

# Improving BEL1D accuracy for geophysical imaging of the subsurface

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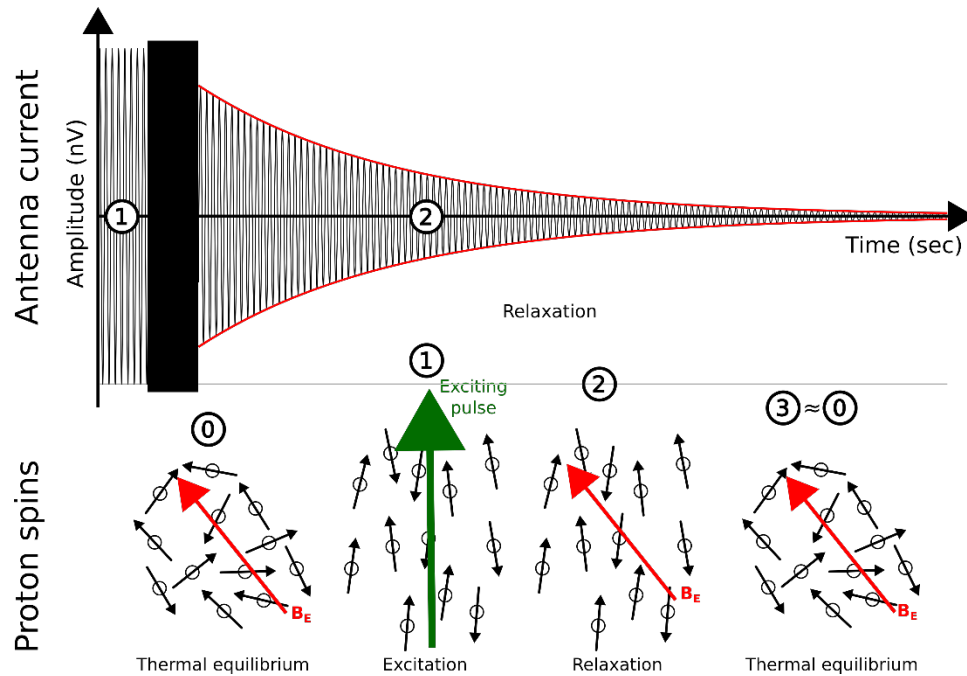


# Table of content

- Basics:
  - sNMR – detecting water from the surface
  - BEL1D (Michel et al., 2020, Computers & Geoscience)
- Numerical benchmark:
  - Applying BEL1D
  - Improving with Iterative Prior Resampling (IPR)
  - Comparison with MCMC
- Case study: Mont Rigi
- Conclusion and perspectives

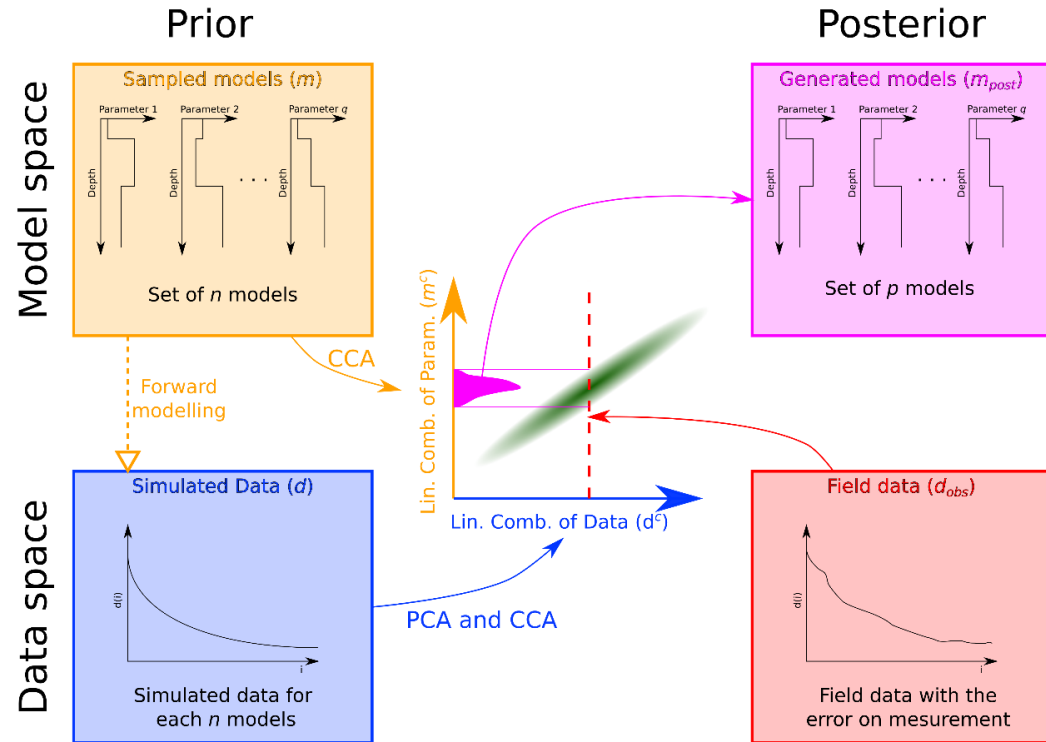
# sNMR

- sNMR = surface Nuclear Magnetic Resonance
- Detecting groundwater from the surface
- After inversion:
  - Water content distribution
  - Relaxation time distribution



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# BEL1D



- Adaptation from BEL (Schiedt et al., Quantifying Uncertainty in Subsurface Systems, 2018)
- Building a relationship between:
  - Synthetic models
  - The associated datasets
- Extracting the posterior from this relationship

