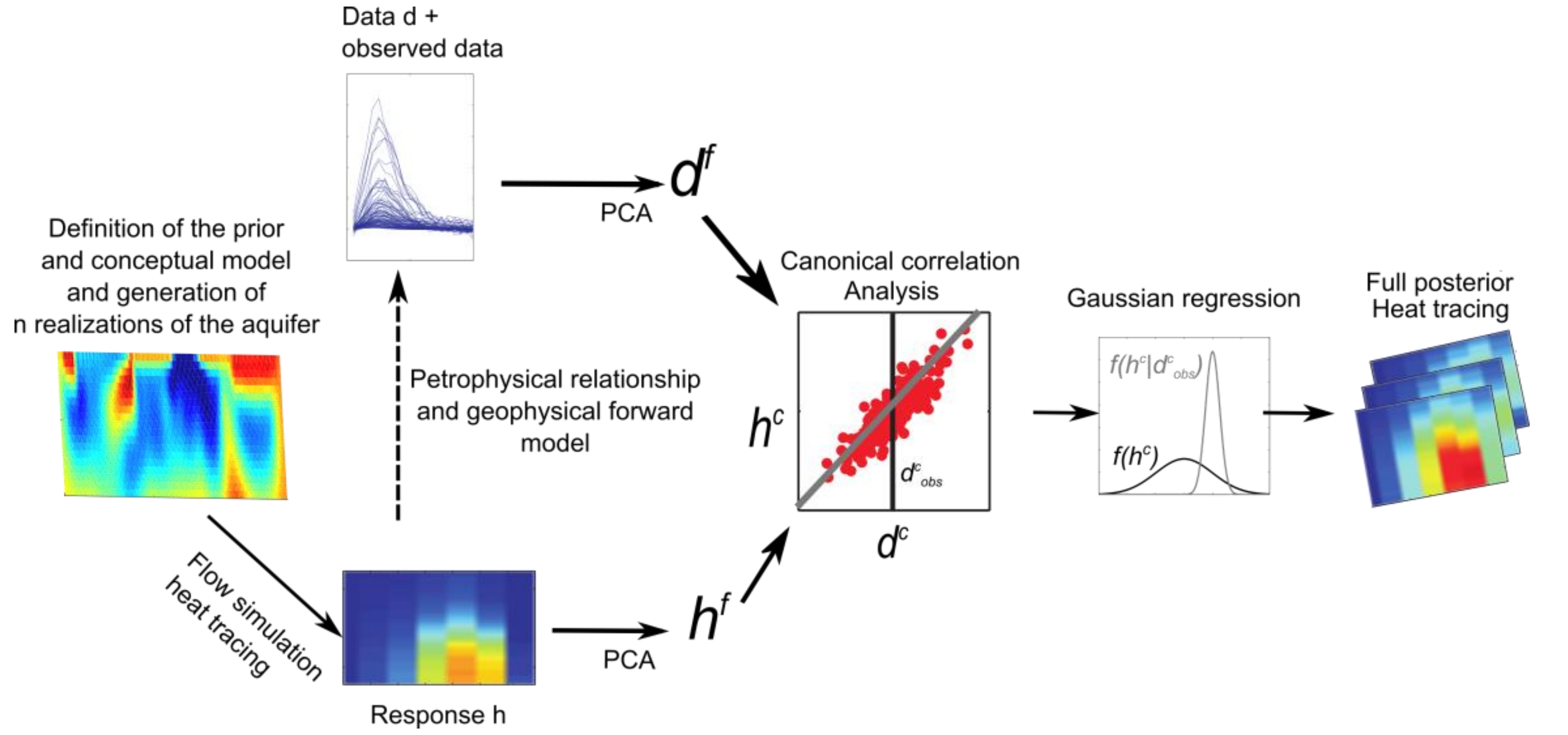



Fig. 1: Bayesian Evidential learning framework applied to time-lapse geophysical interpretation

The objective of Bayesian Evidential Learning (BEL) is to find a direct relationship between data and predictions without explicit inversion [1]. BEL relies 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 and the data
3. Reduction of the dimension of the data and prediction variables (e.g., PCA).
4. Linearization of the relationship between reduced data and prediction (e.g., CCA, regression trees)
5. Sampling of the posterior distribution in the low dimension space (e.g., Gaussian regression, Kernel density)
6. Back-transformation in the original space

The method has been demonstrated for 2D cross-borehole time-lapse ERT [2,3]. We extend it to 3D surface time-lapse ERT (4D).

