

# GHENT UNIVERSITY



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## COMPARING WELL AND GEOPHYSICAL DATA FOR TEMPERATURE MONI-TORING WITHIN A BAYESIAN EXPERIMENTAL DESIGN FRAMEWORK

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## INTRODUCTION



## **OUR RESEARCH**

A new framework for Experimental Design in Earth Sciences using Bayesian Evidential Learning (BEL4ED)

- Predictions in Earth Sciences are fraught with uncertainty due to the subsurface's complexity and lack of knowledge.
- To reduce uncertainty, obtaining the most informative data set is extremely **valuable**.
- For large-scale problems, however, its identification becomes increasingly difficult.
- We propose using the Bayesian Evidential Learning framework to stochastically solve this problem under large uncertainty.



## **BAYESIAN EVIDENTIAL LEARNING**

#### Bayesian?

$$\mathsf{p}(\mathsf{h}|\mathsf{d}_{\mathsf{obs}}) = rac{
ho(d_{obs}|h)
ho(h)}{
ho(d_{obs})}$$
 (1)

#### Evidential?

Evidential learning directly models how the predictor can influence the target.

#### Learning?

Every learning requires "examples," which are generated by a-priori model realizations (m) via forward modelling.



Figure: Goal: Build a statistical model for directly predicting h from  $d_{obs}$ .

- Define prior model choose an adequate number of models N (typically a few hundreds)
- 2 Simulate experiment *N* times (forward modelling)
- 3 Dimension reduction of predictor and target (PCA) (if necessary)
- Canonical Correlation Analysis (CCA) to find linear relationships between predictor and target (learning step)
- **5** Estimation of posterior distribution of unknown target (prediction step)

## AQUIFER THERMAL ENERGY STORAGE (ATES)



Figure: ATES - www.iftechnology.com/aquifer-thermal-energy-storage

## DESIGN OF THE EXPERIMENT



## SYNTHETIC STUDY: HEAT INJECTION + ERT







Figure: Volume of interest  $(16 \times 16 \times 14) \times 106$ 9/20

## **TEMPERATURE FIELD (OUR TARGET)**



Figure: Snapshots of the temperature field at time steps 4 (A), 14 (B), 61 (C) and 74 (D) for one example.

## **OBJECTIVES OF THIS WORK**

#### Prediction of the 4D temperature field's posterior distribution

- Using geophysical (ERT) data
- Using boreholes data (direct temperature measurement)
- Using a combination of both!

#### Experimental (optimal) design

... but we work with high-dimensional data. How to measure information gain?

## PRE-PROCESSING



## PRINCIPAL COMPONENT ANALYSIS



Figure: A. Case (i). Predictor: ERT data, B. Case (i). Target. C. Case (ii). Predictor: Temperature profile from borehole 1. D. Case (ii). Target. E. Case (iii). Predictor: Full combination (ERT data + four boreholes temperature profiles). F. Case (iii). Target. 13/20

## REGRESSION



## CANONICAL CORRELATION ANALYSIS



Figure: Three first Canonical Variate Pairs of the training set (A, B, C). Conditional sampling is made for each pair of canonical components.

## PREDICTIONS OF TEMPERATURE



Figure: Temperature curves across all time steps, at the observation well 4. A. Using the ERT as predictor. B. Using the temperature curves at well 1 as predictor. C. Using the ERT and all the temperature curves at wells 1, 2, 3 and 4 as predictors.

## EXPERIMENTAL DESIGN



### PICK A METRIC... AND A SPACE!



Figure: PCs of the target (temperature field)

## **RMSE** RANKING



Figure: Ranking of the different combinations of data sources ('ds'). The geophysical data is labeled as 'G' and the well data are labeled by their well ID (1, 2, 3, 4). The use of ERT data is indicated by a darker background shade, whereas the use of wells alone is indicated by a lighter shade. A. Average of all folds.



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