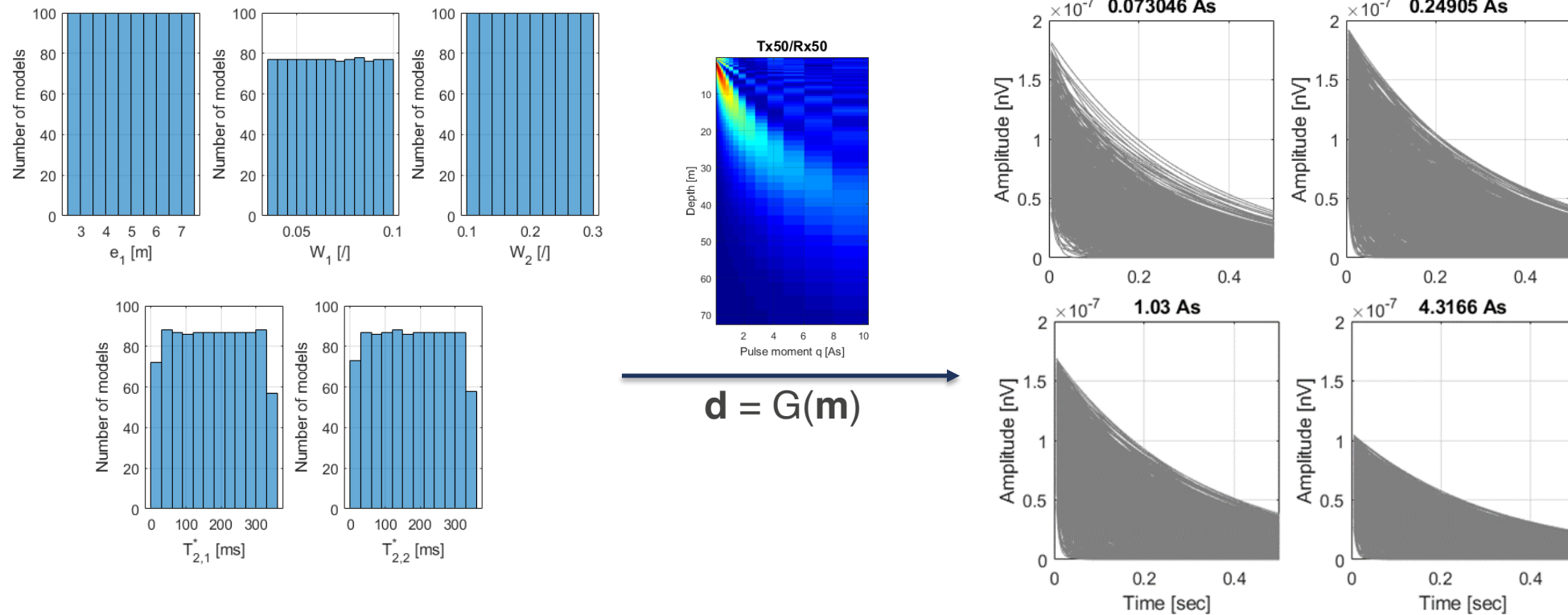
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4



# BEL1D

## Sampling models and forward modelling

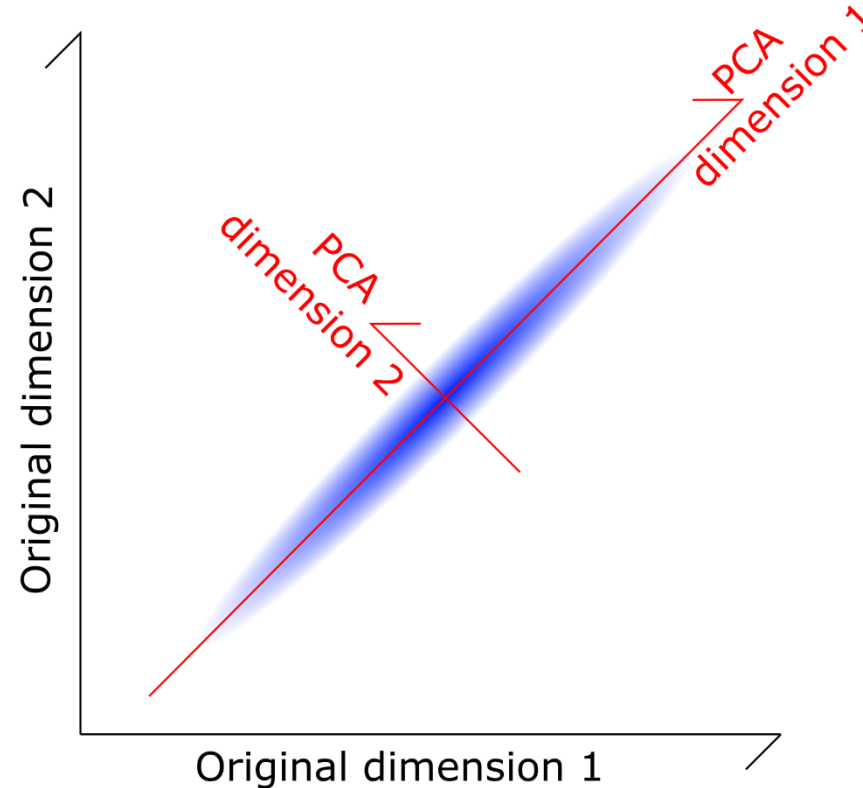


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# BEL1D

## Reducing dimensionality (PCA)

- From 10,000 dimensions in the dataset to around 10
  - Keeping 90% variability
- Not applied to the models
  - Uncorrelated prior
  - Poor performances



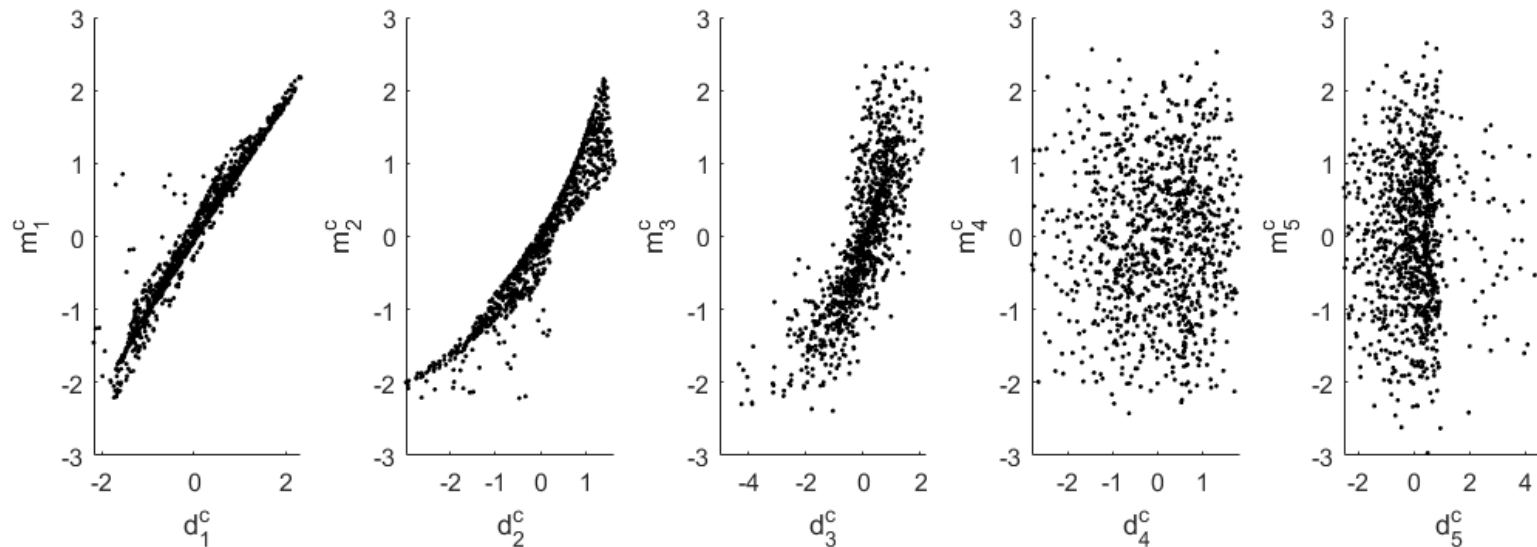
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6

