# Improving Bayesian Evidential Learning 1D imaging (BEL1D) accuracy through iterative prior resampling (H43F-2039)

Hadrien MICHEL [1,2,3] (hadrien.michel@uliege.be), Frédéric NGUYEN [1] and **Thomas HERMANS** [3]
(1) University of Liège, Faculty of Applied Sciences, Urban and Environmental Engineering Departement, Liège, Belgium, (2) F.R.S.-FNRS (Fonds de la Recherche Scientifique), Brussels, Belgium, (3) Ghent University, Faculty of Sciences, Department of Geology, Ghent, Belgium

## 1. Bayesian Evidential Learning 1D imaging

Uncertainty appraisal is a key concern to geophysicists when imaging the subsurface. This issue is classically handled by stochastic inversion (costly CPU) or by error propagation (unrealistic uncertainty).

Bayesian Evidential Learning 1D imaging (BEL1D) is a Bayesian method that enables the stochastic interpretation of 1D geophysical data, with a reasonable CPU cost and realistic uncertainty estimations. The framework is based on Bayesian Evidential Learning *(e.g. Scheidt et al., 2018; Hermans et al., 2016)*.

The method relies on the constitution of statistical relationships between model parameters and the associated data-sets from prior realizations (**Fig. 1**). It offers the advantage not to require the input of biasing information through regularization parameters as is often the case in classical inversion processes. However, the consistent definition of a prior model space is still required. Nonetheless, the method handles efficiently large priors, the impediment being the difficulty to properly constitute representative correlations.

Above all, the method enables the quantification of uncertainty for the model parameters.