## 2. Experimental set-up

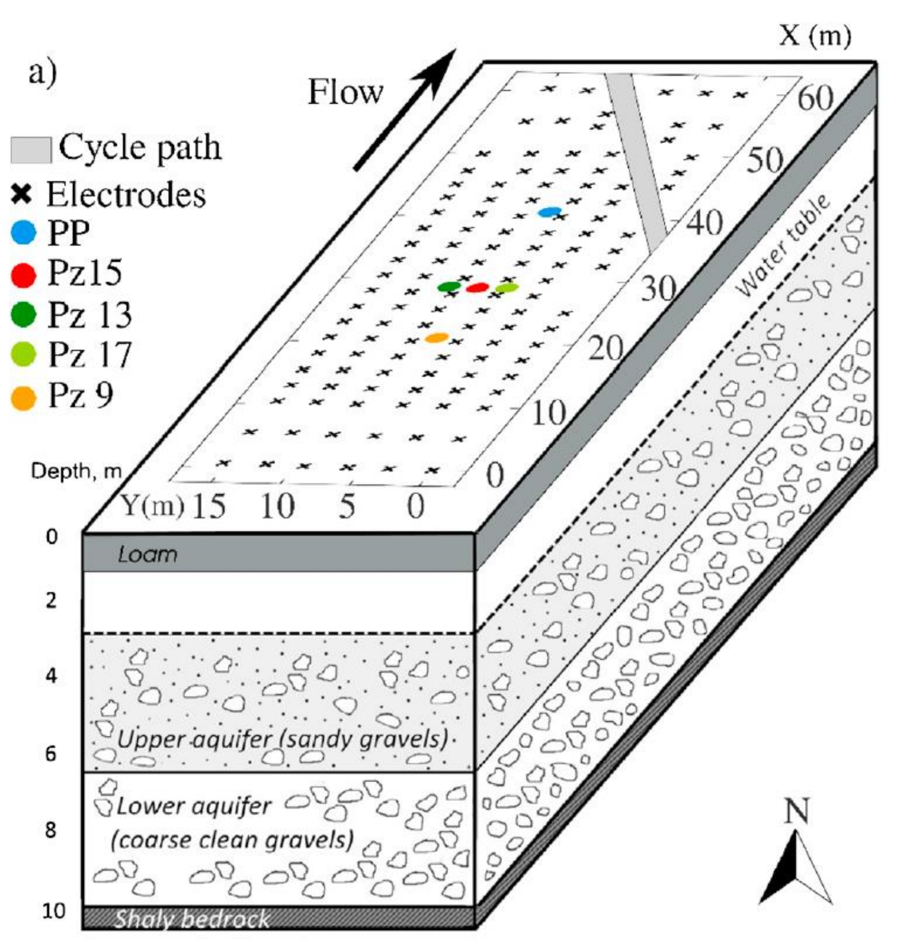



Fig. 2: Experimental set-up

The objective of the study is to derive the temperature distribution during a heat storage experiment using time-lapse electrical resistance data (Fig. 2). 6 parallel profiles of 21 electrodes are used to collect resistance data during the experiment.. It consists in the injection of heated water ($\Delta T = 28.6\ K$) at a rate of 3 m³/h during 6 hours in the upper aquifer followed by a storage period (91 h), a pumping period (15.5 h at 3 m³/h) and a final resting period [see 4].

The alluvial aquifer is modeled using 250 sequential Gaussian simulations based on our prior knowledge of the site (Table 1). The heat storage experiment is simulated using HydroGeoSphere for each simulation. The temperature distribution (prediction h) at 106 time-steps is extracted and transformed into resistivity variations using a petrophysical relationship [2] to simulate the change in resistance data d.