# BEL1D

## Canonical correlation analysis

- Linking the models parameters to the reduced datasets → CCA

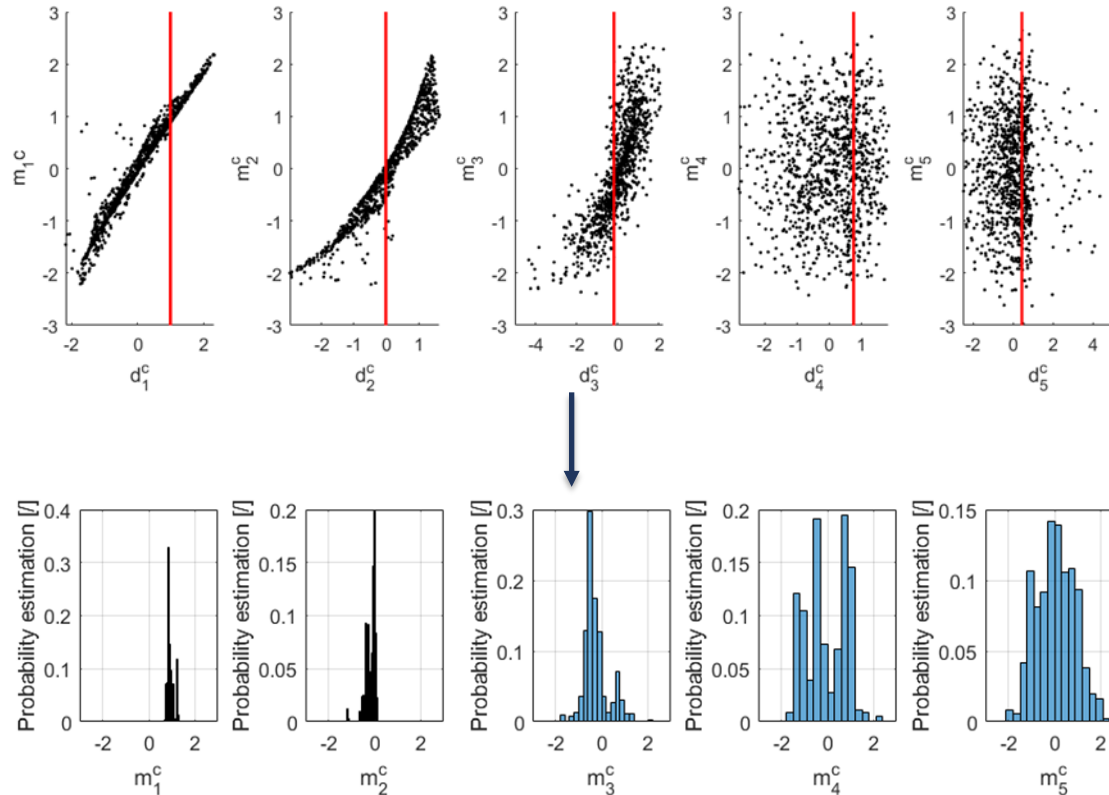


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7

# BEL1D

## Extracting the posterior in reduced space



- Transform the field dataset (PCA and CCA)
- Report in the CCA space
- Extract the obtained distribution (Kernel Density Estimation)

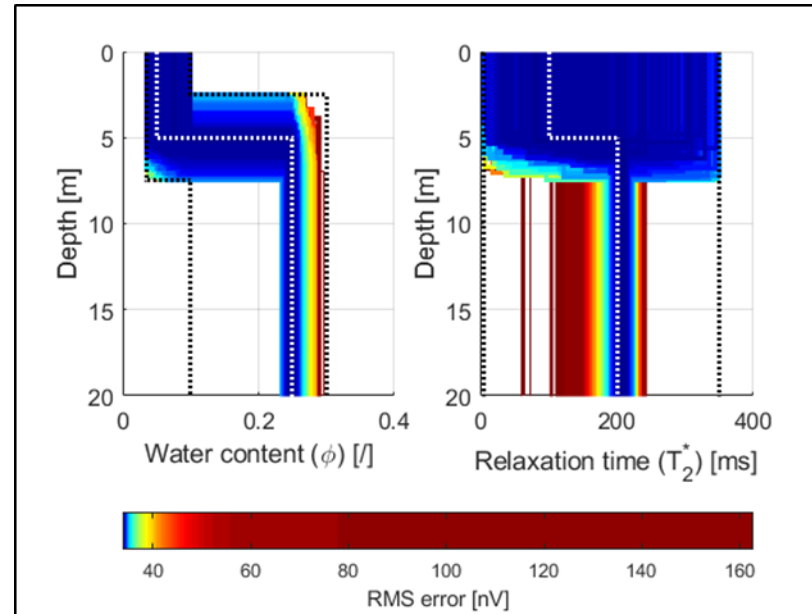
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8