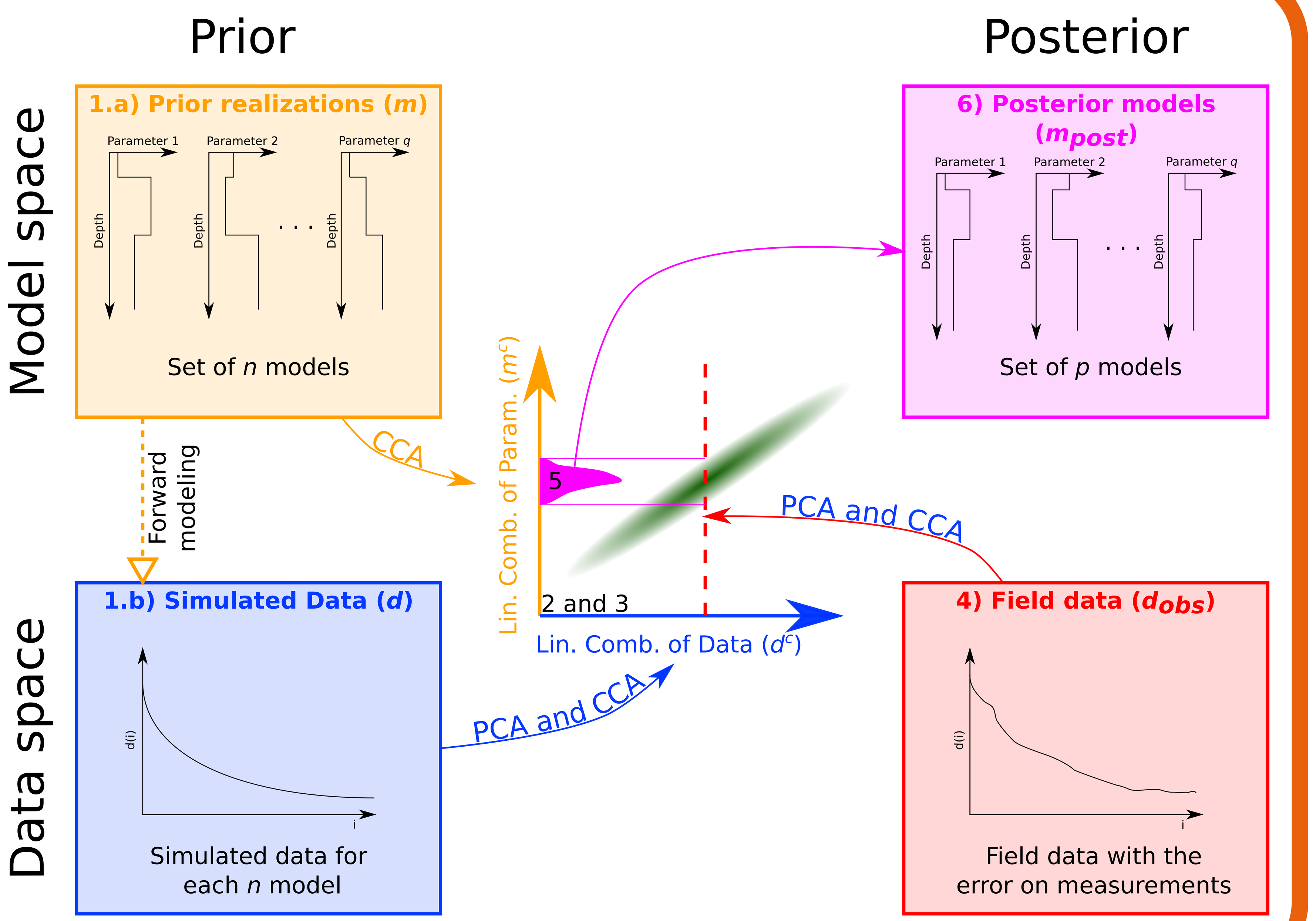


*Fig. 1: Schematic illustration of BEL1D*

## 2. Iterative prior resampling

Iterative prior resampling *(e.g. Cheng et al., 2019)* is relatively simple and may contribute to better estimate the uncertainty. The algorithm (**Fig. 2**) is:

**Iteration 0:** Build the initial prior model space (prior$_0$)
**Iteration 1:** Run BEL1D with prior$_0$ → post$_1$
**Iteration 2:** Run BEL1D with prior$_1$=post$_1$ → post$_2$
**Etc.**

It enables to better constrain models since higher correlations between models parameters and data may be observed.