Table 1. Simulation parameters

| Uncertain Parmeter | Range of value | Uncertain Parmeter | Range of value |
|---|---|---|---|
| $\log K_{mean}$ | Uniform [-1 to -4], $K$ in m/s | Anisotropy ratio | Uniform [0.1 to 0.5] |
| $\sigma^2_{\log K}$ | Uniform [0.05, to 2], $K$ in m/s | Orientation of main range to flow direction | Uniform [0 to $\pi$] |
| Porosity | Uniform [0.05 to 0.3] | | |
| Variogram main range | Uniform [1 to 10 m] | Natural gradient | Uniform [0.05 to 0.167 %] |

## 3. Results

To validate the approach, we select the data set of one of the 250 models that we consider as our ground truth and we use the other 249 models to predict the temperature distribution. The original data set contains 1948 quadrupoles and the prediction is the temperature in a volume composed of 3808 cells, both for 106 time-steps. We first reduce the dimensions of both variables using PCA. (Fig. 3)

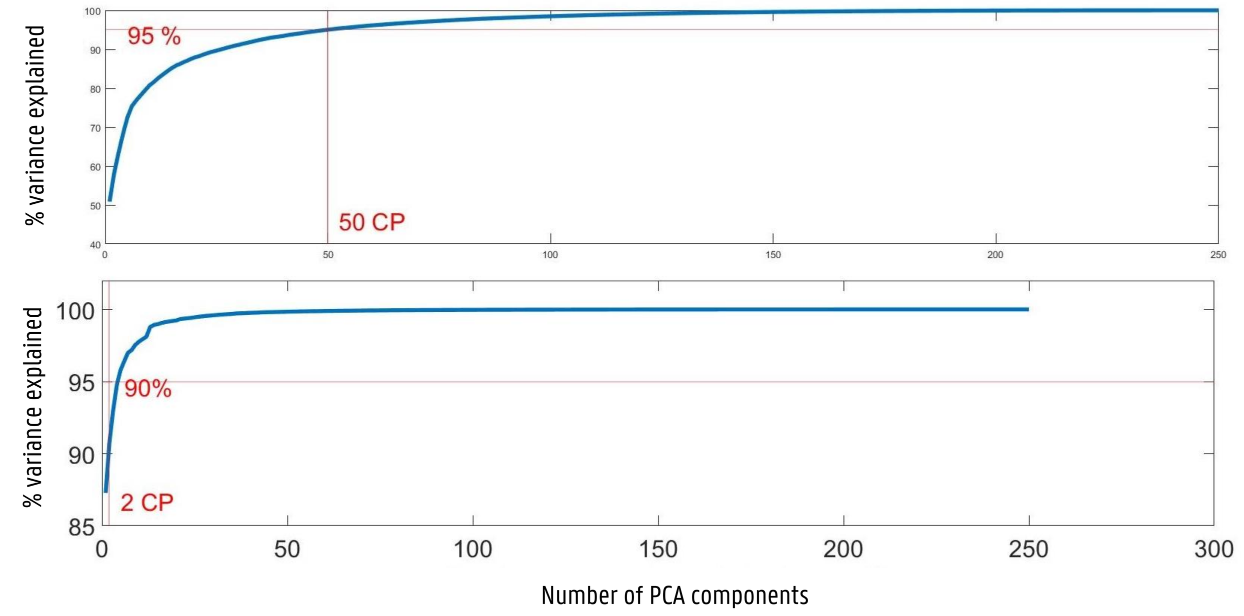



Fig. 3. Dimension reduction of the prediction with PCA and discrete cosine transform

Then, we apply canonical correlation analysis (CCA) (Fig. 4). This process yields a set of independent linearized relationship between the reduced dimensions of the data (d) and the prediction (h). We use 30 dimensions for both.