# BEL1D

## Back-transform into original space

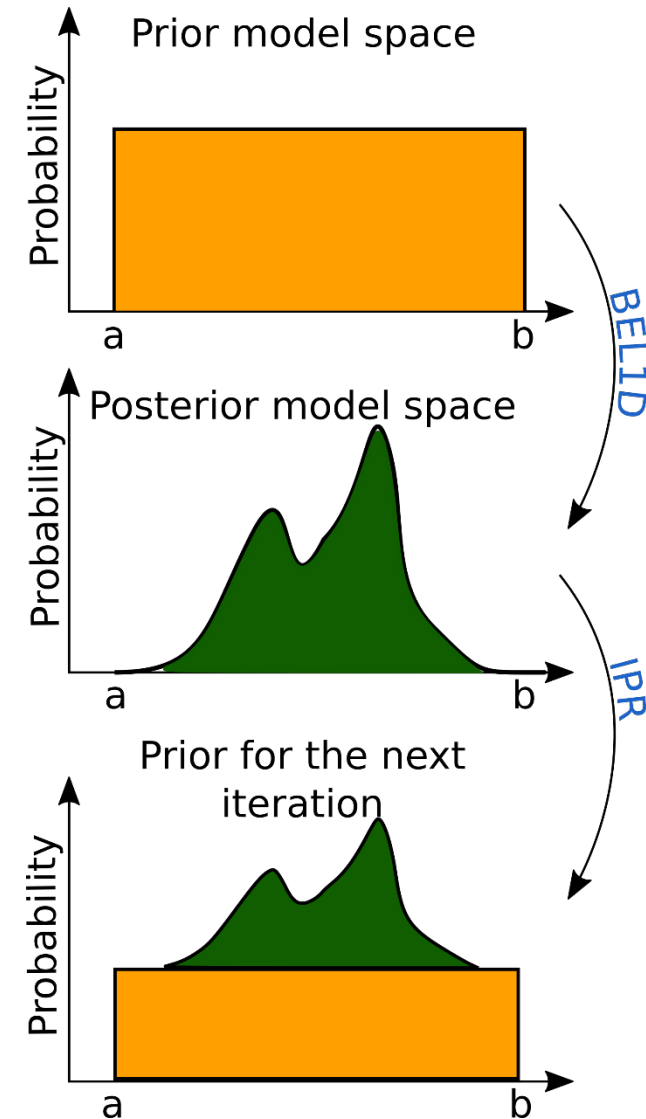
- Apply the inverse transform (CCA) to sampled models in reduced space



# BEL1D

## Improving with IPR, the concept

- IPR = Iterative Prior Resampling
- Inspired by Iterative Spatial Resampling (Mariethoz et al., 2010, Water Resour. Res.) and Sampling Importance Resampling (Dosne et al., 2016, J PHARMACOKINET PHAR)
- Process:
  - Adding the sampled models to the prior
  - Re-running the BEL1D operations
  - Repeat until convergence:
    - Threshold on the difference between the obtained distributions (Wasserstein distance in normalized space)



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10

# Numerical benchmark

- Simple 3-layer model
- Experimental design:
  - Same transmitter/receiver loop
  - 50 m diameter → penetration depth about 50 meters
  - Noise = 10nV (Gaussian)
- Prior defined accordingly but still large

Layer #	Thickness e [m]			Water content W [%]			Decay time T <sub>2</sub> <sup>*</sup> [ms]		
	Min	True	Max	Min	True	Max	Min	True	Max
1	0	25	50	0	5	15	0	100	500
2	0	25	50	15	25	50	0	200	500
Half-space	/	Inf	/	0	10	15	0	50	500

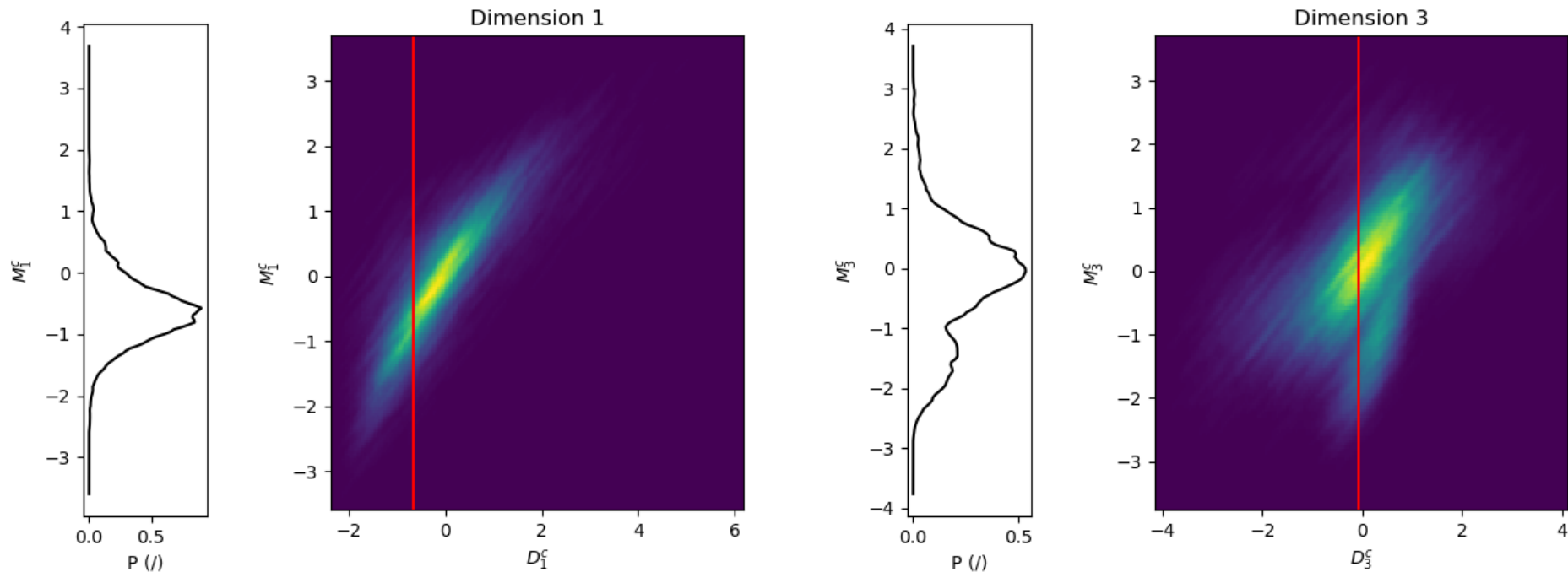
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11