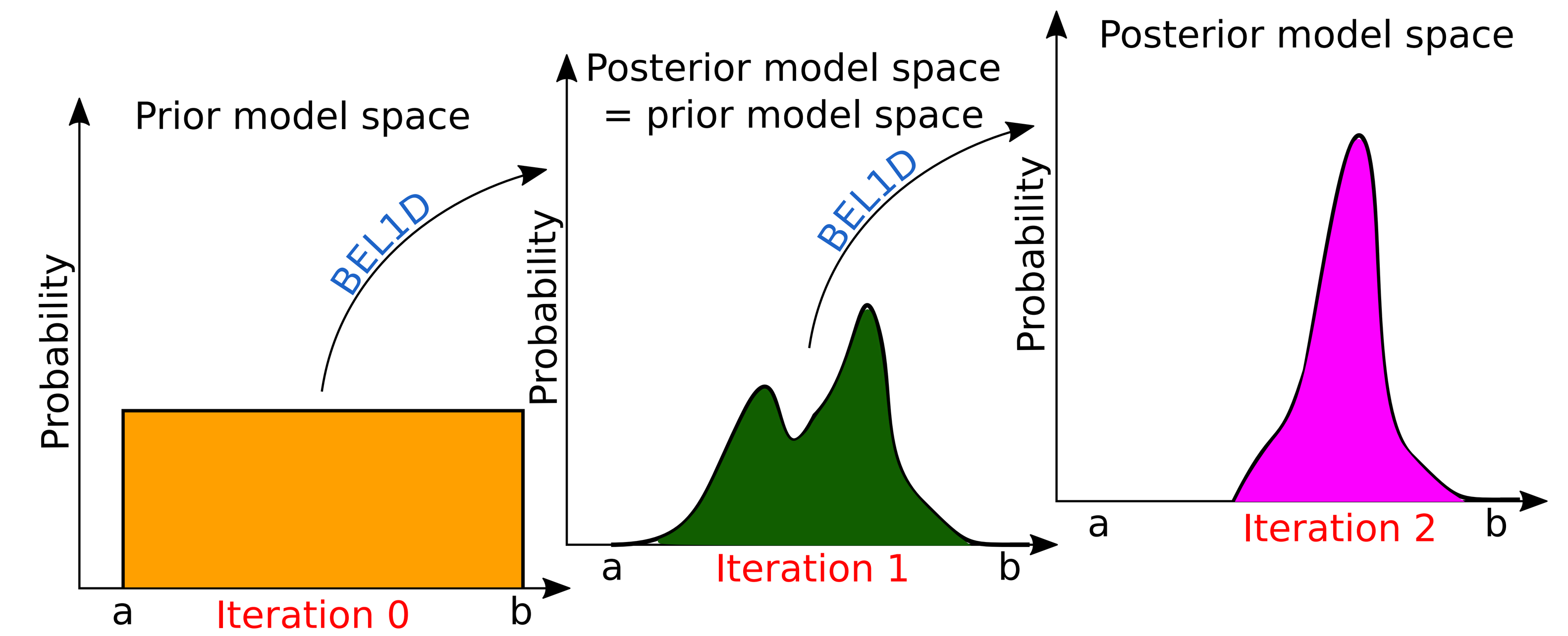


*Fig. 2: Illustration of prior resampling*

## 3. SNMR

Surface Nuclear Magnetic Resonance (SNMR) benefits from the quantum properties of protons ($H^+$) contained in water, hence is directly sounding water in the subsurface. Current is injected/received in an antenna on the ground and interacts with the protons spins as illustrated in **Fig. 3**. The received signal depends on the water content (amplitude) and the way water is linked to the soil particules (relaxation time).