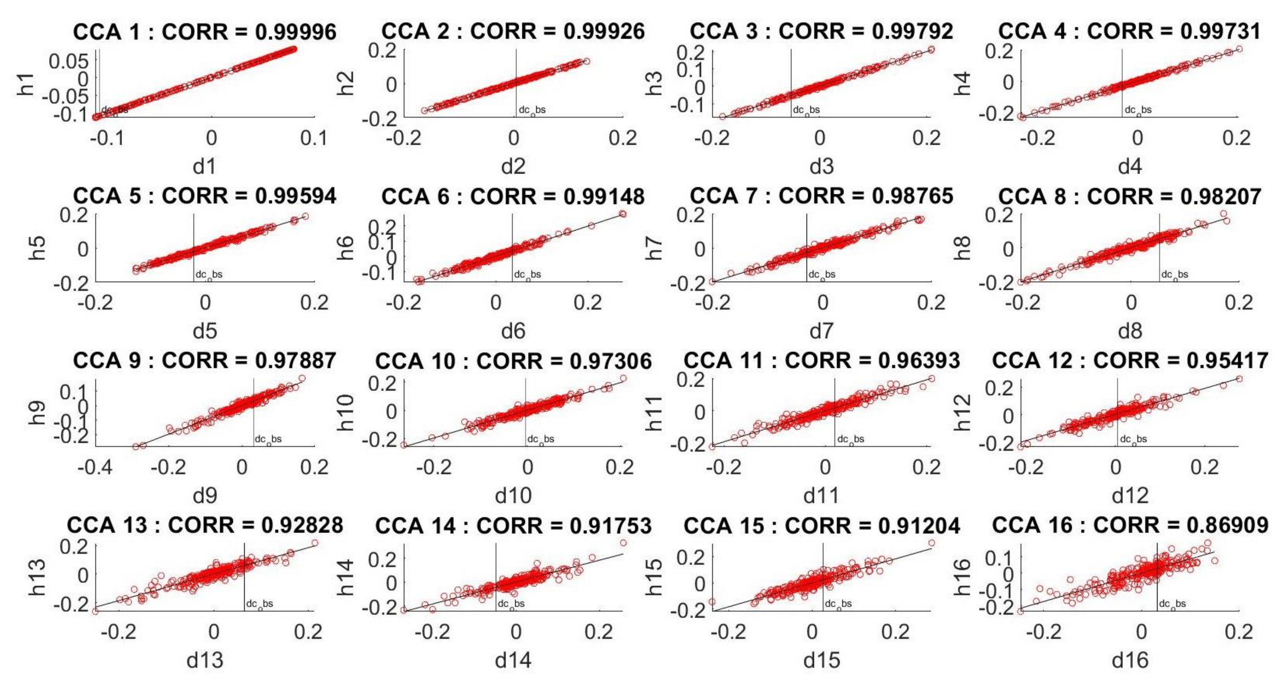
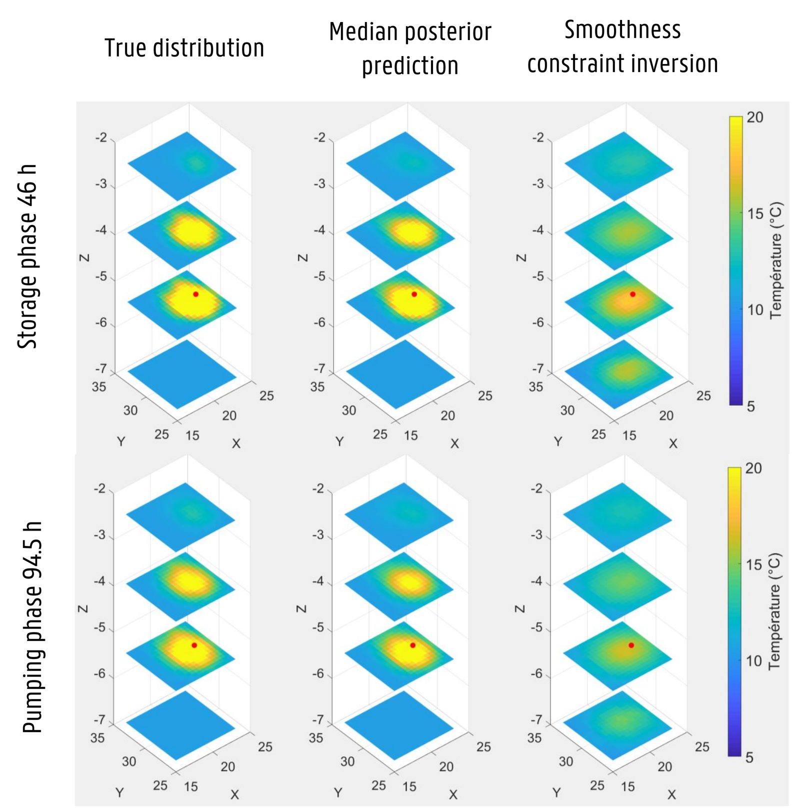



Fig. 4. Statistical relationship between d and h using CCA (first 16 dimensions)




Once the relationship is known, it is straight-forward to sample the posterior distribution $p(h|d)$ in the low dimensional space and back-transform it to the original space (Fig. 5).

We use Kernel density estimation in the CCA space to derive $p(h|d)$

Fig. 5. True, one predicted and smoothness-constraint temperature distribution for 2 different time-steps

The comparison of the predicted and true temperature shows the excellent ability of BEL to predict the temperature in the aquifer from time-lapse ERT, without explicit inversion and thus without smoothing (FiG. 5).

