FACULTY OF SCIENCES

DEPARTMENT GEOLOGY
RESEARCH GROUP HYDROGEOLOGY AND APPLIED GEOLOGY

HOW INFORMATIVE ARE SINGLE WELL TRACING EXPERIMENTS? AN ASSESSMENT USING BAYESIAN EVIDENTIAL LEARNING

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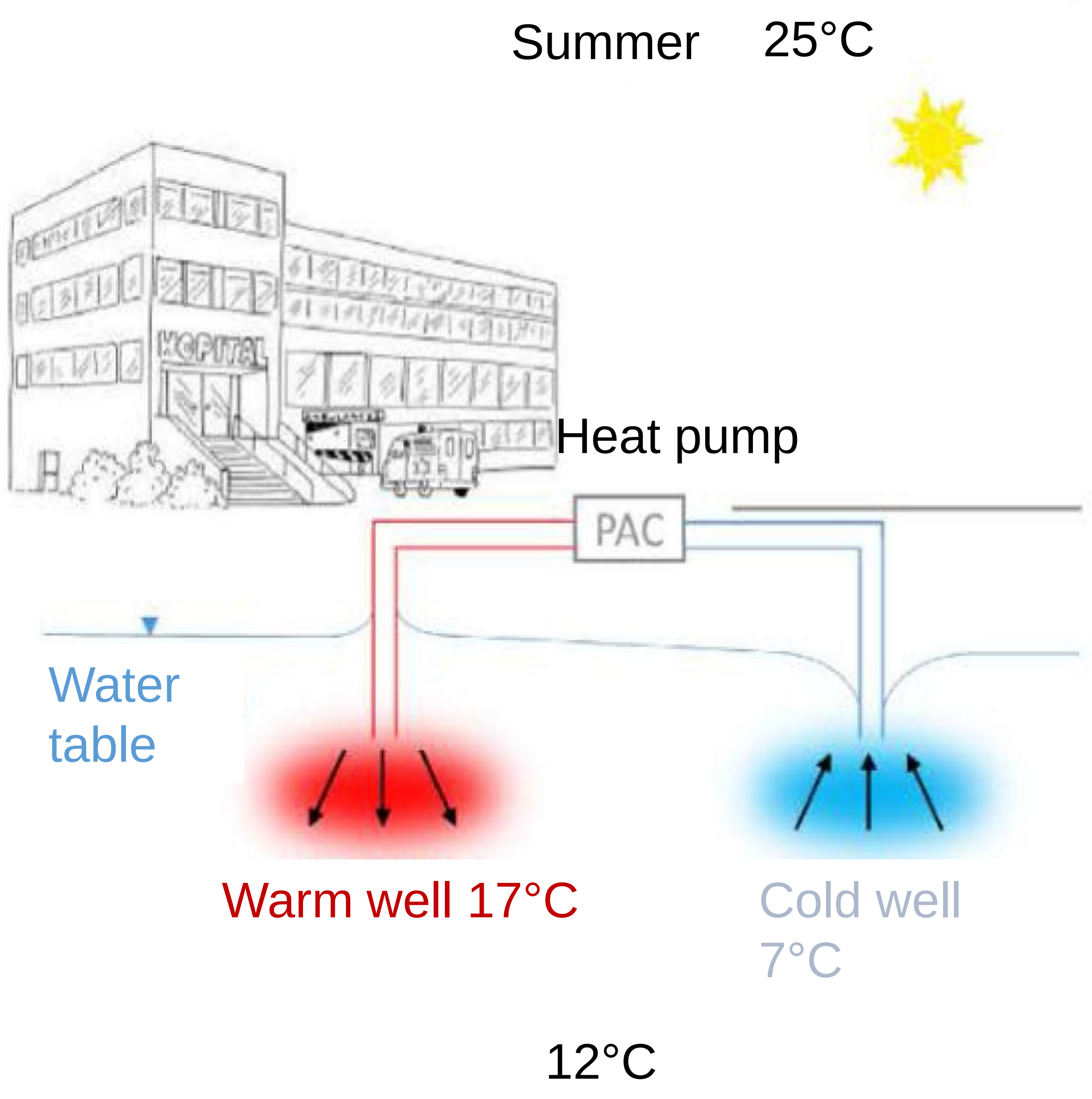
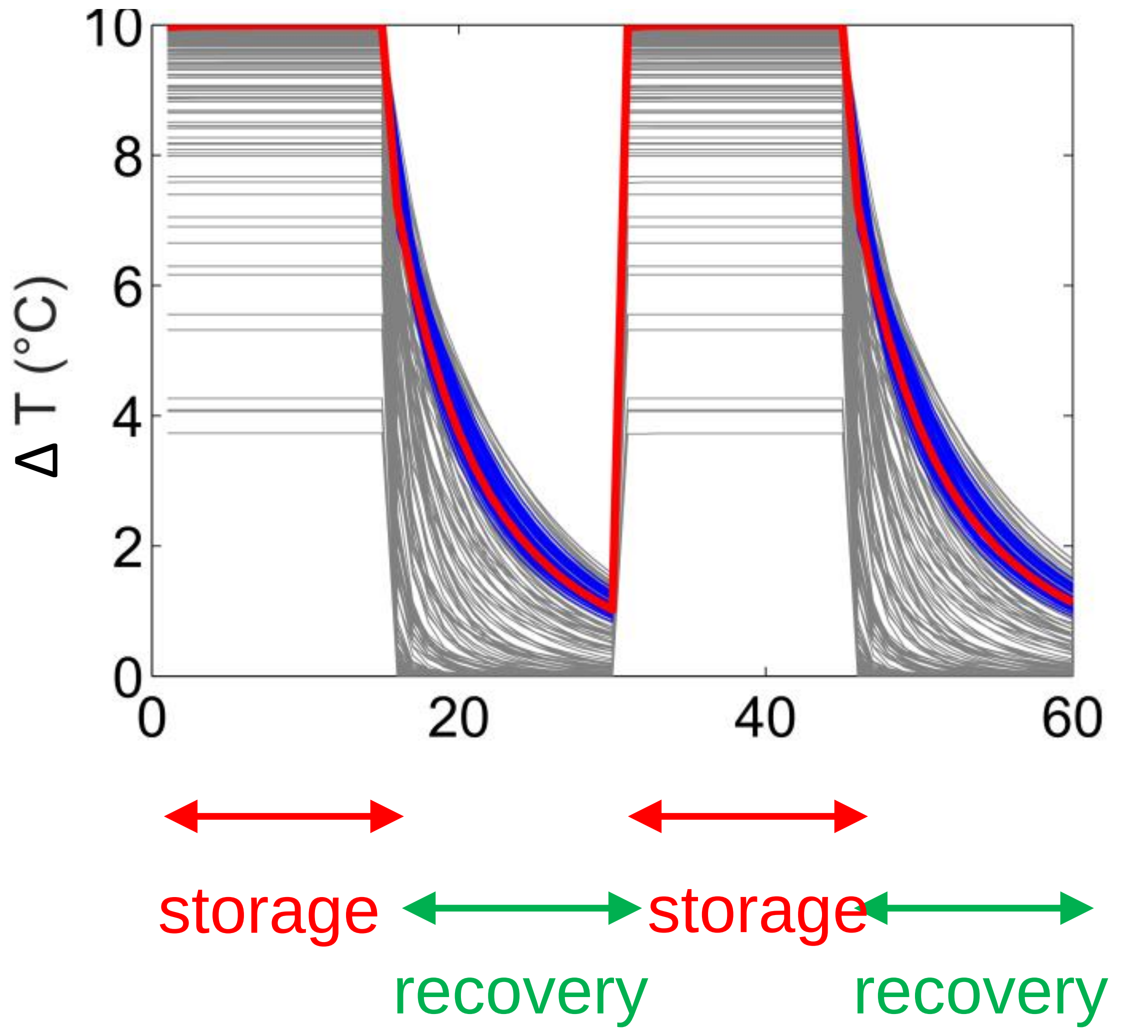
CASE STUDY INSPIRED BY ATES DESIGN



Required prediction + uncertainty



Budget limitations

→ only wells for the ATES are drilled

→ Only single-well experiments are possible

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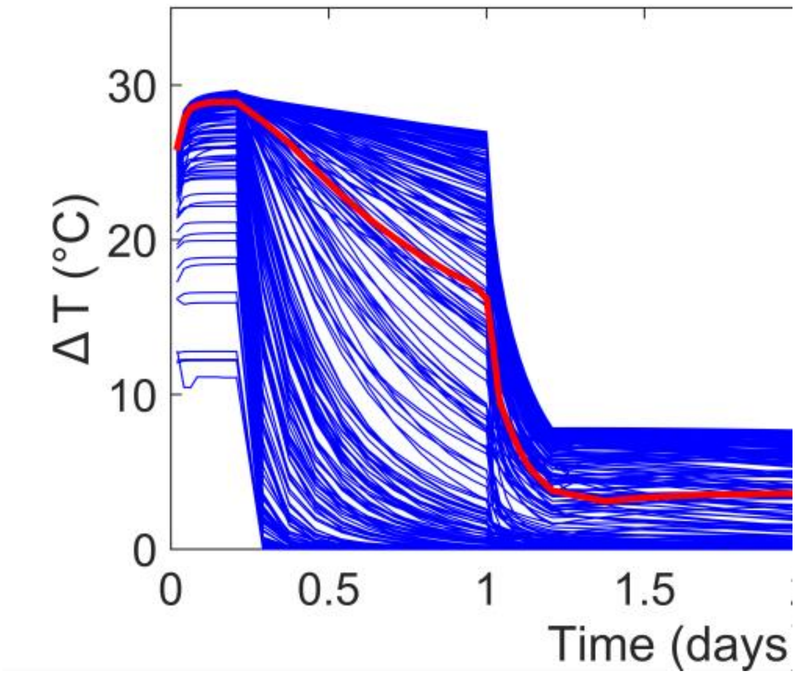
HOW DO WE GET THIS PREDICTION

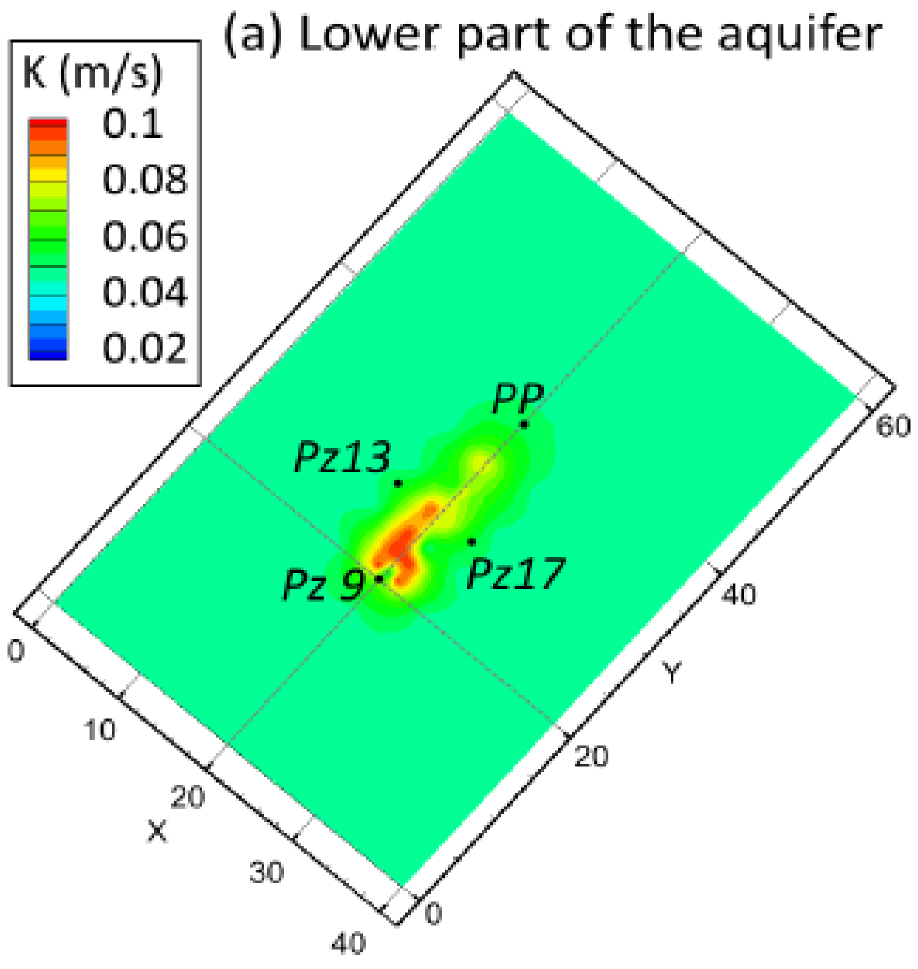
"Standard Method"