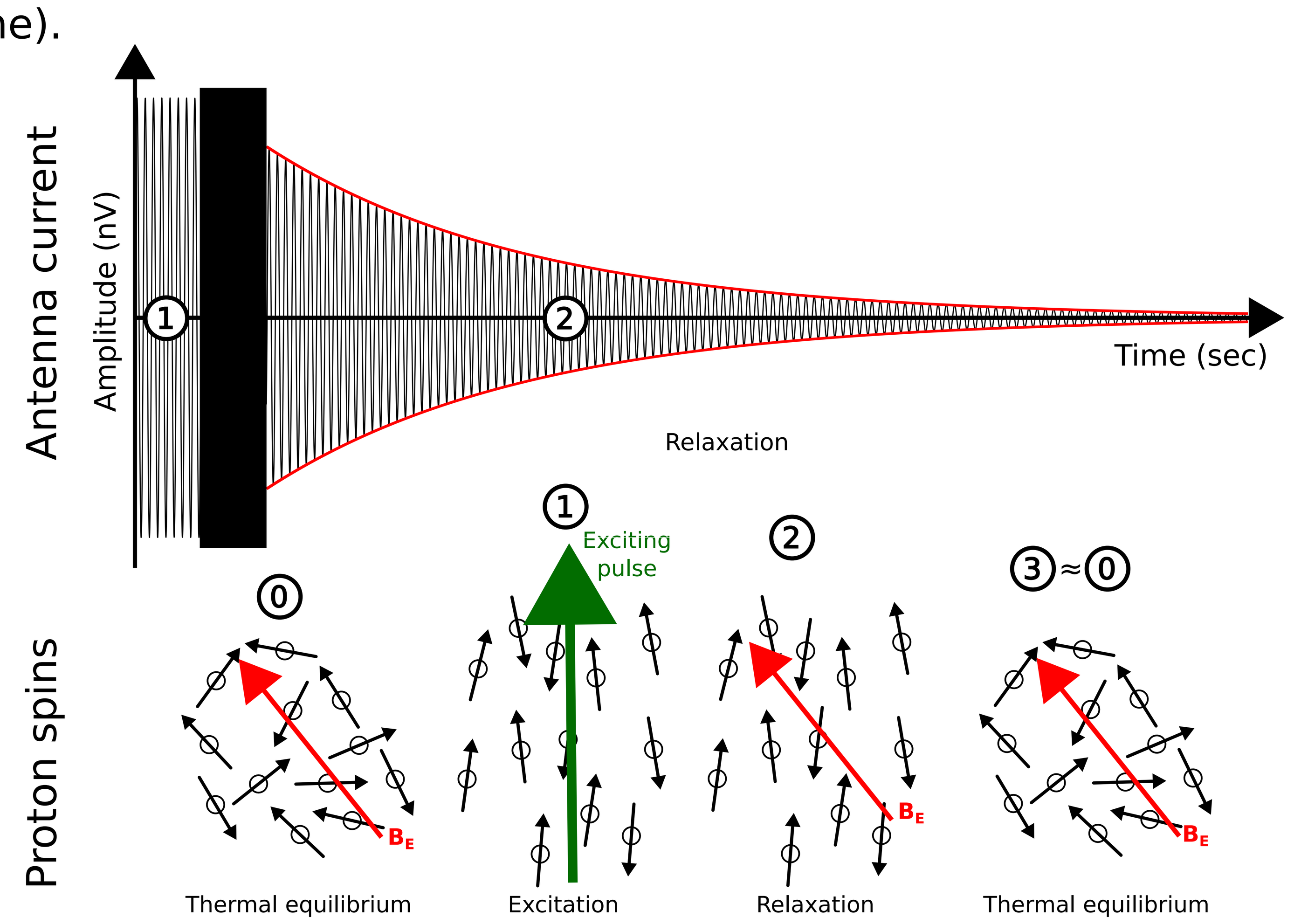


*Fig. 3: Principle of NMR (FID pulse sequence)*

## 4. Results

Prior resampling is applied to a simple 2-layers model (**Fig. 4**):

- As expected, we obtain a better estimation of the model parameters
- Trends in the model are discovered (increasing $T_2^*$)
- RMSE are lower