# Numerical benchmark

## Applying BEL1D

### Building the CCA space relationship



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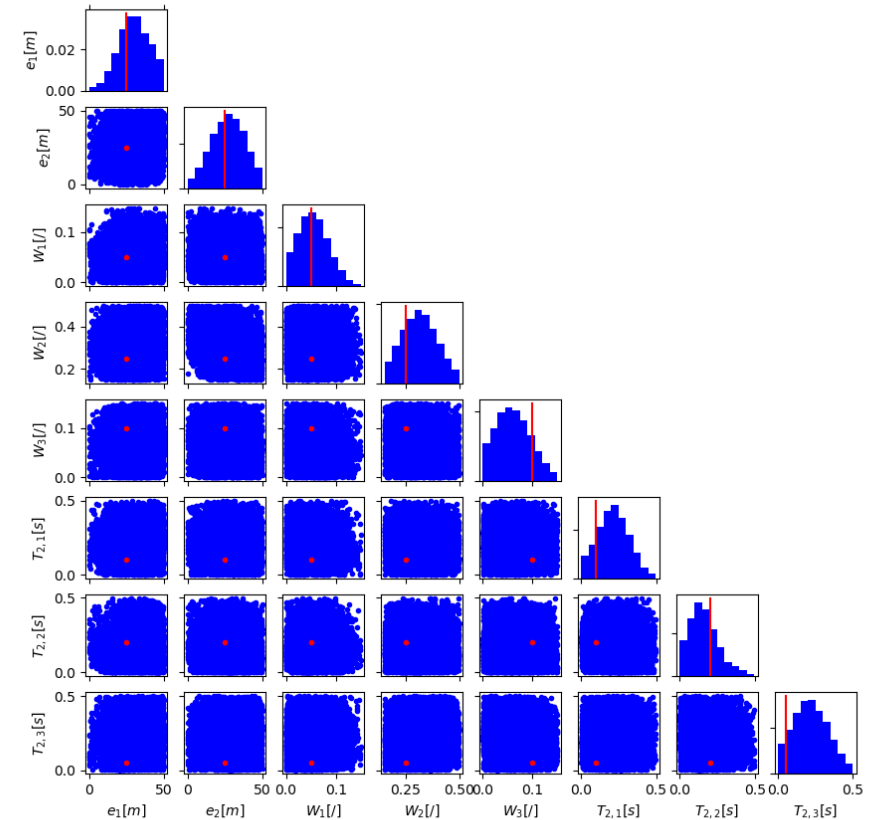
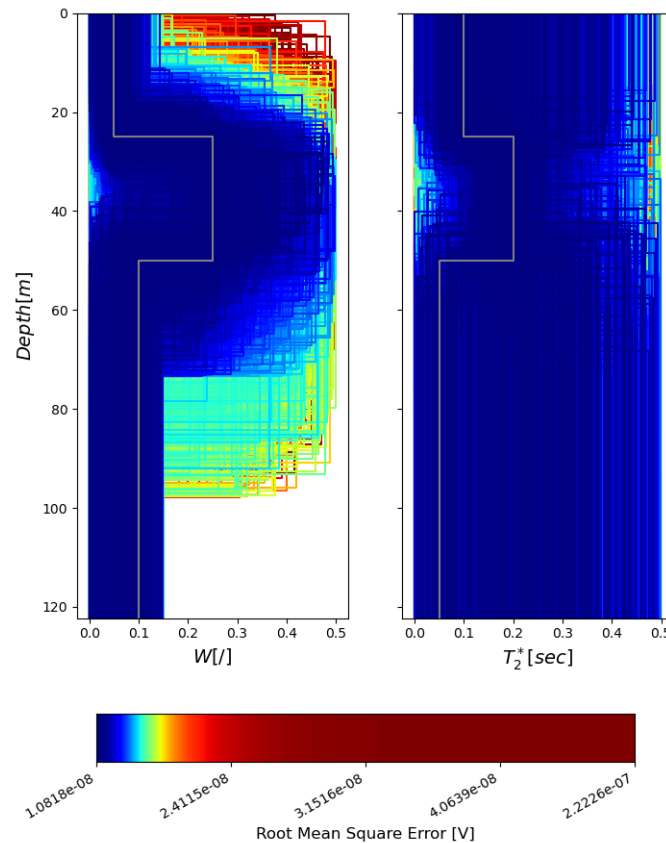
12



# Numerical benchmark

## Applying BEL1D

- Reduced uncertainty
  - Still very large!
  - RMSE above noise level
- Room for improvement



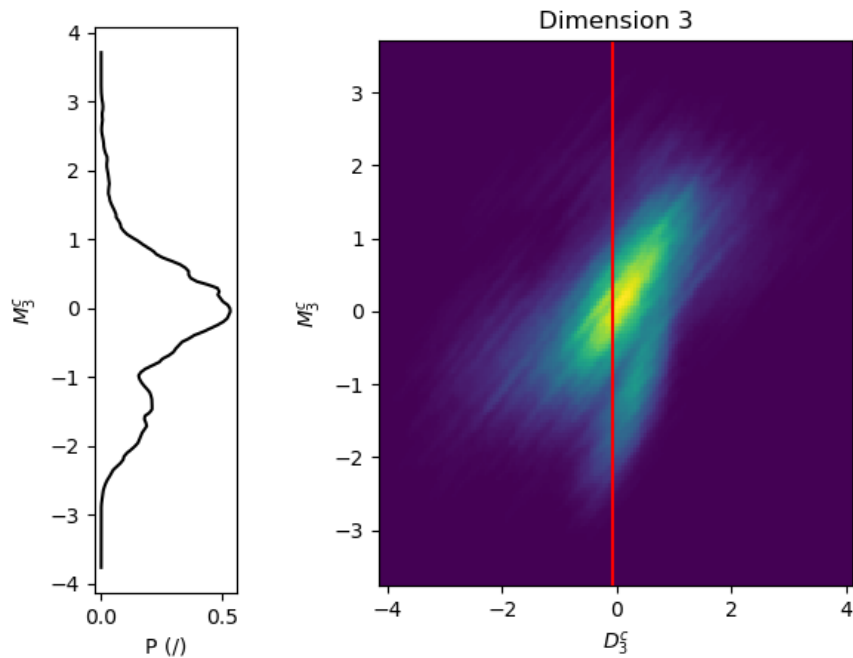
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13