Data → **Models** → **Prediction**

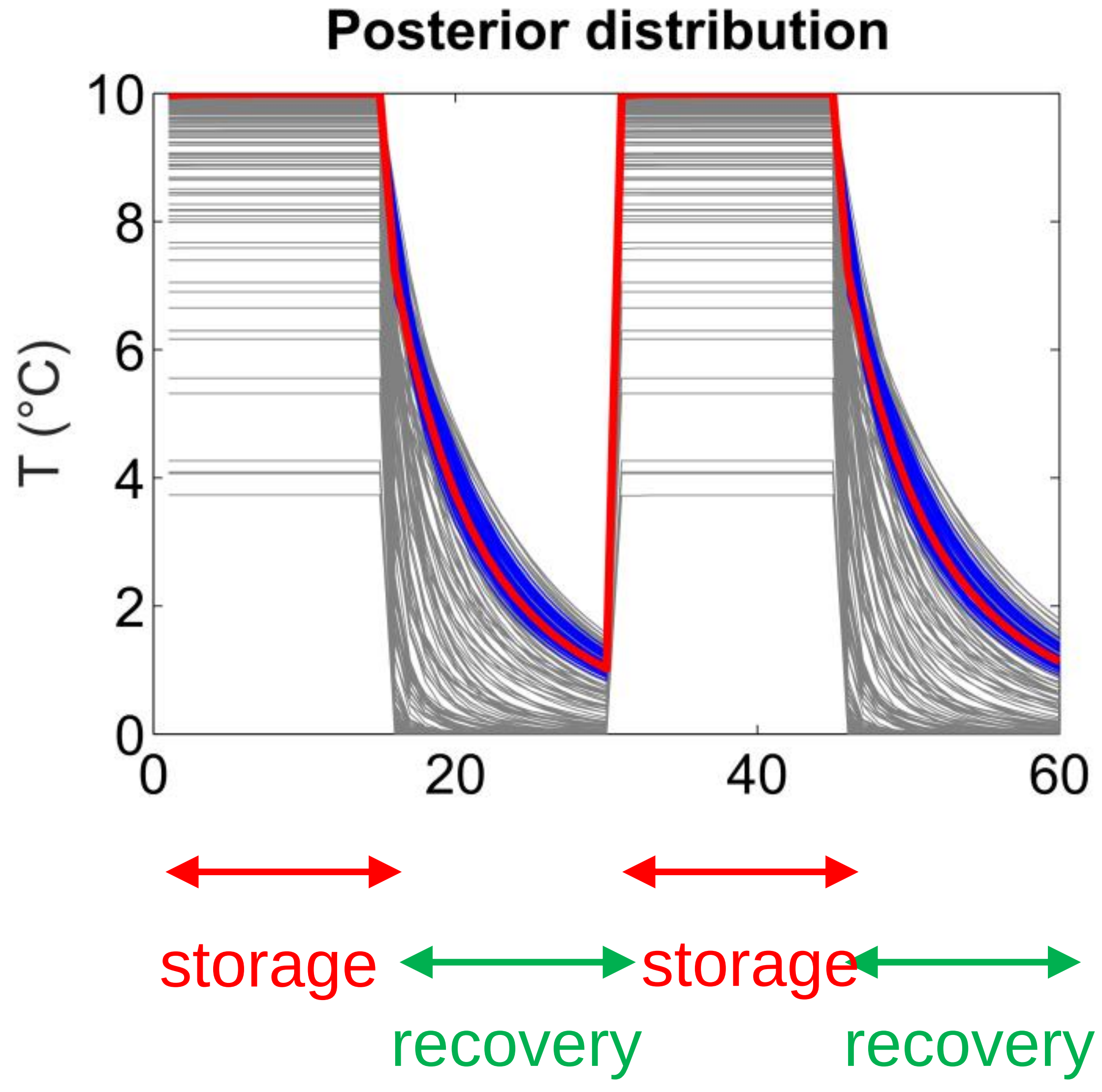


TRT, Push-pull

Tracing, etc.



(Klepikova et al., 2016, JoH)



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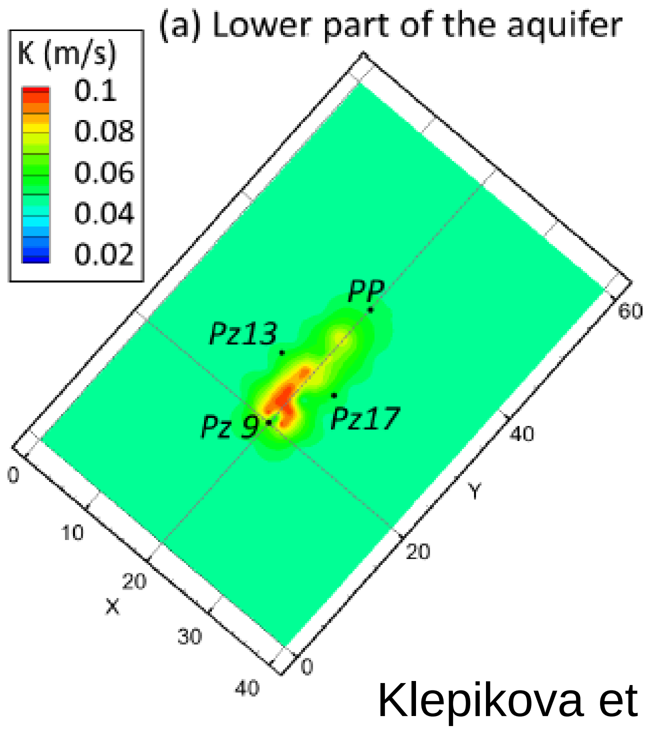
IS THIS APPROACH SATISFACTORY ?

Models

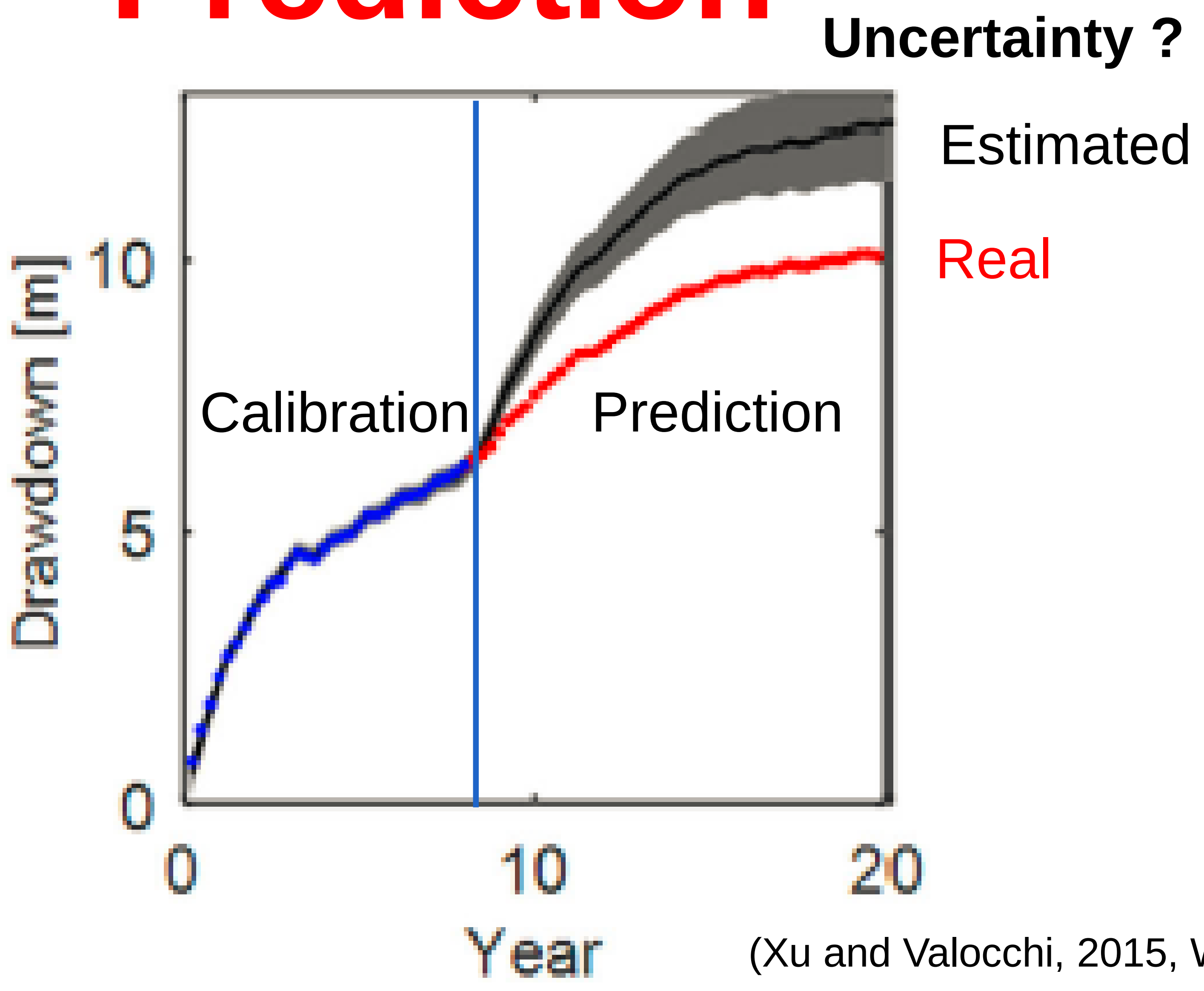
Parameterization : zonation, layered model, simplification to reduce the number of unknowns, etc. Choice of the boundary conditions, type of parameters (flow, heat transport, etc.)

Deriving models with just single-well data ?



Klepikova et al., 2016

Prediction



(Xu and Valocchi, 2015, WRR)

Can we make long-term prediction based on single-well experiments only ?

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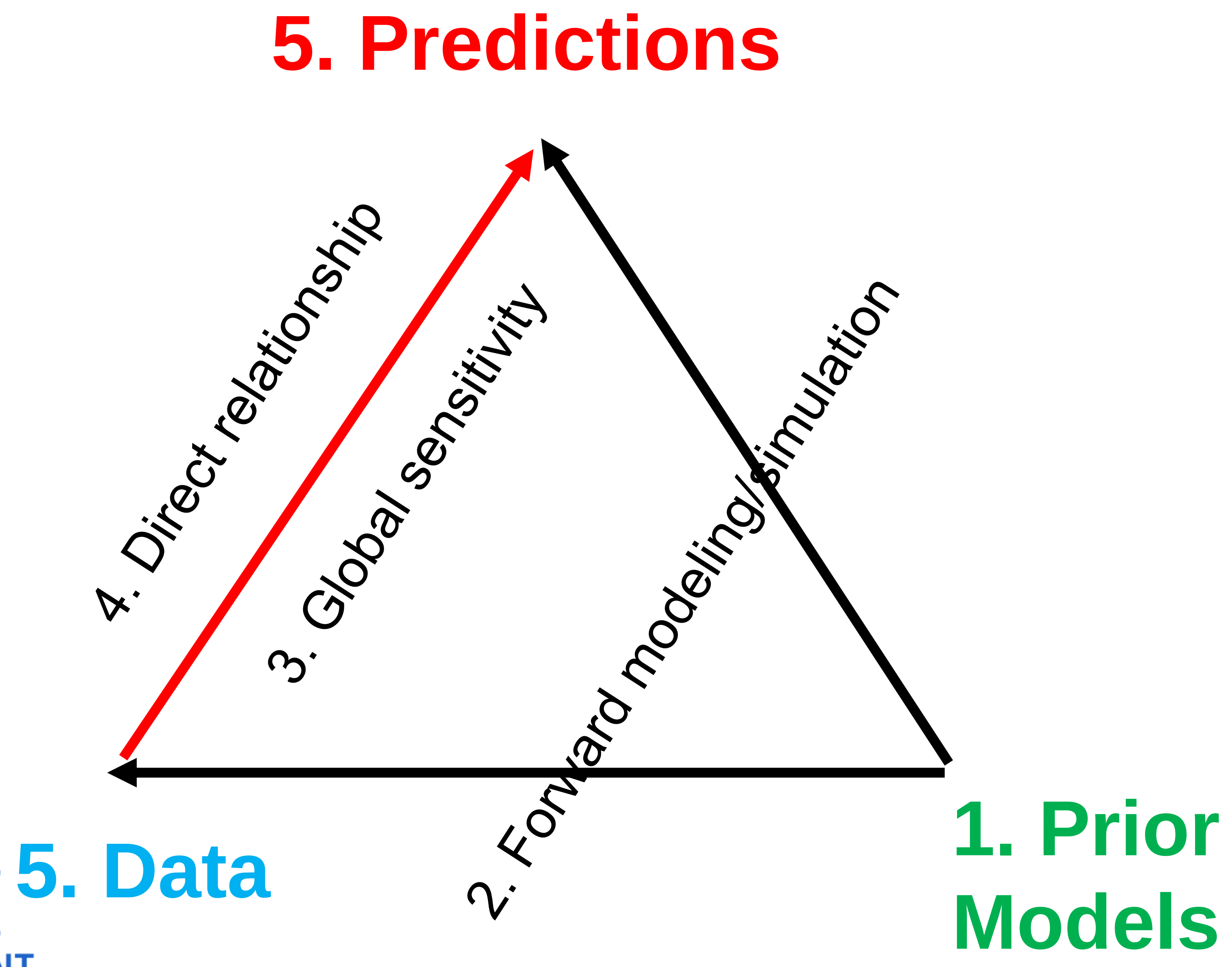
BREAKING THE LINE

Bayesian Evidential Learning

New paradigm



1. We generate **realistic models (not calibrated)** based on our geological knowledge
2. We simulate our data sets and our prediction
3. We assess the sensitivity of both: **is the data informative ?**
4. We seek a direct relationship between data and prediction
5. We **estimate the real prediction** based on field data

(Hermans, 2017, GW)