## 4. Validation and improvement

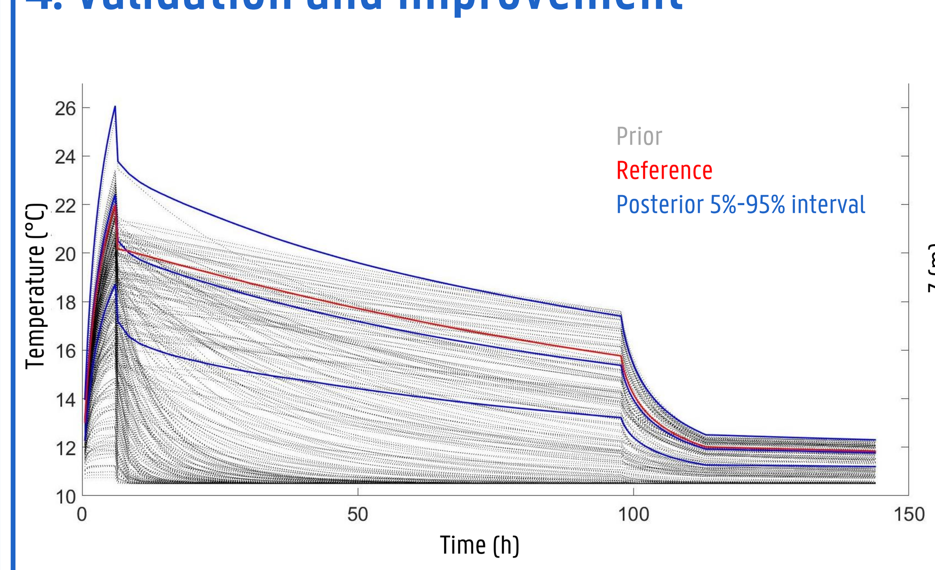



Fig. 6. Average temperature around the well

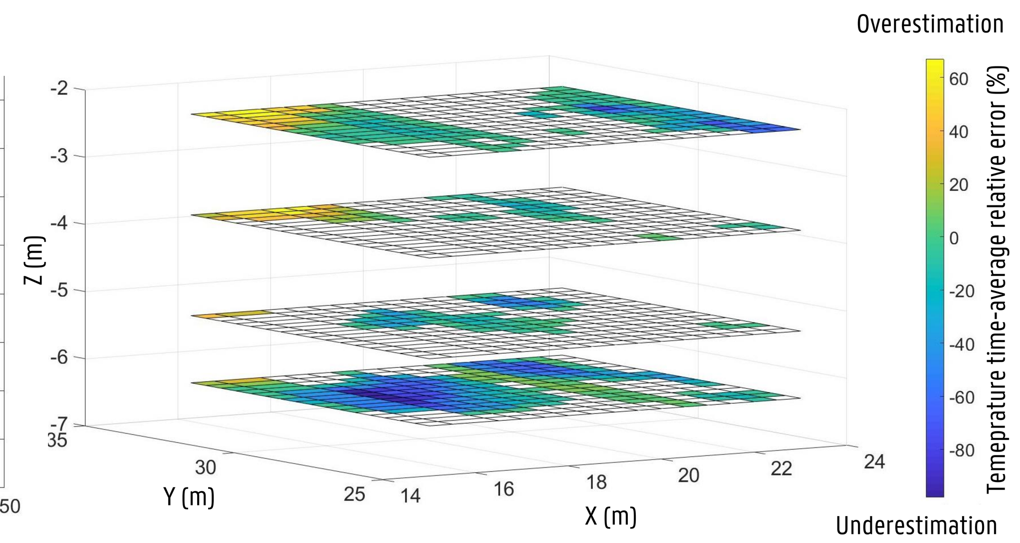



Fig. 7. Spatial distribution of cells for which the 5%-95% prediction interval does not contain the true temperature

We validate the temperature distribution by comparison with the true temperature around the well (Fig. 6). We see that the median sample of the posterior is very close to the reference. The 5%-95% interval indicates the range of uncertainty on the temperature from ERT. Spatially, most model cells with a true temperature outside the 5%-95% interval for at least one time-step (Fig. 7) lie in areas at the edge of the model with very low temperature (see Fig 5), so that the absolute error on temperature is very limited. Therefore, BEL does not create artifacts.