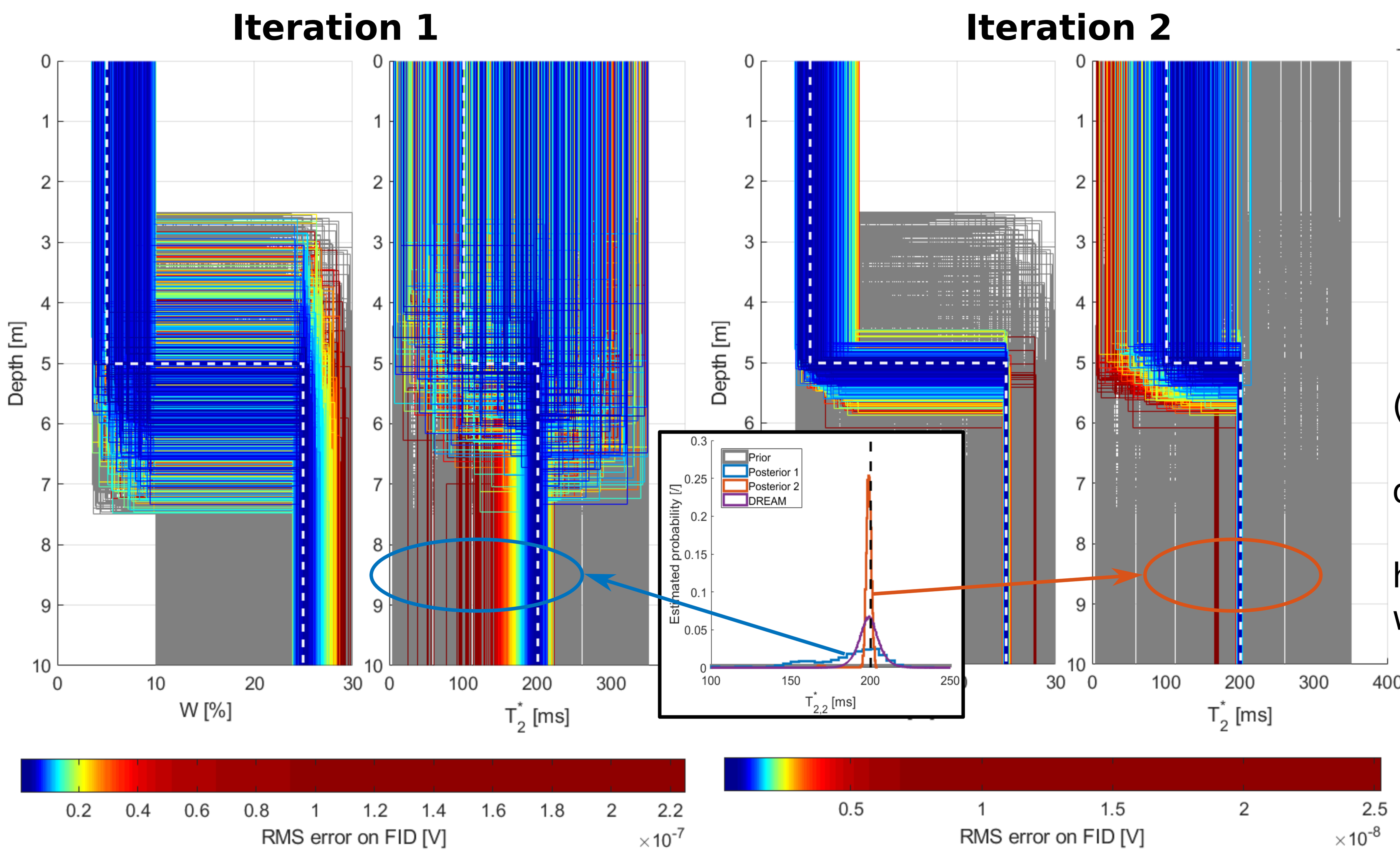


*Fig. 4: Prior resampling results*

Prior resampling applied to BEL1D:

- Benefits from better correlation between the parameters and the data (**Fig. 5**)

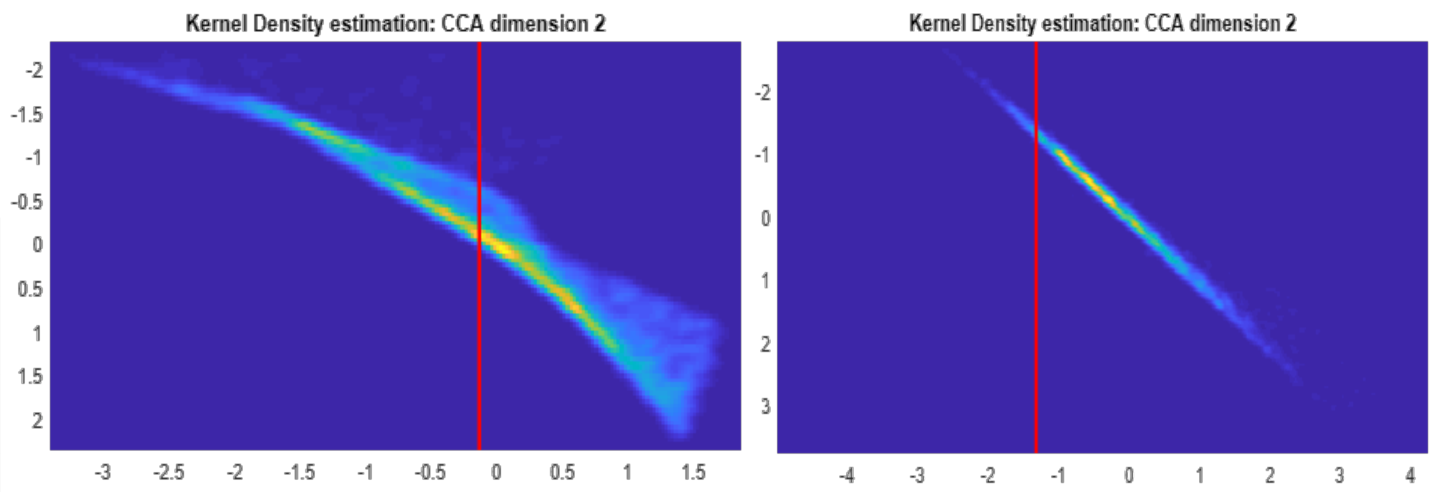


*Fig. 5: Exemple of correlation at iteration 1 (left) and 2 (right)*

- Enables a better estimation of the models parameters (espacially in the case of large priors)
- Permits to discriminate low probability modes in posterior distribution
- The McMC software DREAM (Vrugt, 2016) took about half an hour to converge towards an acceptable level of uncertainty whereas BEL1D needed about 3 minutes.

**Find the BEL1D codes on Github: github.com/hadrienmichel/BEL1D**

Hermans et al. (2016). Direct prediction of spatially and temporally varying physical properties from time-lapse electrical resistance data. Water Resources Research, 52(9), 7262–7283.
Scheidt et al. (2018). Quantifying Uncertainty in Subsurface Systems (Wiley-Blackwell).
Cheng et al. (2019). An iterative Bayesian filtering framework for fast and automated calibration of DEM models. Computer Methods in Applied Mechanics and Engineering, 350, 268–294.
Vrugt, J.A (2016). Markov chain Monte Carlo simulation using the DREAM software package: Theory, concepts, and MATLAB Implementation. Environmental Modelling & Software, 75, 273-316.