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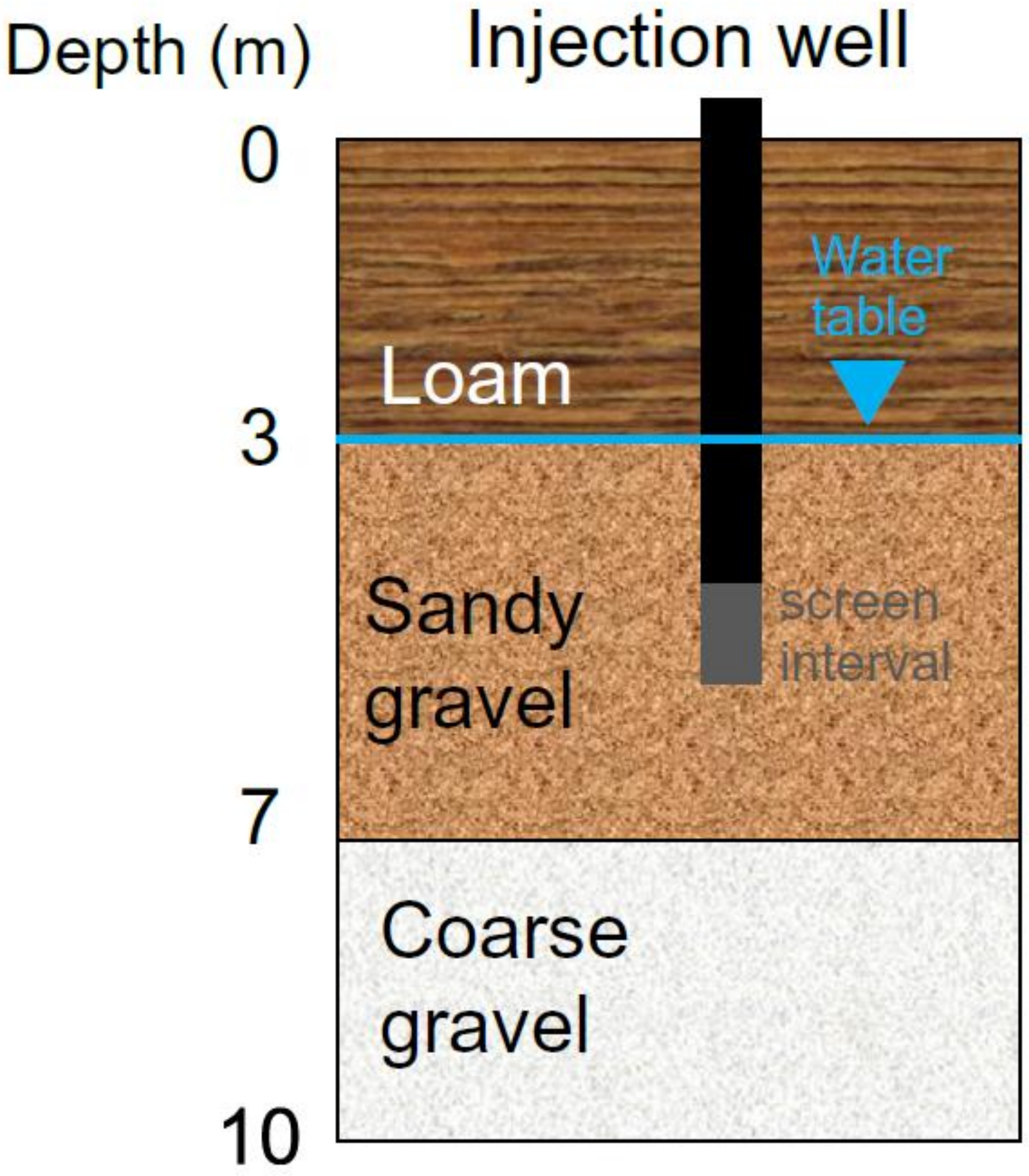
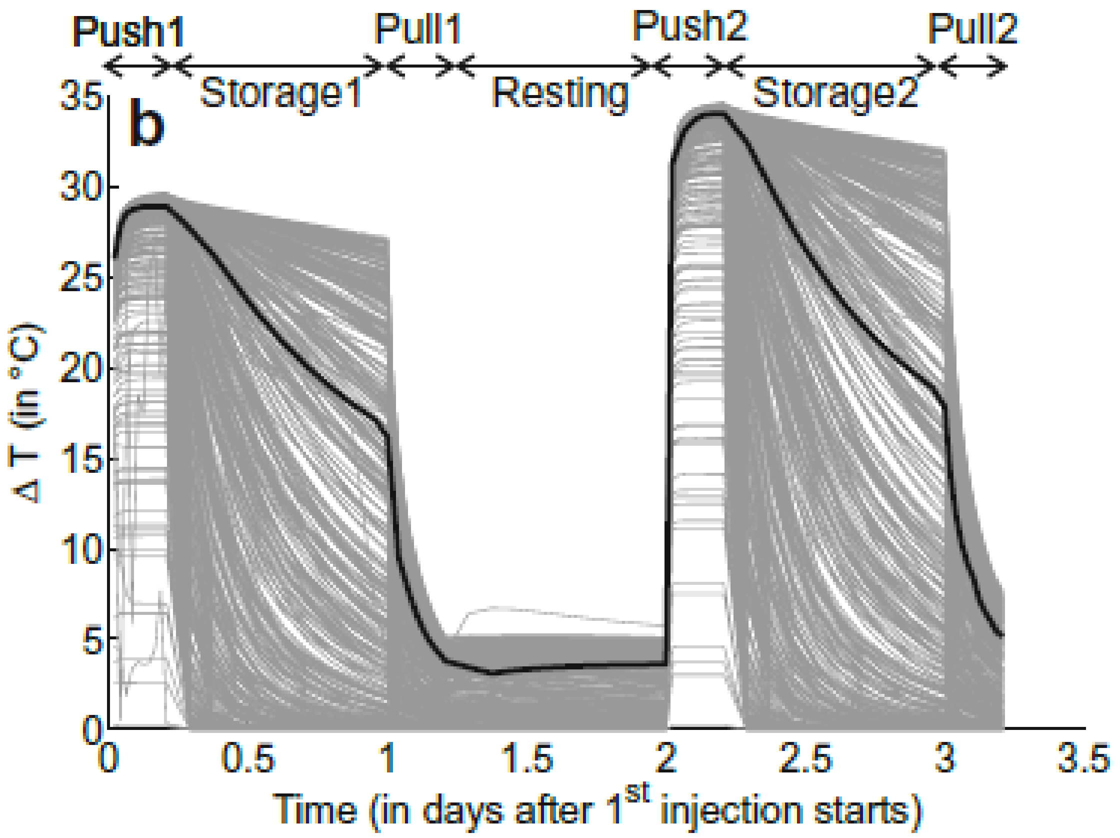
HEAT STORAGE IN A SHALLOW AQUIFER



Prediction

Simulation of an ATES system

Temperature in the hot well



(Hermans et al., 2019, Hydrog. J.)

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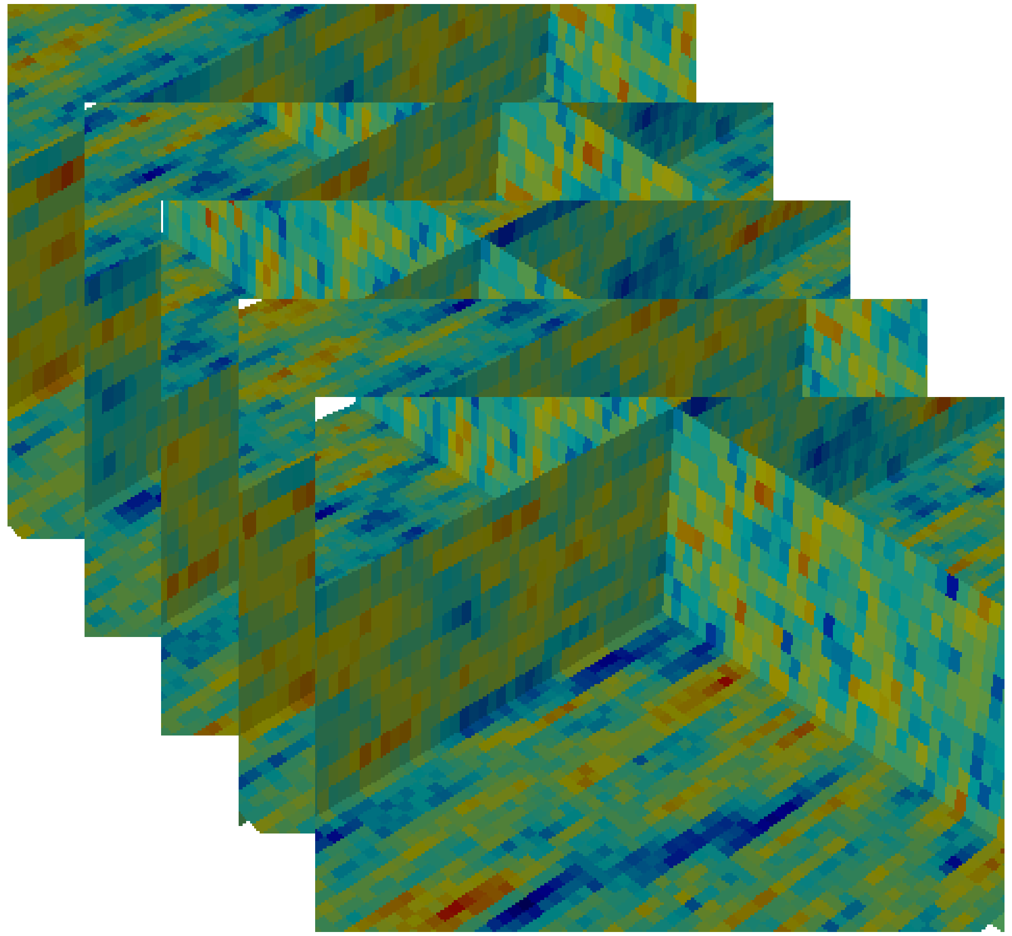
GENERATING MODELS

Models



500 realizations =
prior models

What do we know, what do we ignore ?

Parameters	Status	Value
Mean of $\log_{10}$ K (m/s)	Variable	U[-4 -1]
Variance $\log_{10}$ K (m/s)	Variable	U[0.05 2]
Range (m)	Variable	U[1 10]
Anisotropy ratio	Variable	U[0.1 0.5]
Orientation	Variable	U[0 π]
Porosity	Variable	U[0.05 0.30]
Gradient (%)	Variable	U[0.083 0.167]
Other parameters	Fixed	

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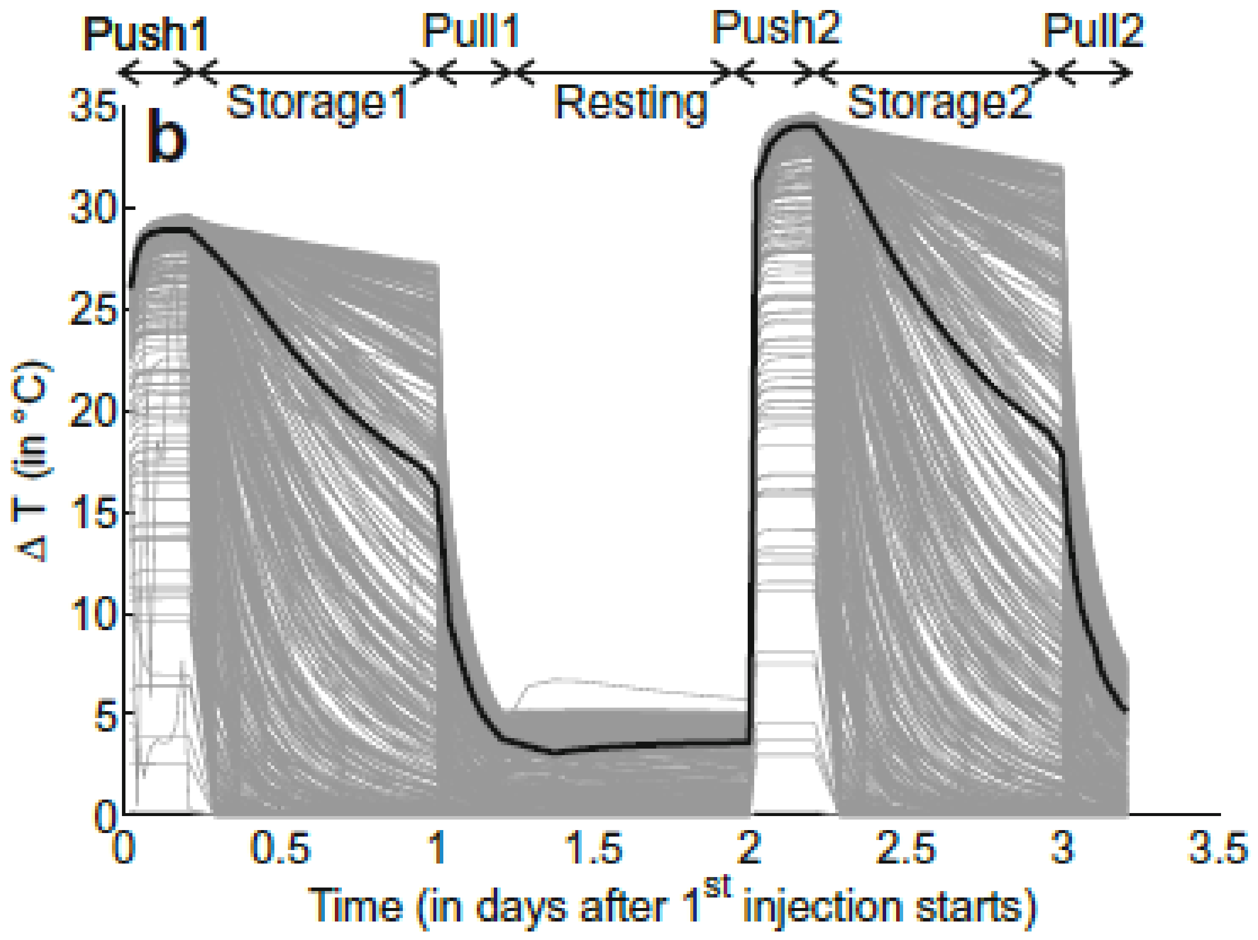
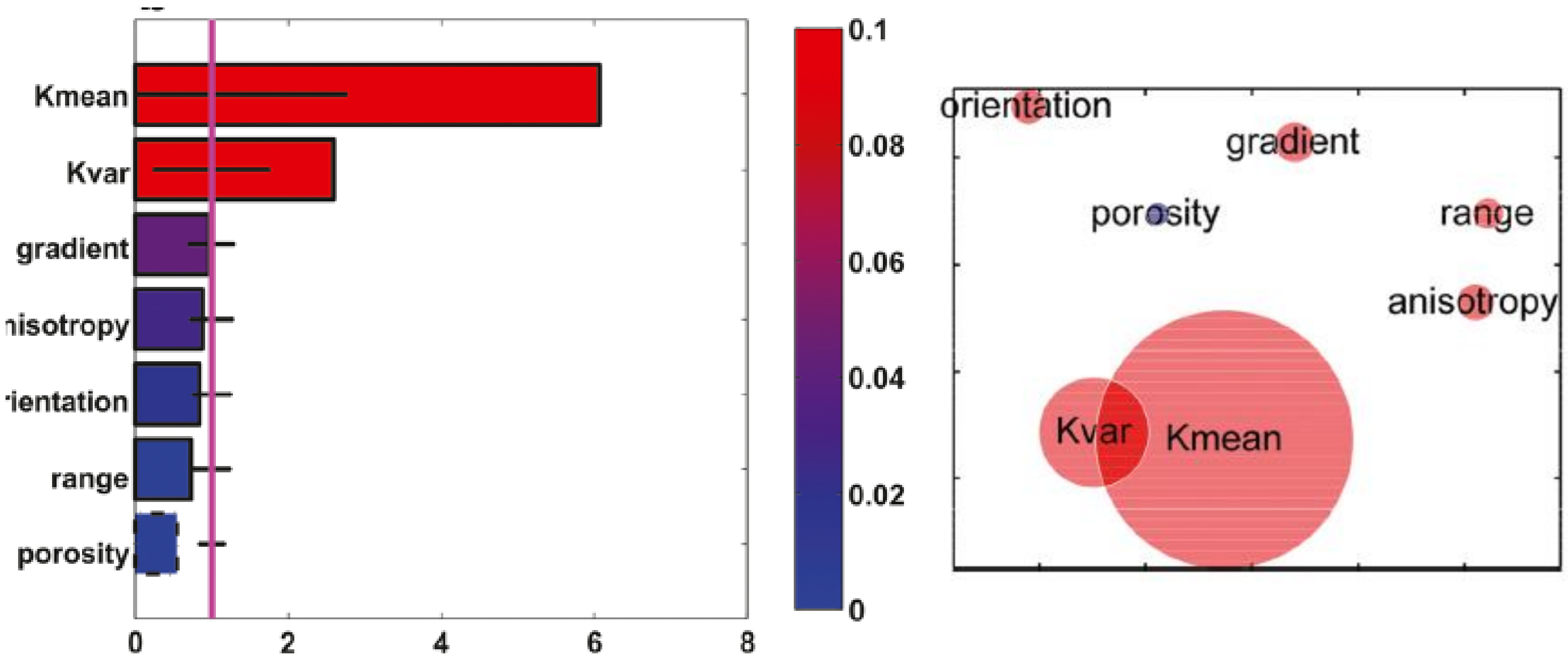
SENSITIVITY ANALYSIS OF THE PREDICTION