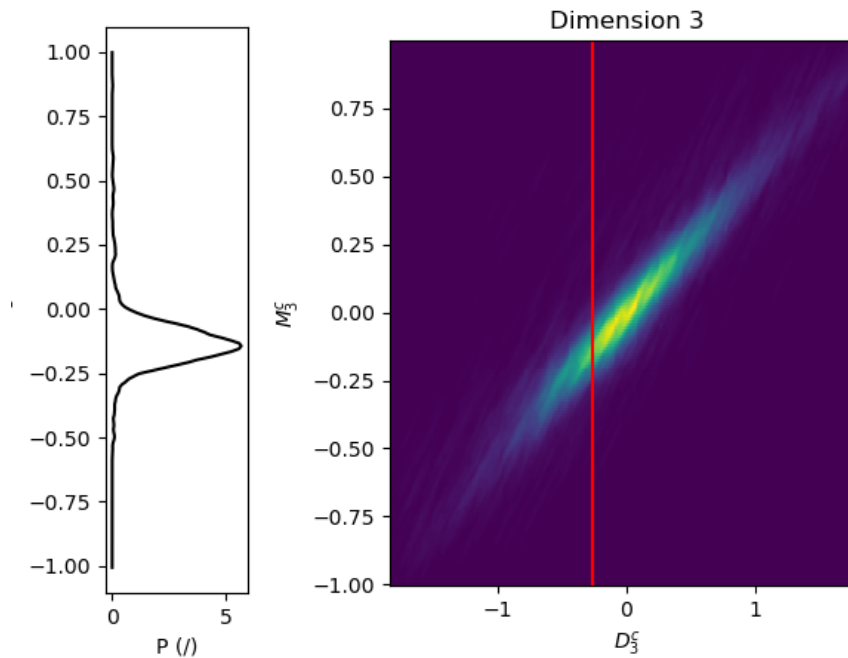
# Numerical benchmark

## Improving with IPR

### 1st iteration



### Last iteration



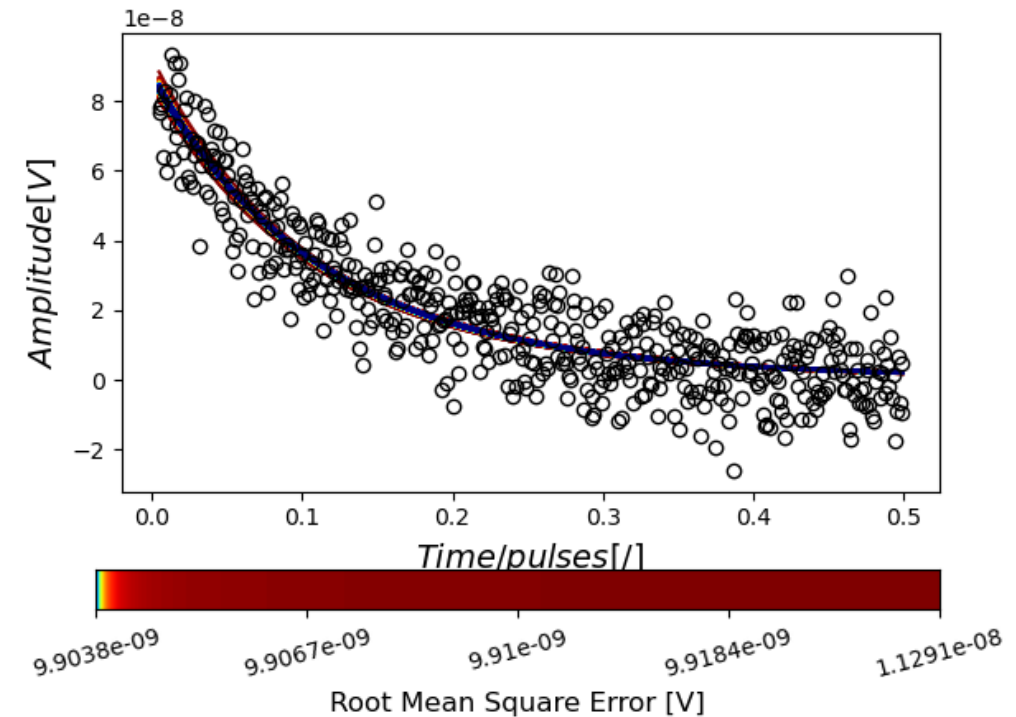
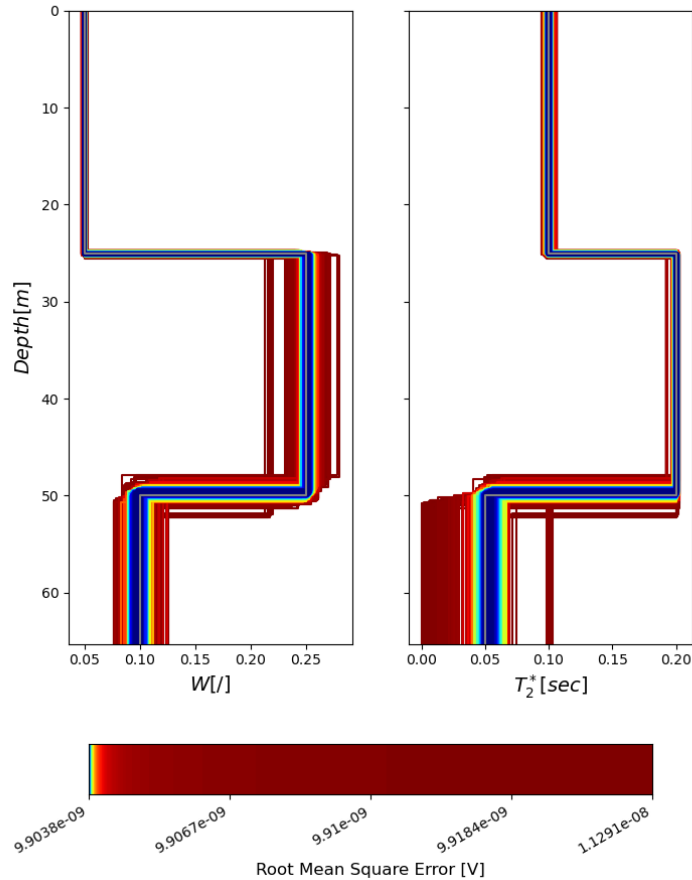
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14