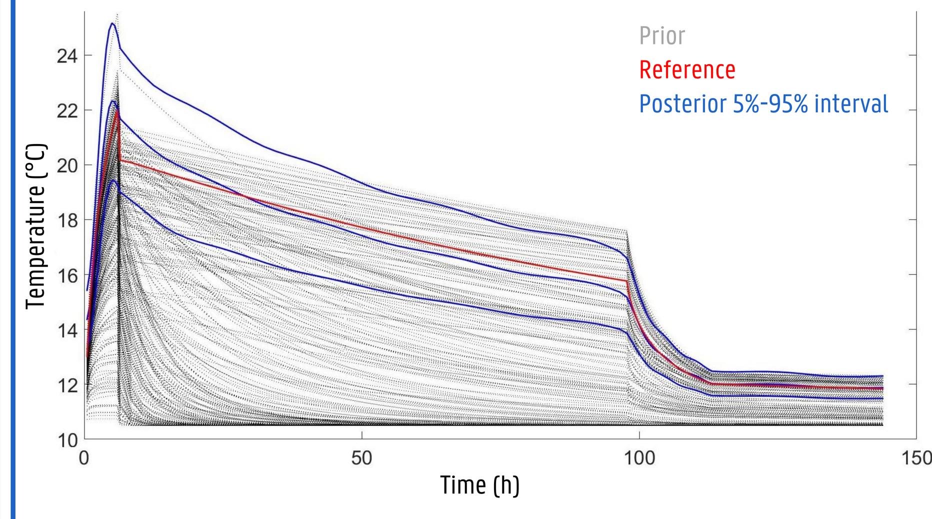



Fig. 8. Average temperature around the well when using discrete cosine transform to reduce the prediction

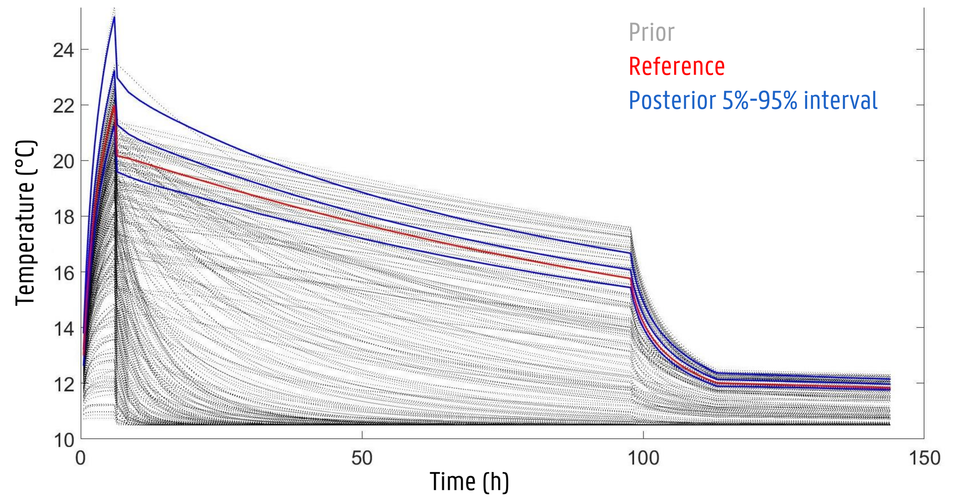



Fig. 9. Average temperature around the well when adapting the Kernel bandwidth to the correlation coefficients in CCA

The results can be further improved by using alternative procedures in BEL. In Fig. 8, we reduce the dimension of the prediction using discrete cosine transform (DCT) instead of PCA. DCT is more performant to reduce the dimension (Fig. 3) and yield a reduced uncertainty range. Similarly, the uncertainty range can be reduced by noticing that the correlation coefficient in CCA for the 6 first dimensions is above 99% (Fig. 4). It means that a narrower bandwidth can be used when estimating the posterior. In that case, the uncertainty range becomes smaller than 1.5°C in the area around the well (Fig. 9).

## Conclusion and perspectives

- We demonstrate the ability of Bayesian Evidential Learning to derive the temperature distribution in an alluvial aquifer during a heat storage experiment monitored by 3D surface ERT
- The framework allows to generate the posterior distribution without any explicit inversion
- Compared to standard methods, this approach yields more geologically realistic samples, avoiding smoothing due to regularization and enables to assess uncertainty by generating many possible solutions consistent with the data
- The approach only requires independent forward runs and can be parallelized
- The method has a huge potential for hydrogeophysical predictions, but more generally to any prediction problems.
- We are planning to apply the method to field data and further investigate the influence of noise on the results

References

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