Prediction

Distance-based global sensitivity analysis (DGSA, Park et al., 2016, C&G)





Identification of the most sensitive parameters and their interaction

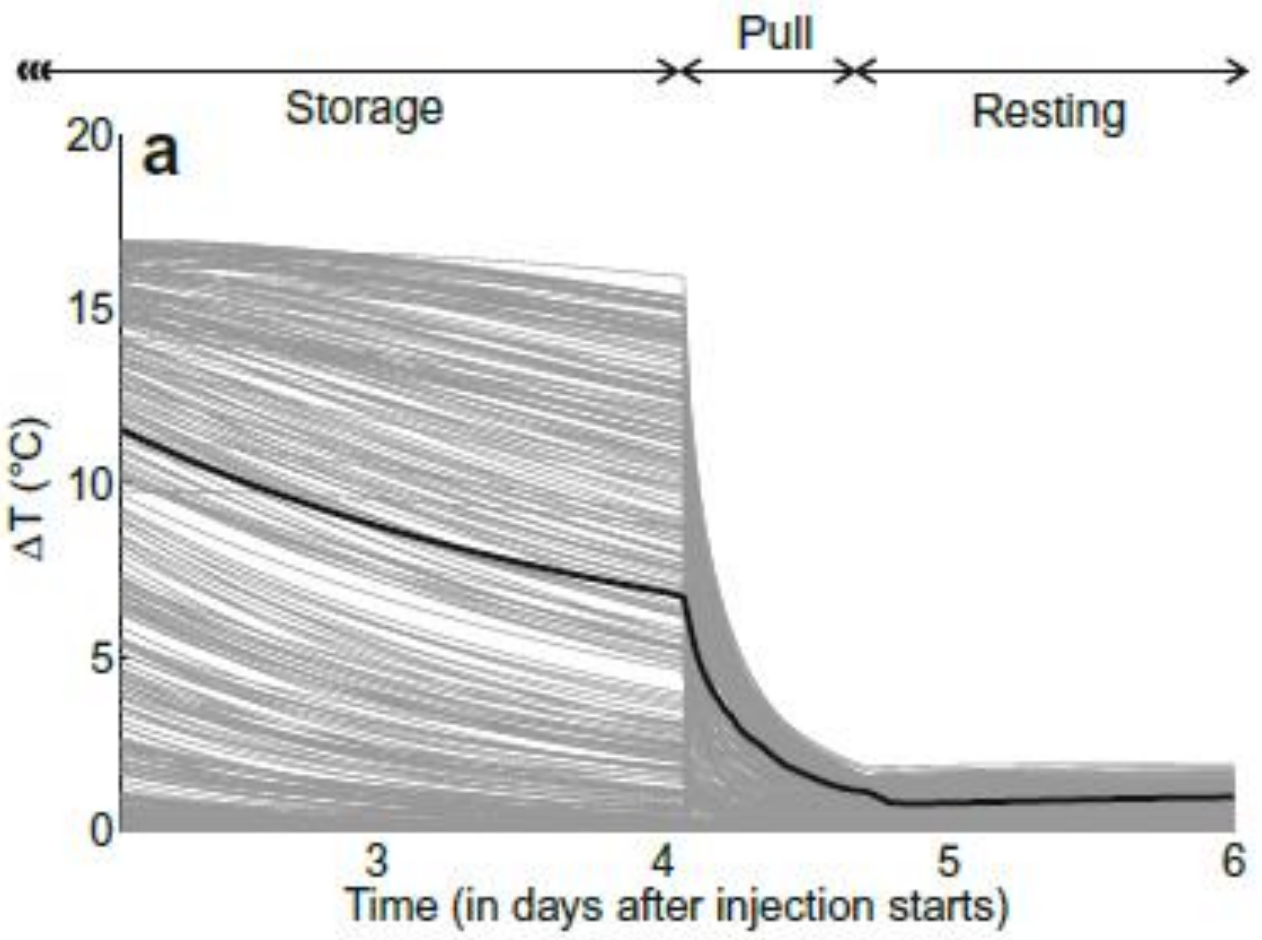
IDENTIFICATION OF INFORMATIVE DATA SET(S)

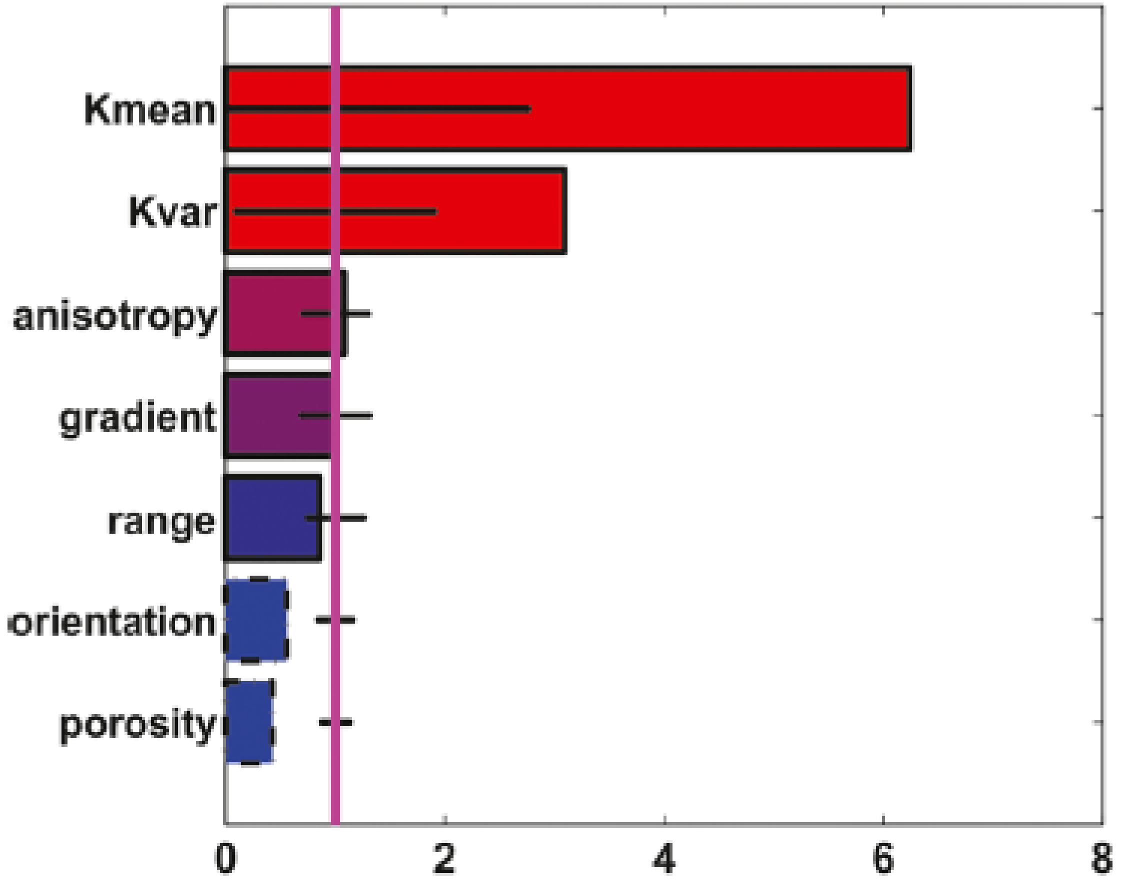
Data

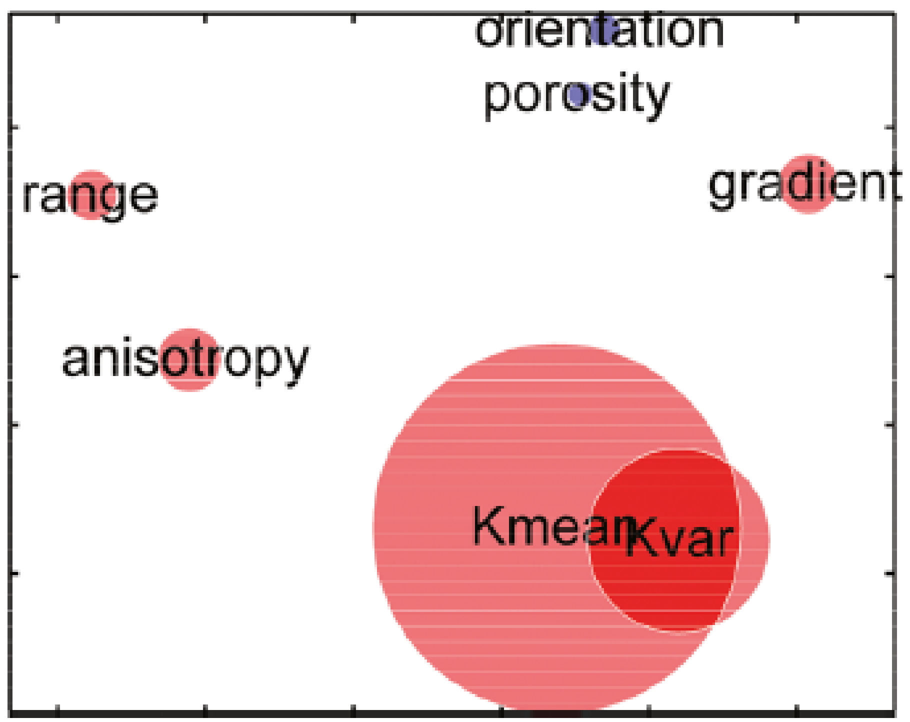
Designing an informative experiment

Push-Pull test ?

Standard Push-Pull test
Injection 3m³/h +25°C for 6h
Storage for 91h
Pumping 3m³/h for 15.5 h
Temperature at the well







Data sensitive to the same parameters as the prediction !