# Numerical benchmark

## Improving with IPR

- Narrow uncertainty
- Sensitivity lower in depth
  - From experimental design



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15

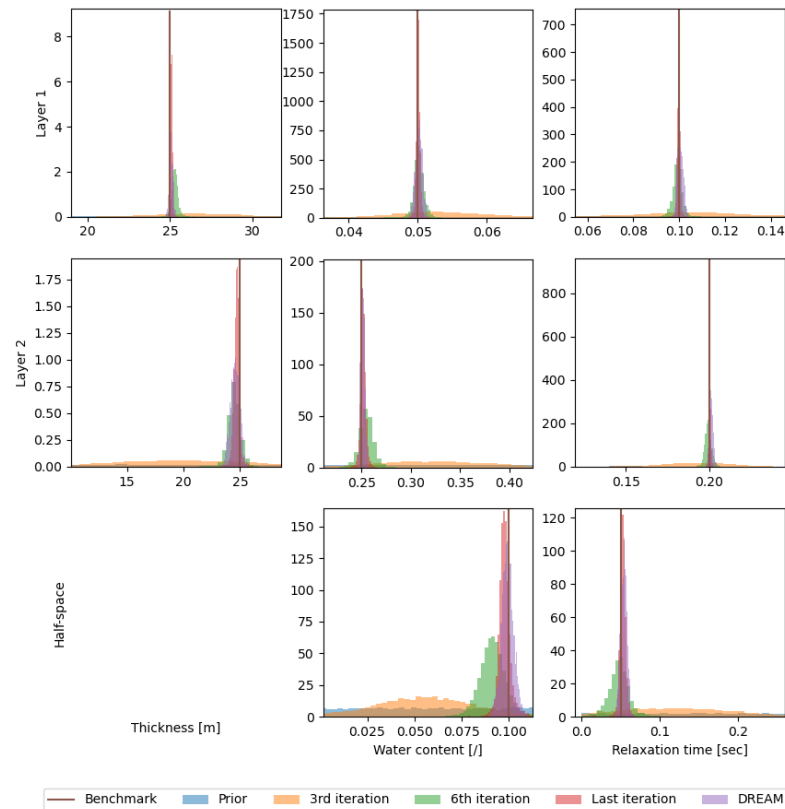
# Numerical benchmark

## Comparing with McMC

- Using DREAM<sub>(zs)</sub> (e.g., Vrugt, 2016, ENVIRON MODELL SOFTW and Laloy et al., 2018, Water Resour. Res.)
- Tuned to convergence:
  - Number sequences: 20
  - Samples per chain: 10,000
  - Jump rate: 0.1

# Numerical benchmark

## Comparing with McMC



- The last iteration coincide with results from DREAM
- However:
  - CPU time is lower (250 seconds for BEL1D vs 500 for DREAM<sub>(zs)</sub>)
  - Difficulty to tune to convergence in DREAM

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17

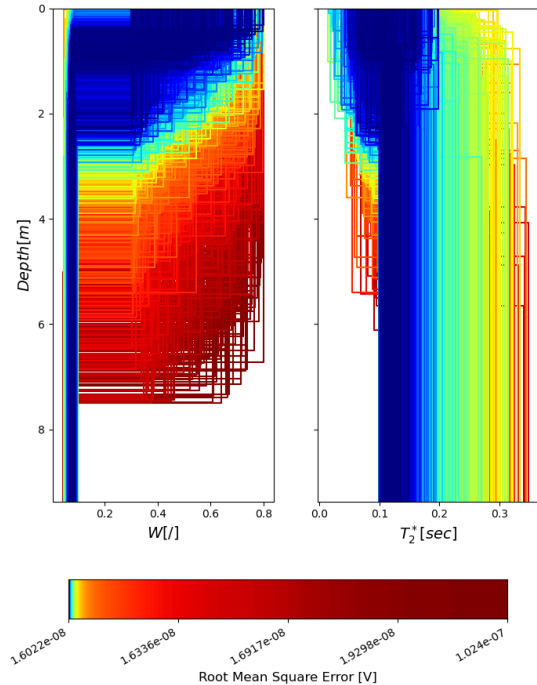
# Case study: Mont Rigi



- Natural reserve in the Eastern part of Belgium
- Metric peat above Cambrian bedrock
- Experiment:
  - Single transmitter/receiver
  - 20 meters in diameter
  - Noise  $\sim 18$  nV

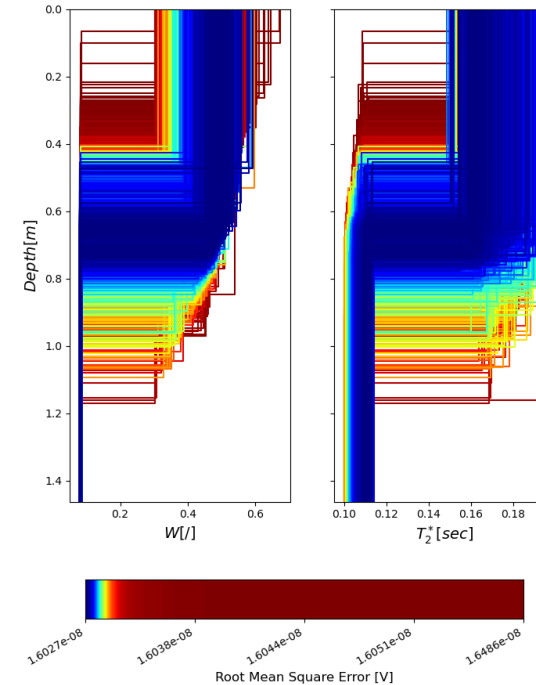
# Case study: Mont Rigi

## First iteration



- Significant reduction of uncertainty
- Still an observable ( $W_1$ ,  $e_1$ ) link
- Trend for the relaxation time
- CPU time = 30 sec

## Last (6th) iteration



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19

# Conclusion and perspectives

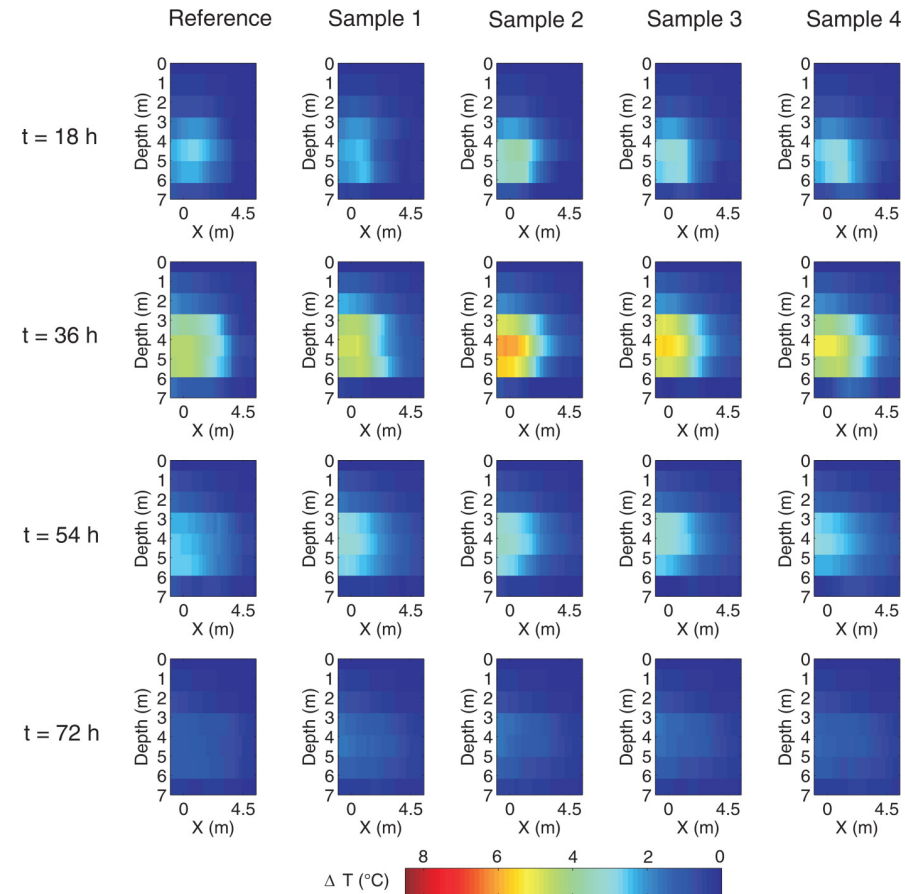
- BEL1D combined with IPR is:
  - Accurate (comparison with McMC)
  - Efficient (CPU time)
  - Easy to tune to convergence
- Significant improvement over BEL1D without iterations
- Currently developing other use case (MASW, EM)
- Near future: Smooth models, 2D, etc.