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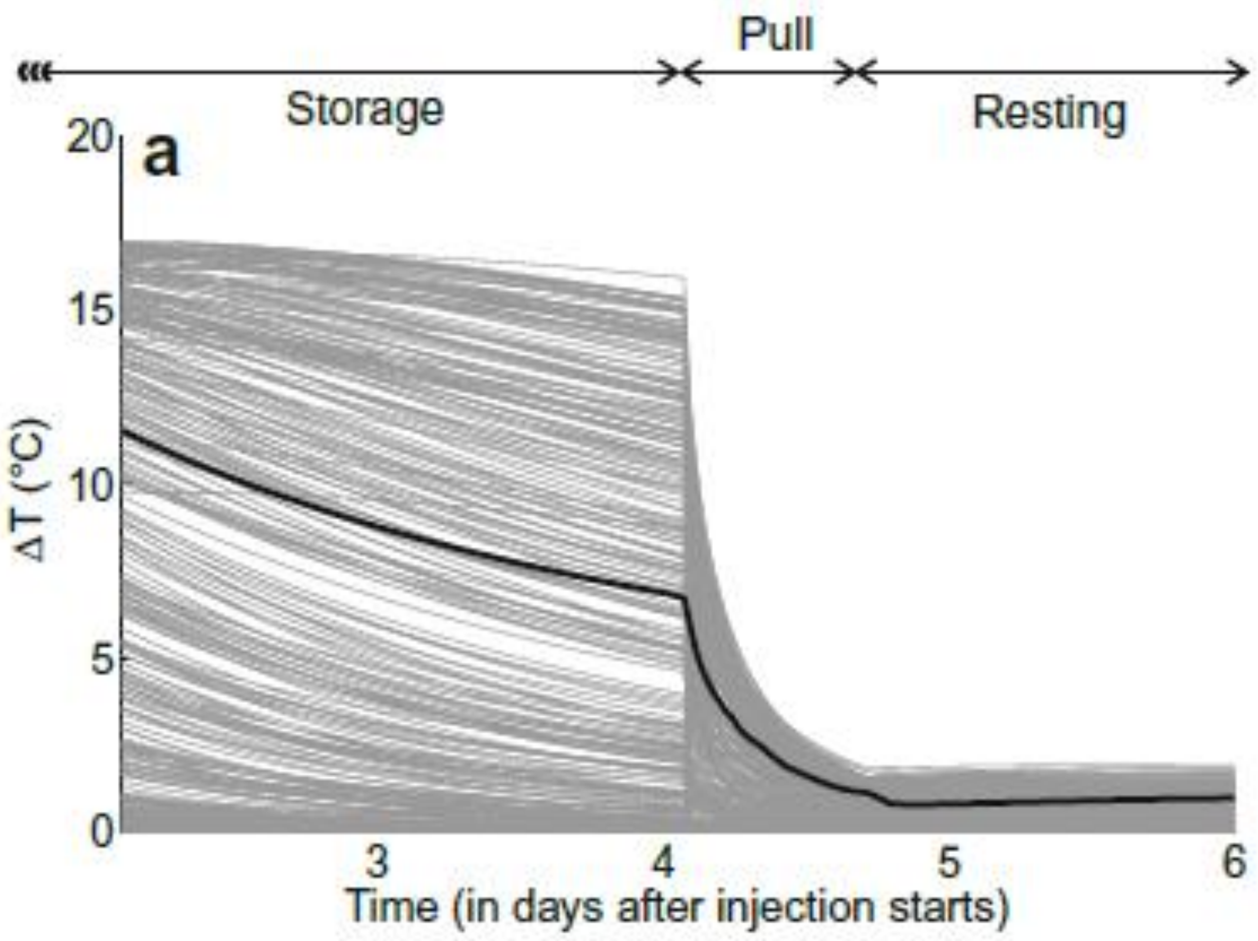
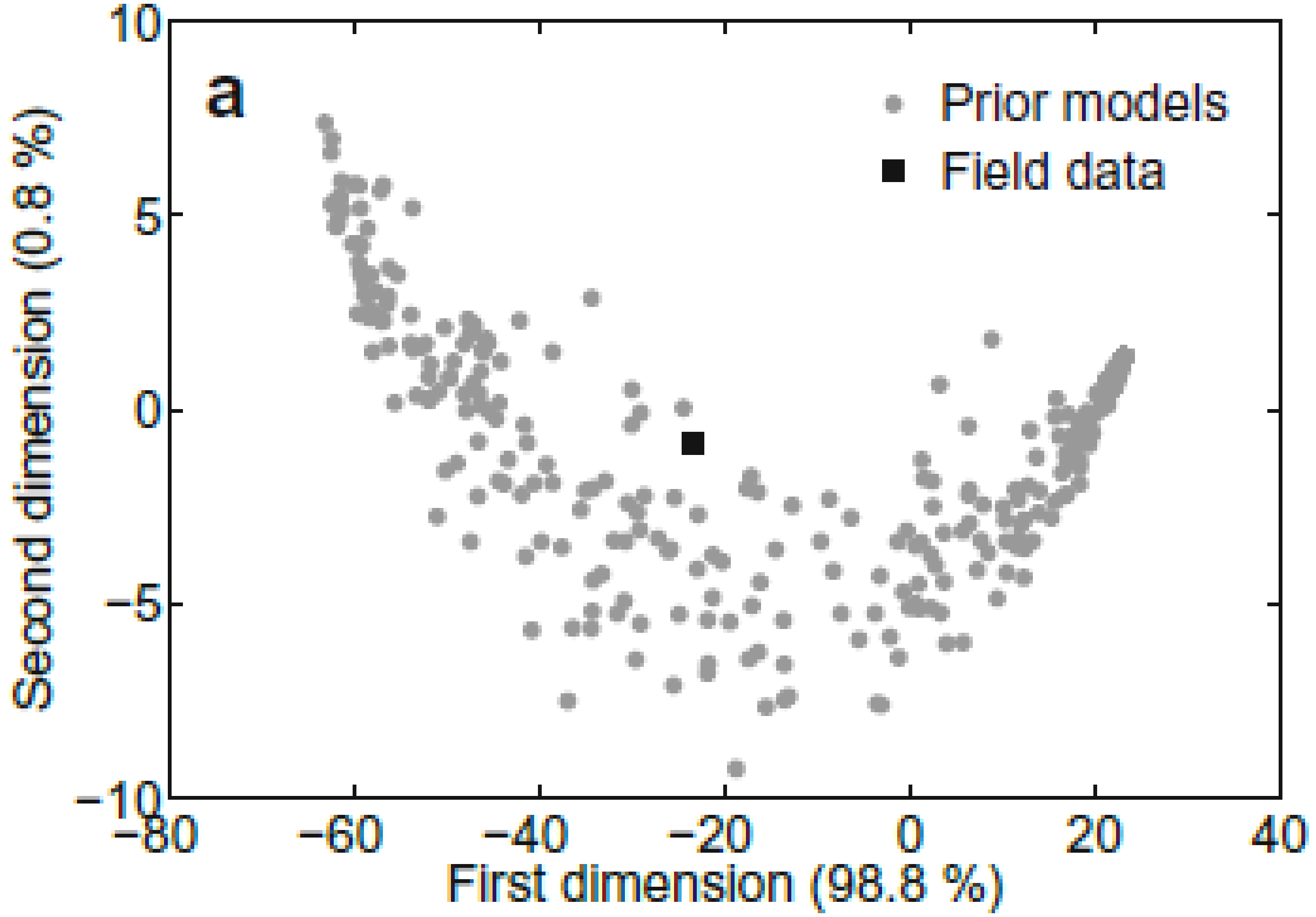
ARE OUR PRIOR MODELS CONSISTENT ?

Consistency with field data





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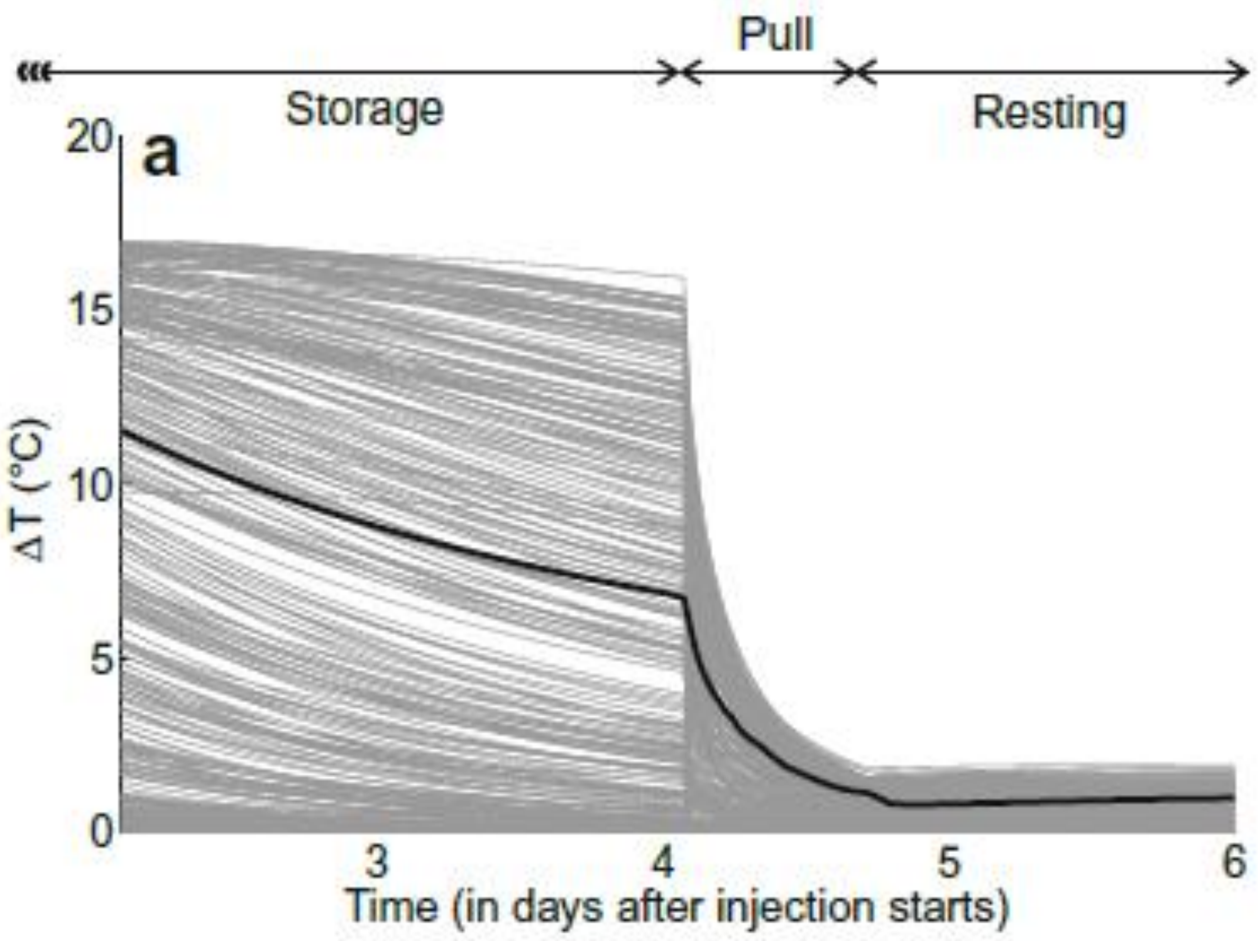
LEARNING STEP

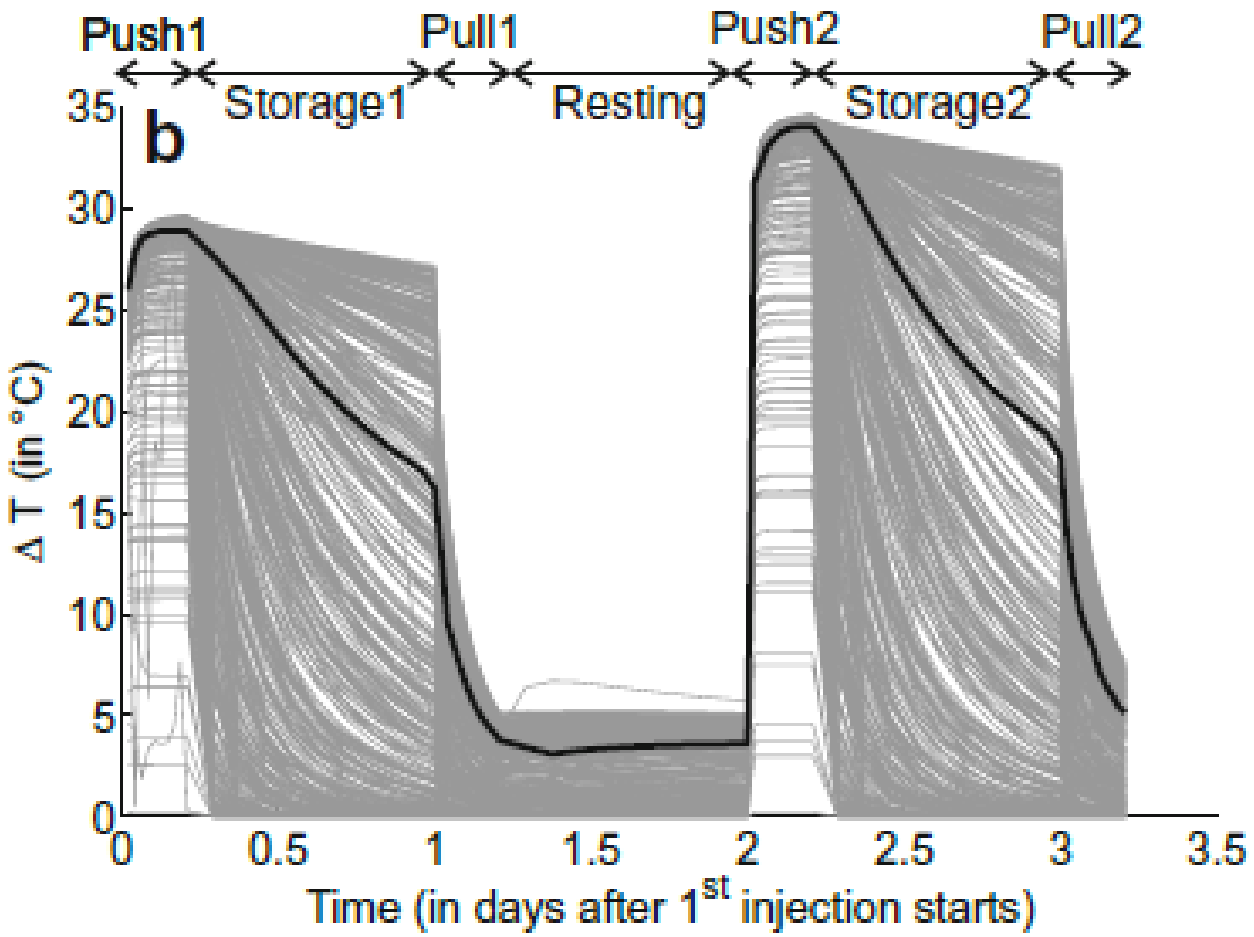
Finding a direct relationship between data and prediction

Data



???

Prediction



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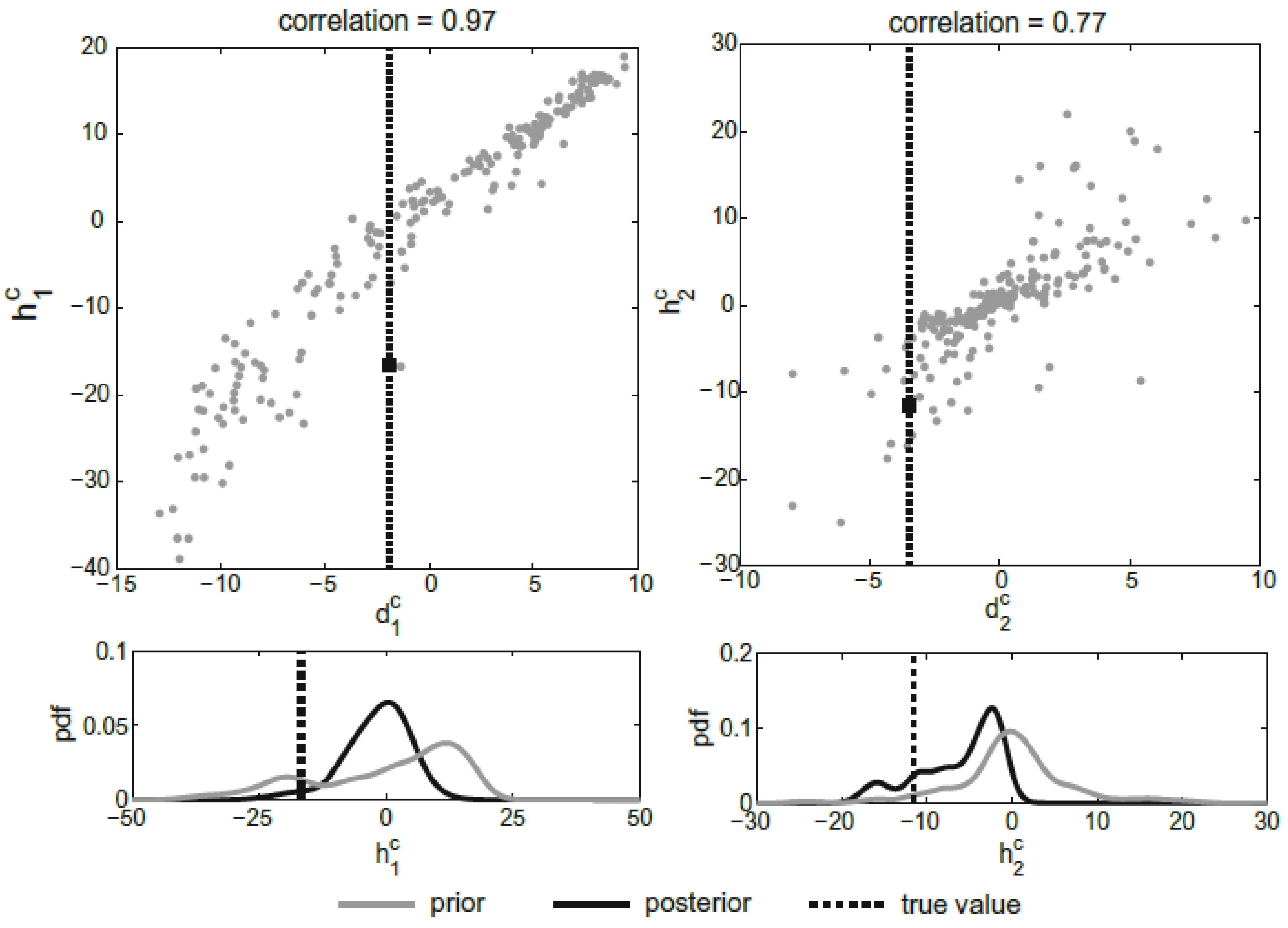
LEARNING STEP

Finding a direct relationship between data and prediction

1. Dimension reduction (PCA)
2. Linearization (CCA)
3. Kernel density estimation



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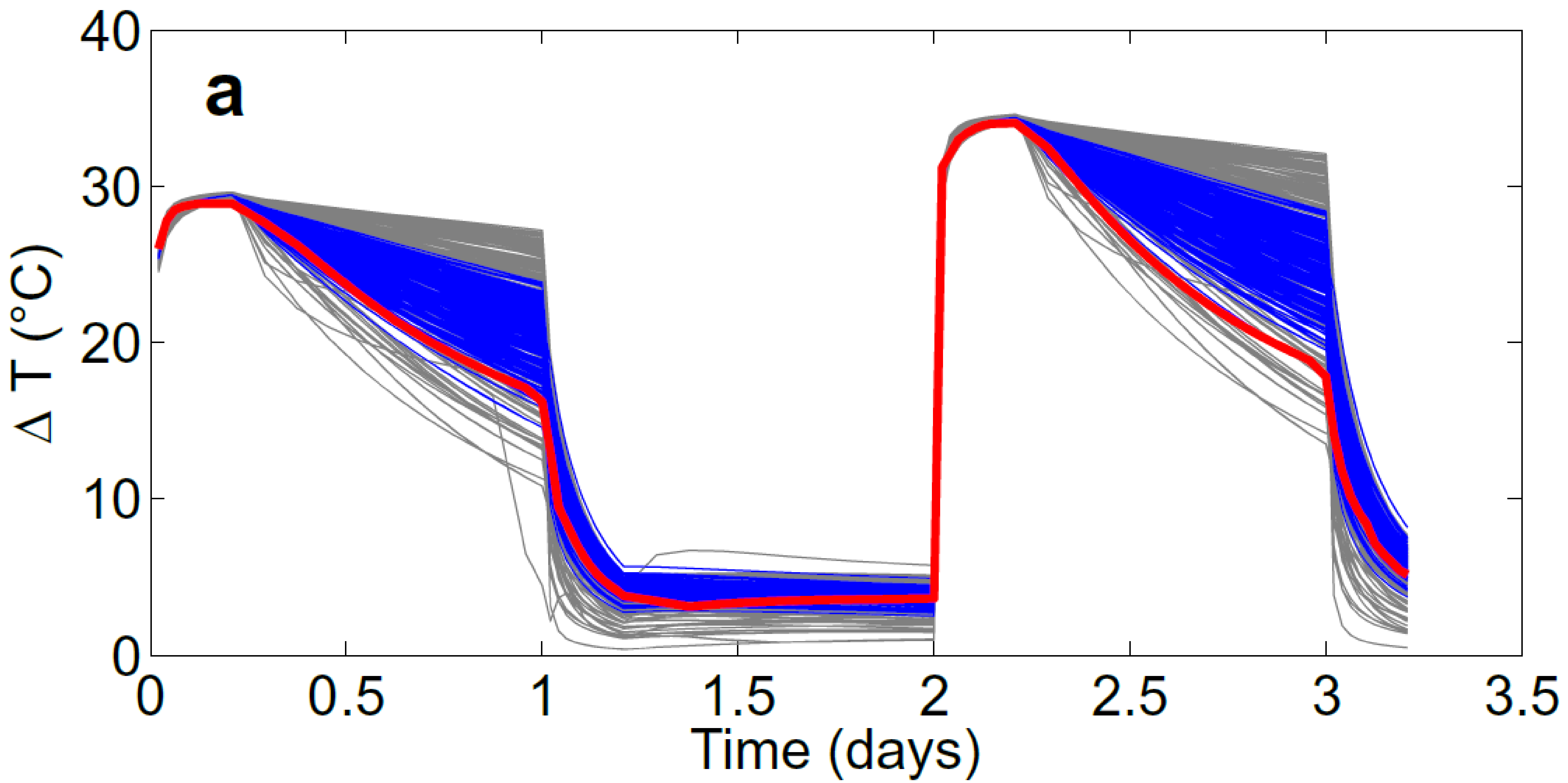
ESTIMATING THE PREDICTION + UNCERTAINTY

1) Sampling the posterior in reduced dimension space
2) Back-transform the samples in the original space



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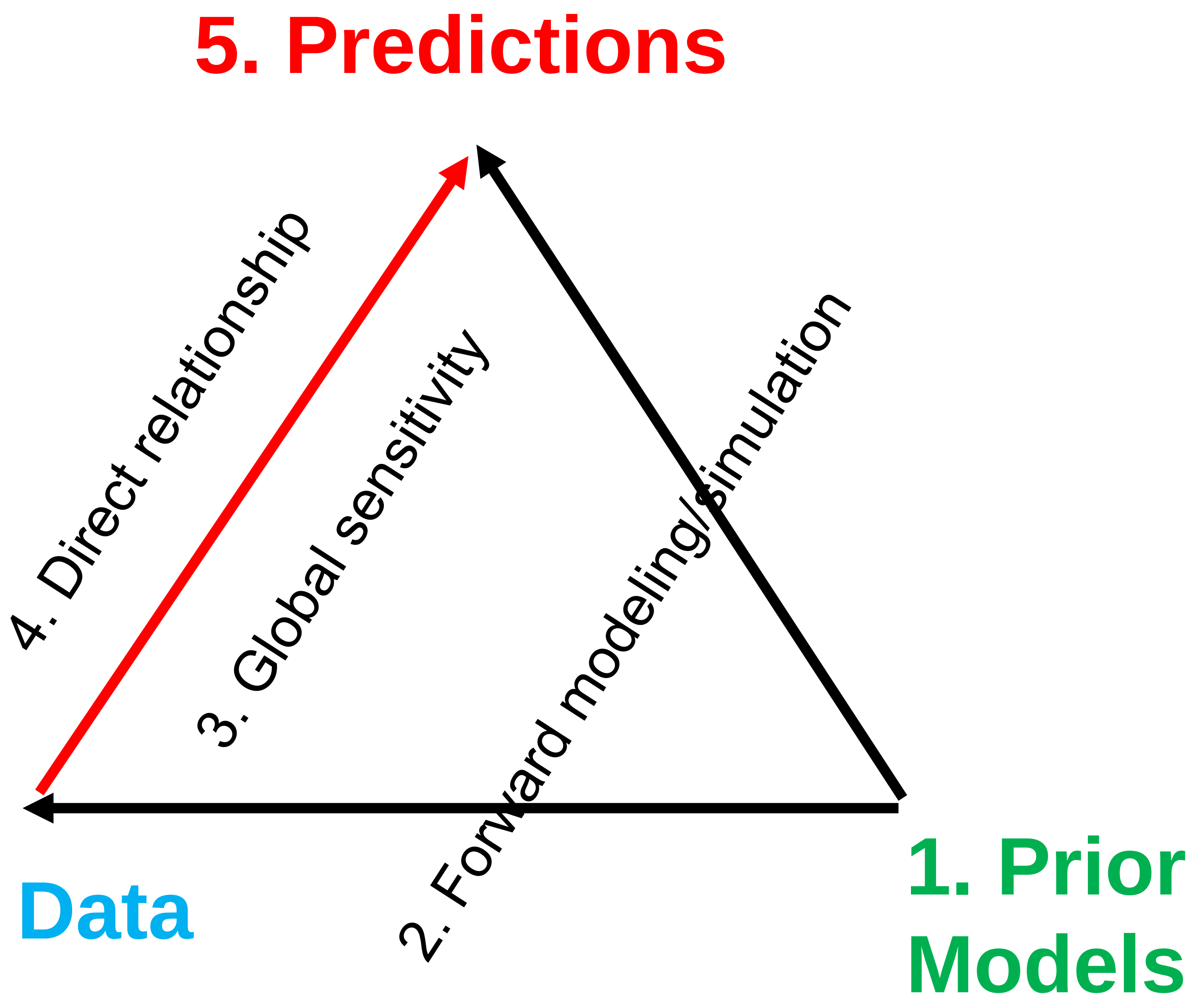
EXPERIMENTAL DESIGN

Bayesian Evidential Learning



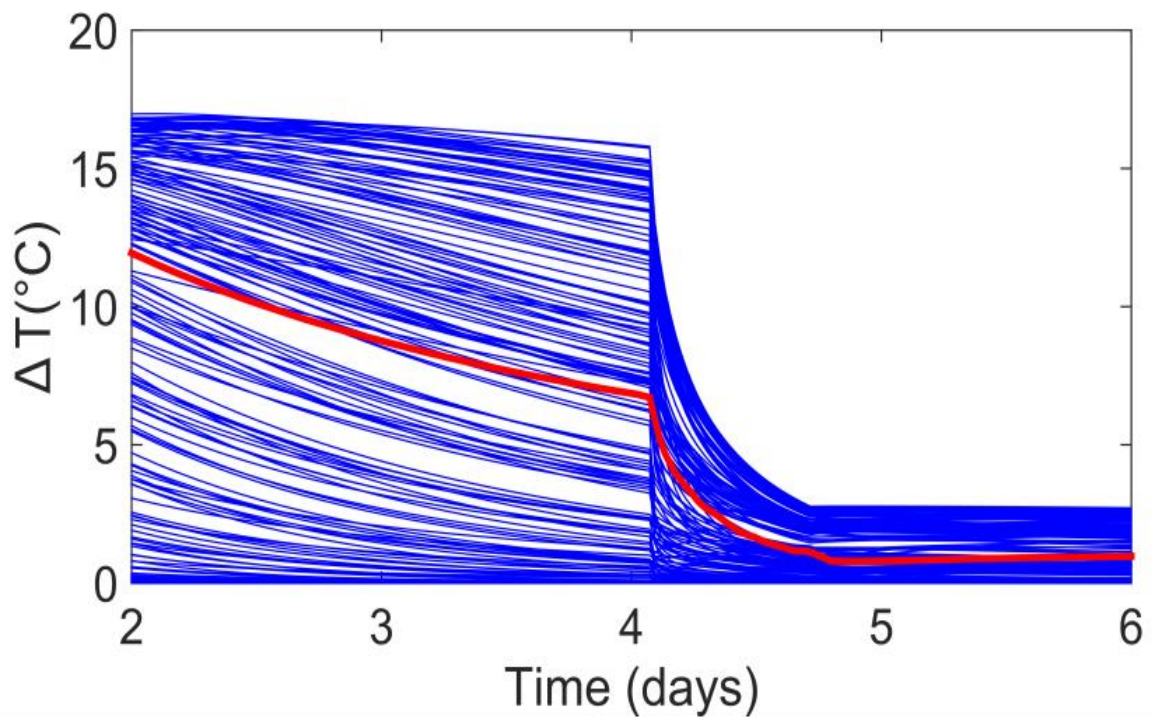
Now that we have a framework to quickly estimate uncertainty

→ We can use it to test hypothesis and optimise data acquisition

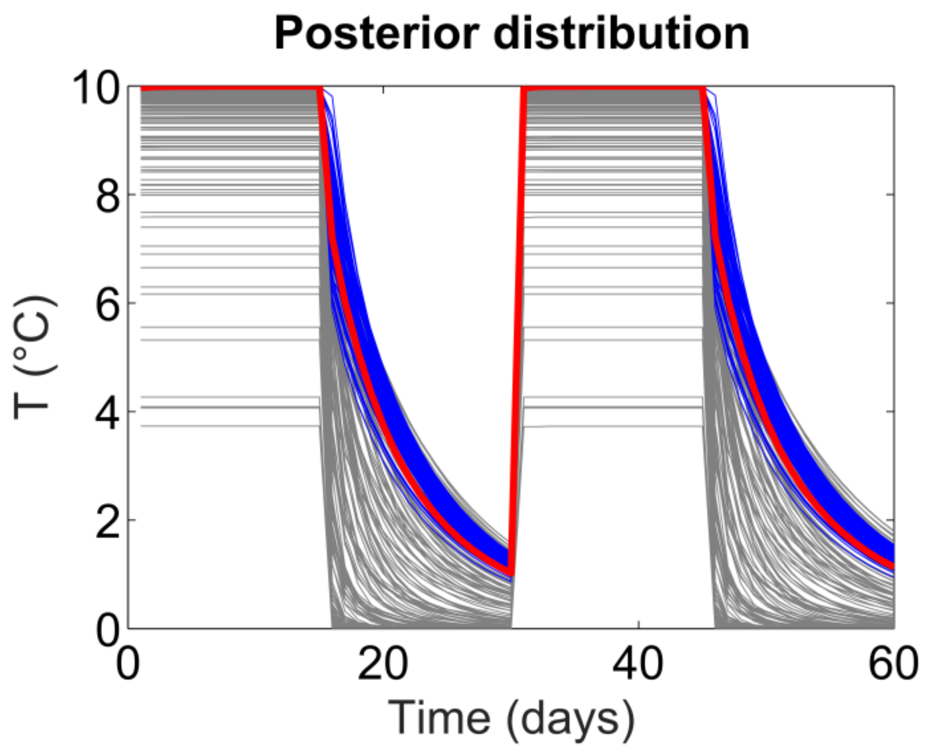
(Hermans, 2017, GW)

USING PUSH-PULL ? 1 OR MULTIPLE CYCLES ?

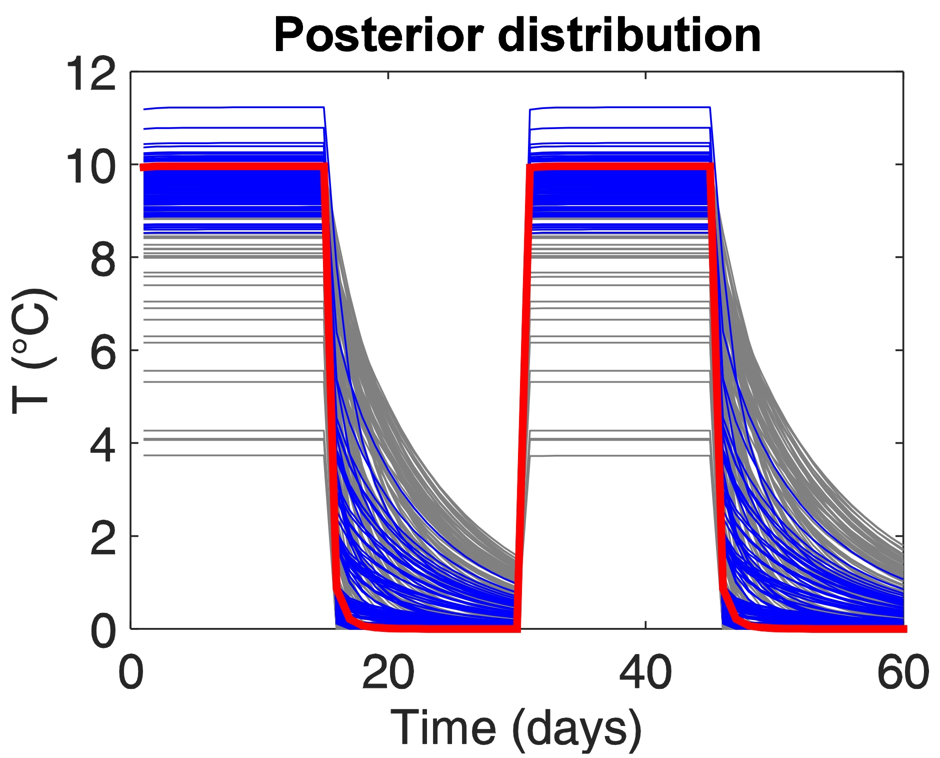
Data 1



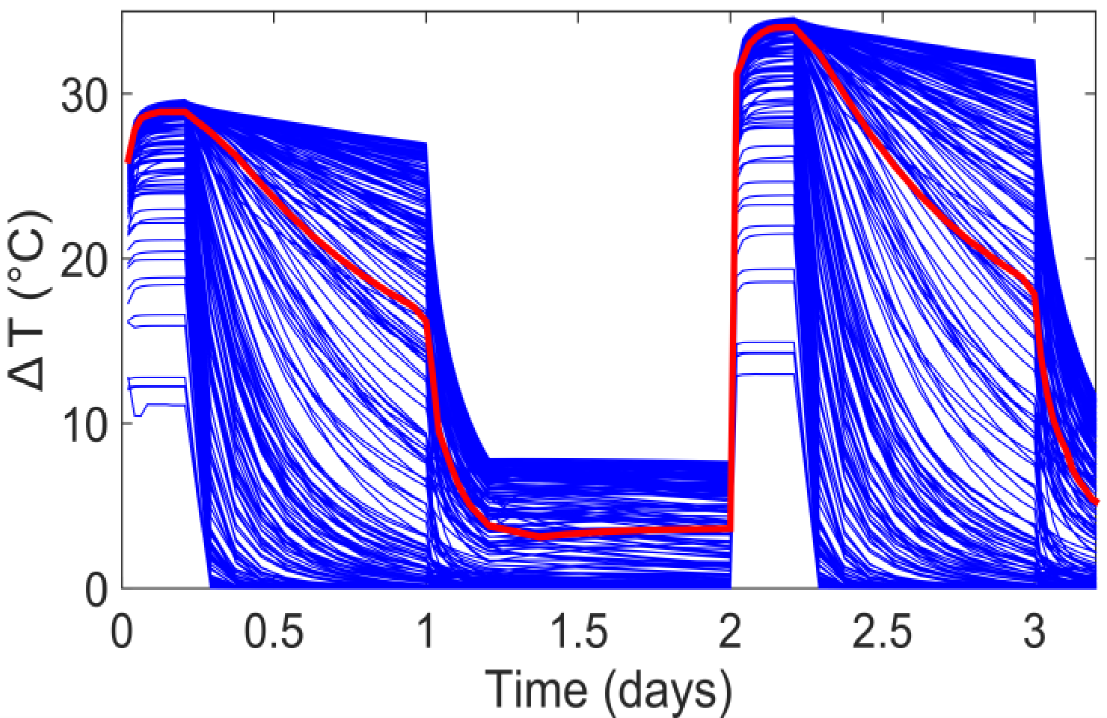
Test 1

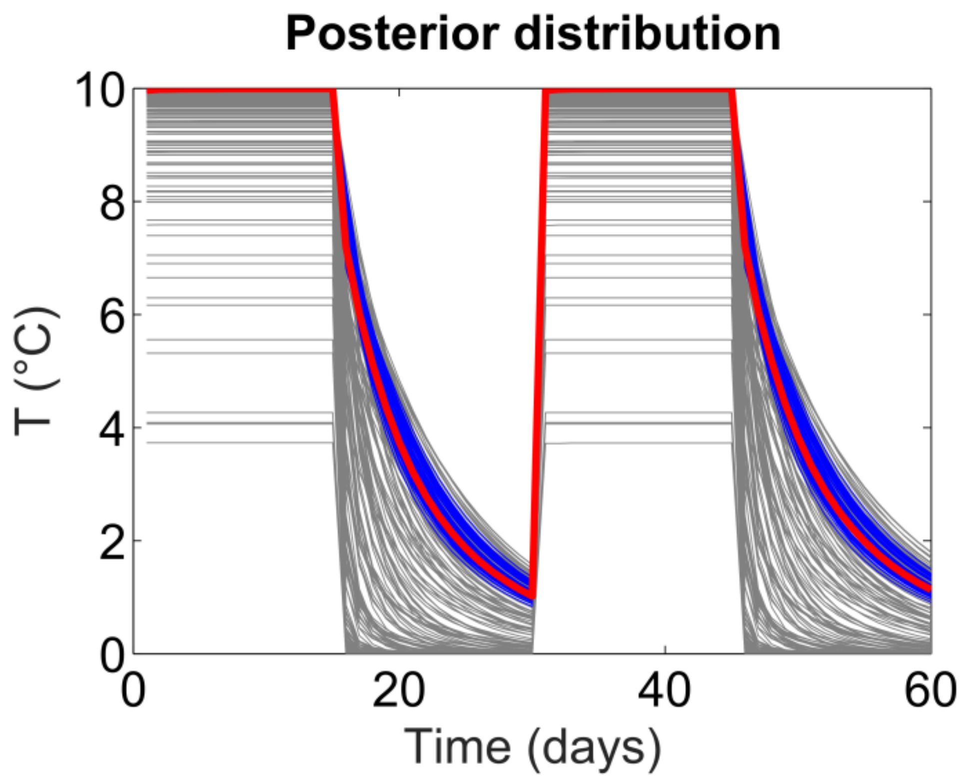


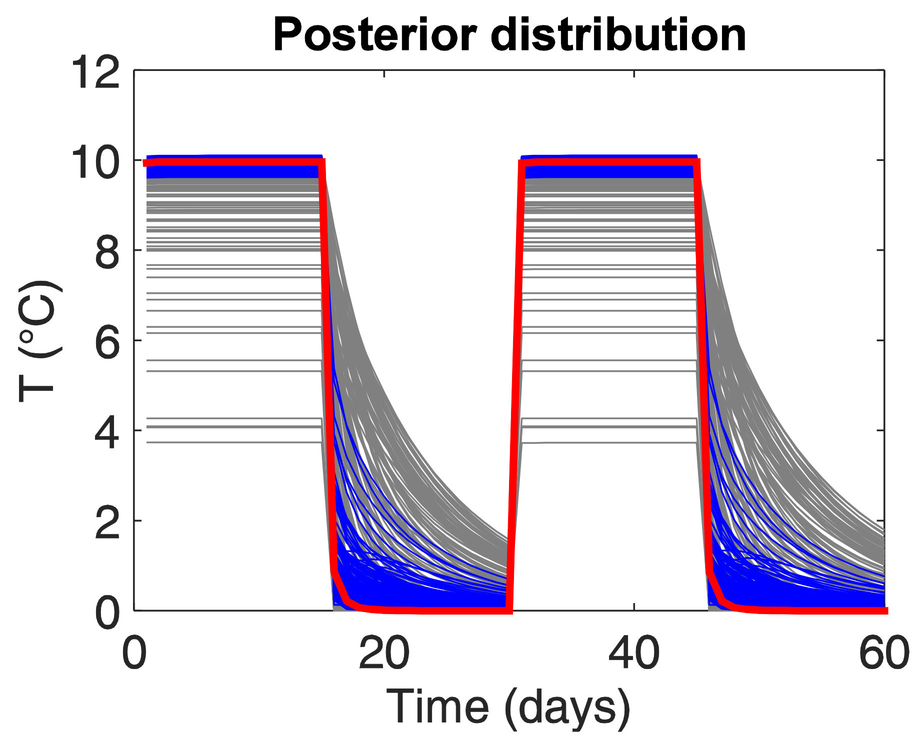
Test 2



Data 2



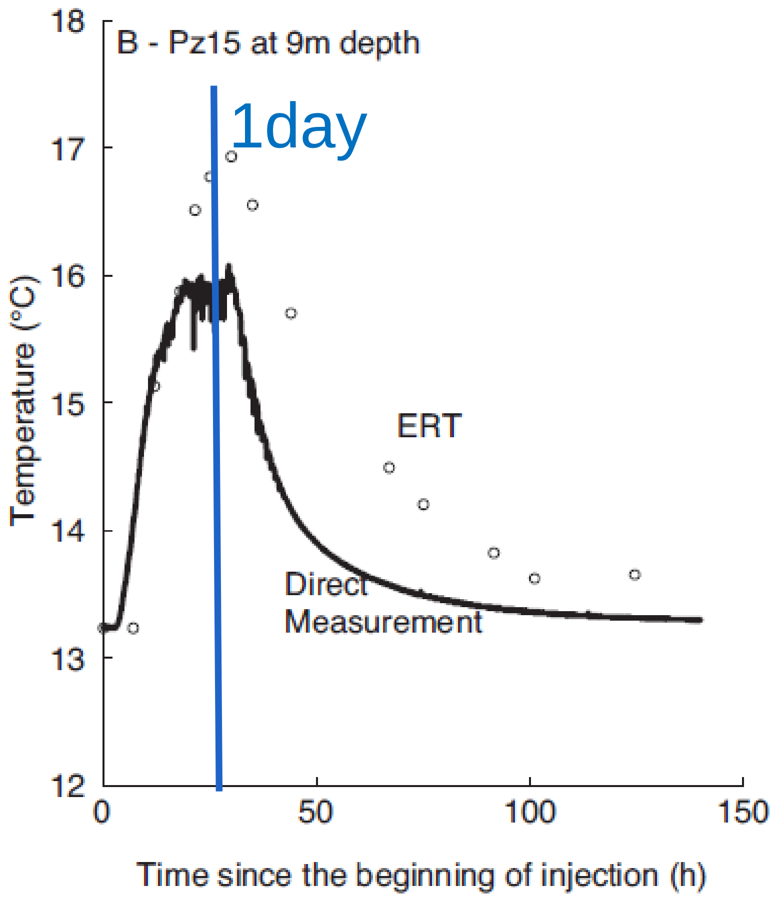




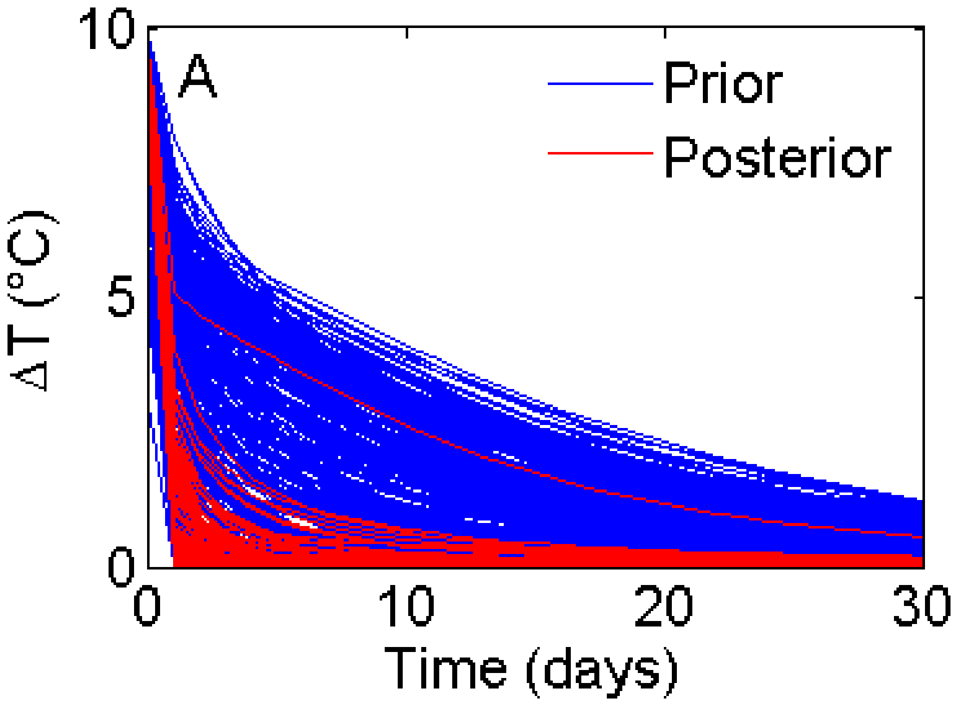
TRACING EXPERIMENT : 1-DAY VS 5-DAY

1-day experiment = we stop the experiment without recovering all the tracer

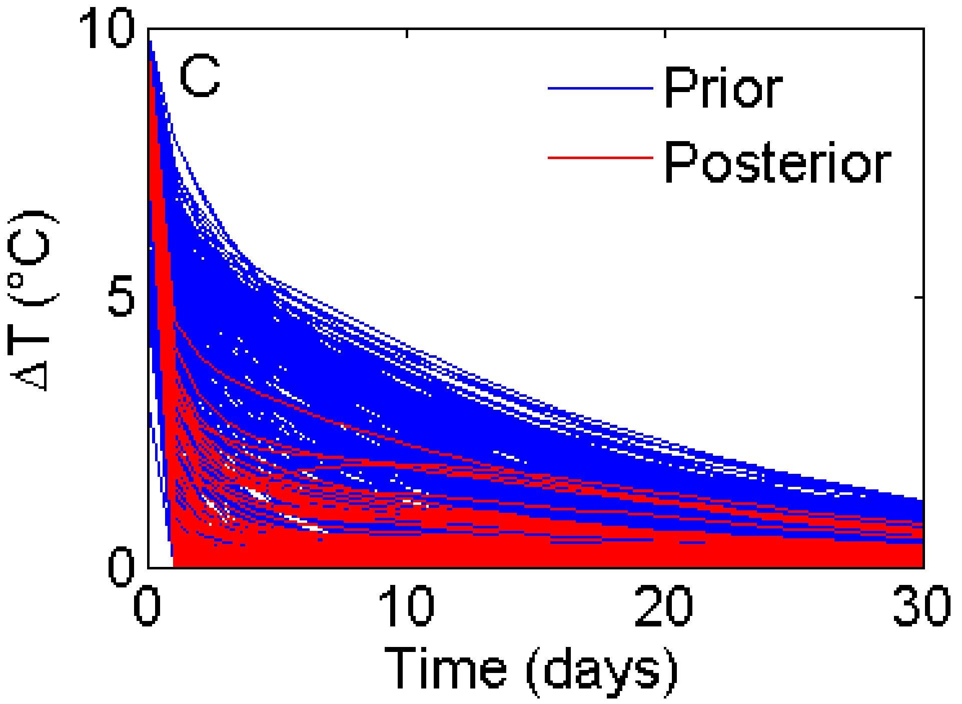
5-day experiment = we continue the experiment until initial conditions are met



1-day



5-day



Same results, similar uncertainty

Is the 1-day experiment « sufficient »?

CONCLUSIONS

Bayesian Evidential Learning

- No inversion only forward modeling + learning
- Much faster (no iterative steps) → full paralellization
- Large uncertainty is integrated at the beginning of the process

Applications

- Uncertainty of prediction
- Experimental design

Usefulness of single-well experiment

- Appropriate as long as the prediction is sensitive to the same parameters

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PAPER

Bayesian evidential learning: a field validation using push-pull tests

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Abstract
Recent developments in uncertainty quantification show that a full inversion of model parameters is not always necessary to forecast the range of uncertainty of a specific prediction in Earth sciences. Instead, Bayesian evidential learning (BEL) uses a set of prior models to derive a direct relationship between data and prediction. This recent technique has been mostly demonstrated for synthetic cases. This paper demonstrates the ability of BEL to predict the posterior distribution of temperature in an alluvial aquifer during a cyclic heat tracer push-pull test. The data set corresponds to another push-pull experiment with different characteristics (amplitude, duration, number of cycles). This experiment constitutes the first demonstration of BEL on real data in a hydrogeological context. It should open the range of future applications of the framework for both scientists and practitioners.

Keywords Bayesian evidential learning · Push-pull tests · Tracer tests · Heterogeneity · Uncertainty

CONCLUSIONS

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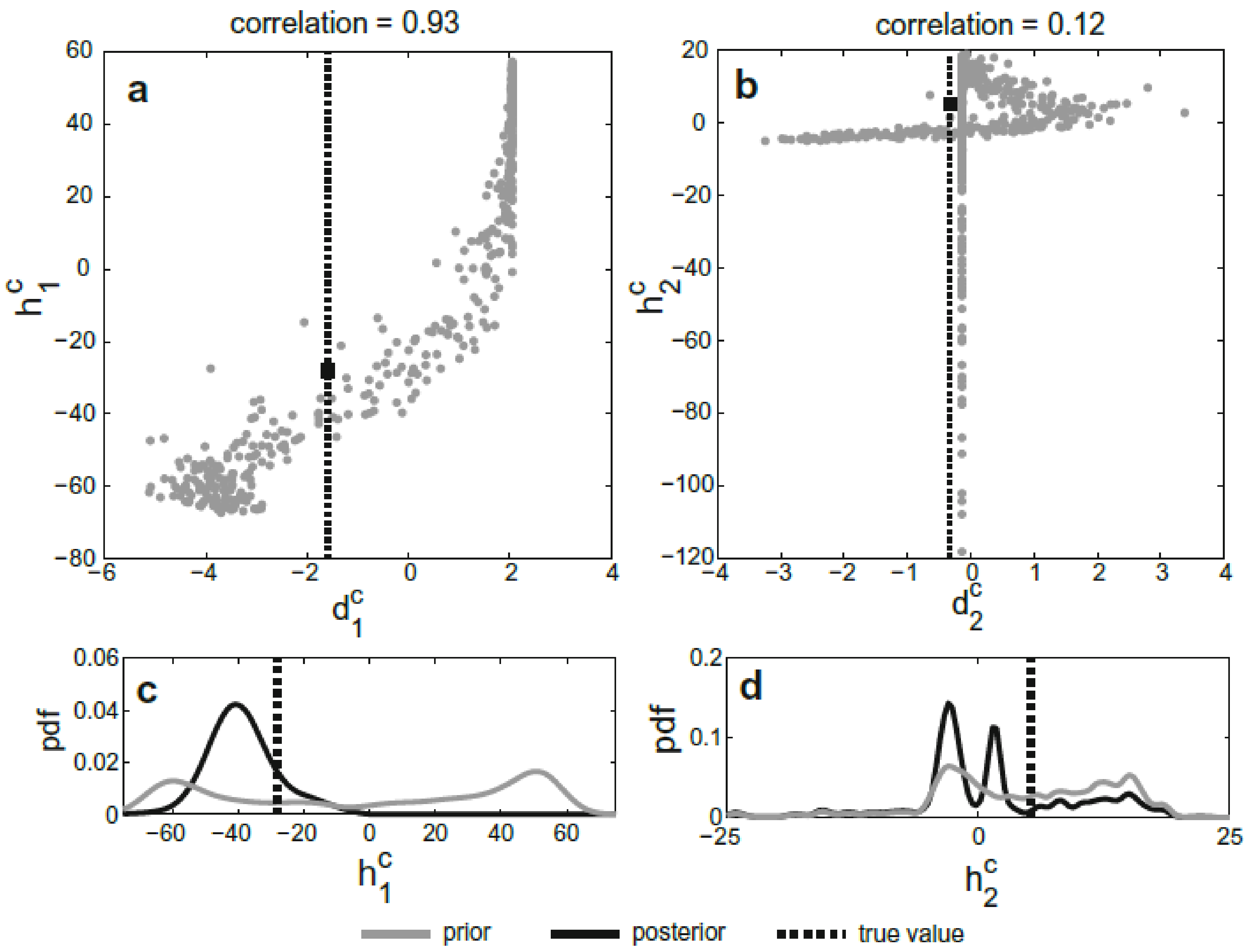
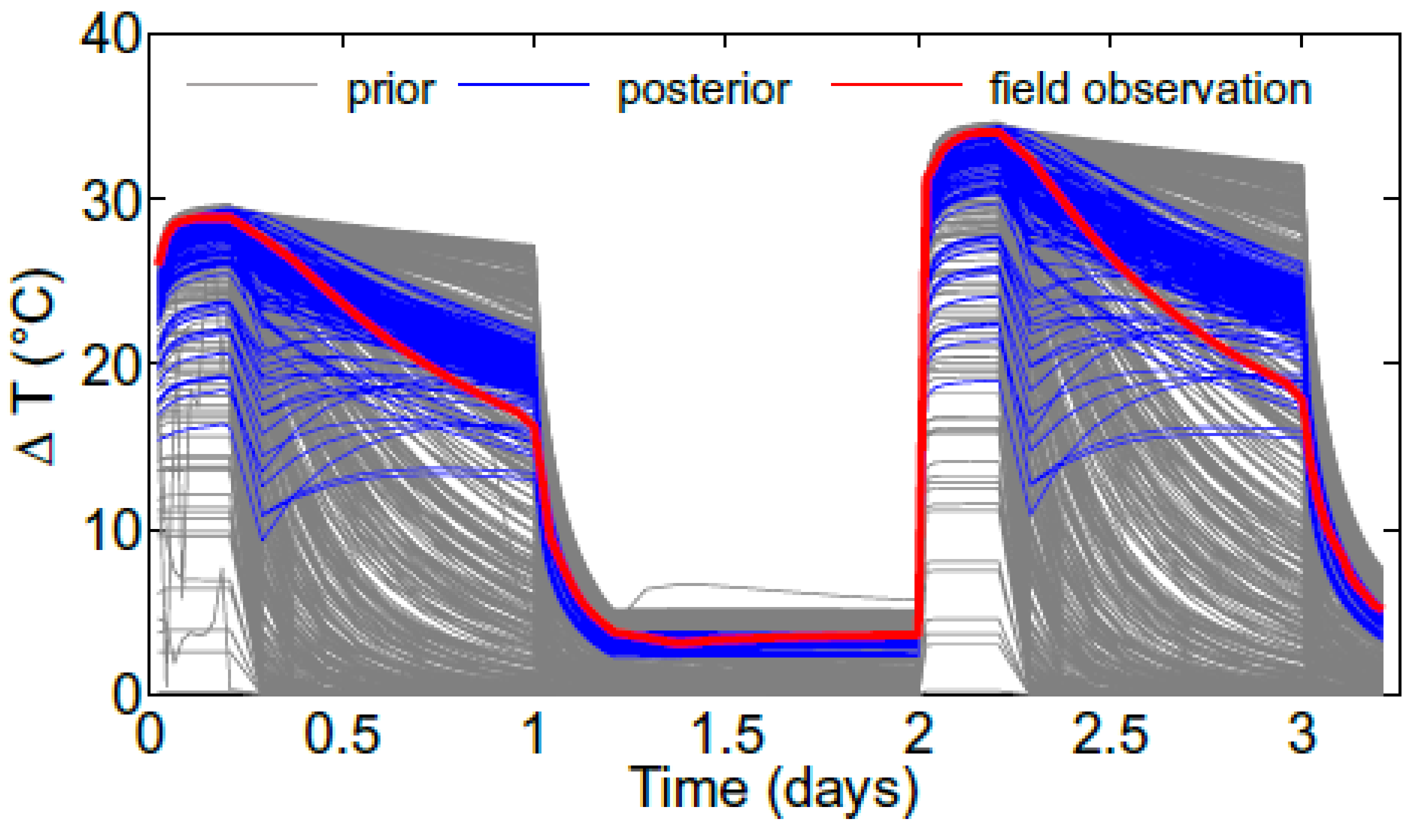
PRIOR REDUCTION





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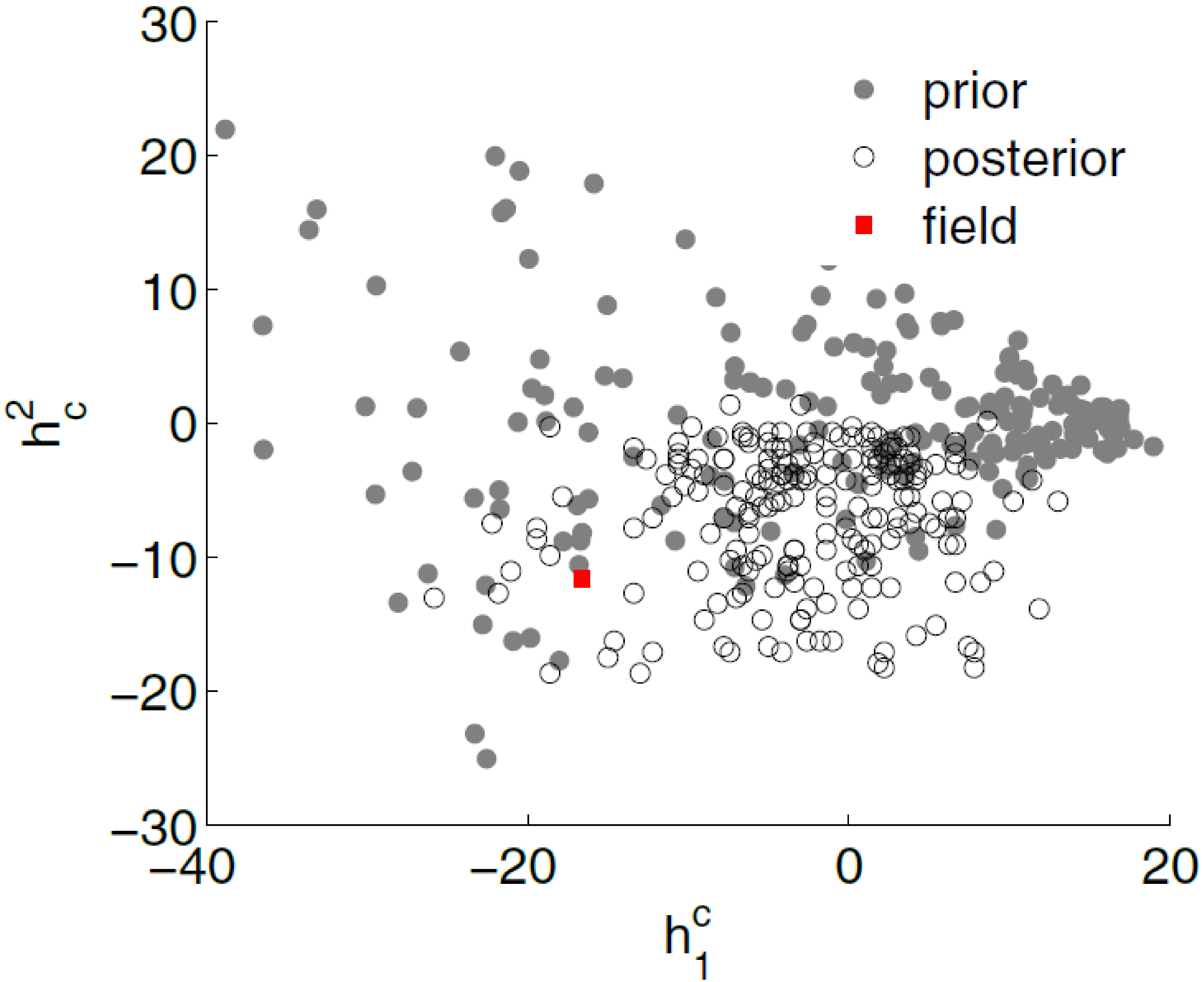
SAMPLING



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