# Conclusion and perspectives

## 2D case – Time-Lapse ERT

- Time-lapse ERT (Hermans et al., 2016, Water Resour. Res.)
- Heat tracer experiment
- Captures the behavior of the heat tracer.



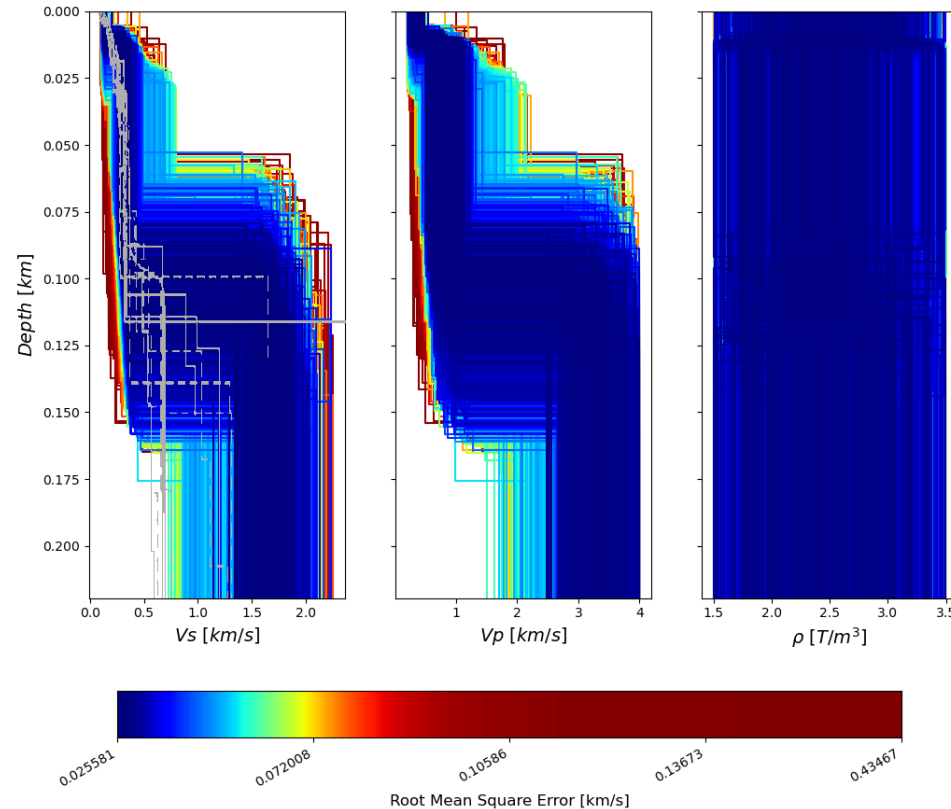
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21

# Conclusion and perspectives

## Work in progress – Surface waves preview

- Mirandola (Italy) case study from INTERPacific (Garofalo et al., 2016, SOIL DYN EARTHQ ENG)
- Comparison of the results with IPR with the different experts curves



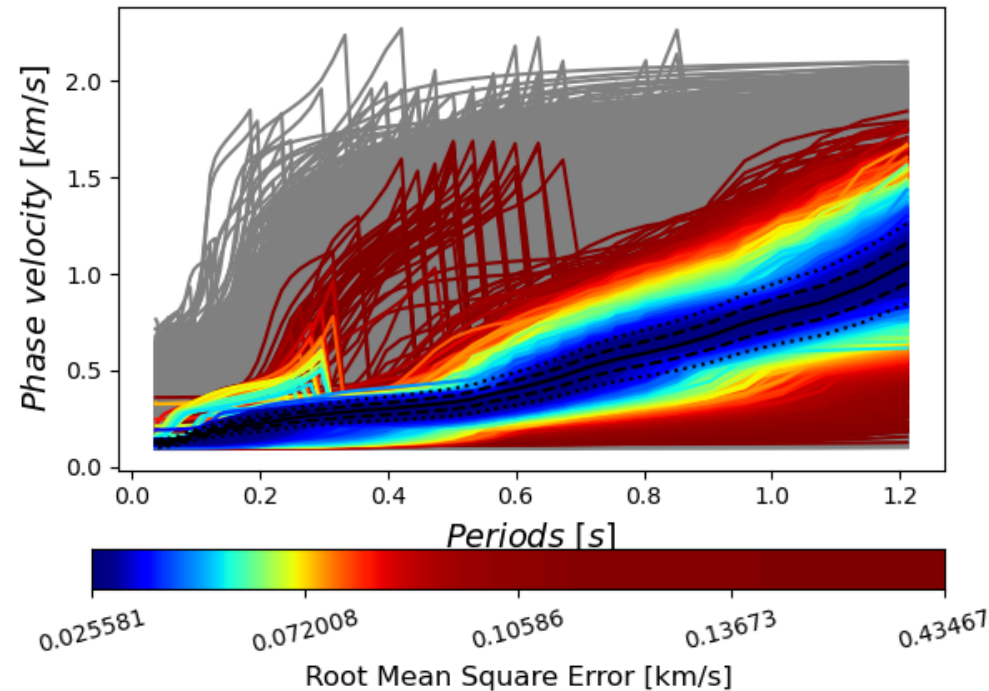
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22

# Conclusion and perspectives

## Work in progress – Surface waves preview

- Efficient reduction of the dataspace from the prior (gray) to the posterior at the last (15<sup>th</sup>) iteration
- The error model fits nicely the posterior dataspace
  - The noise is not of the same kind as the one in sNMR



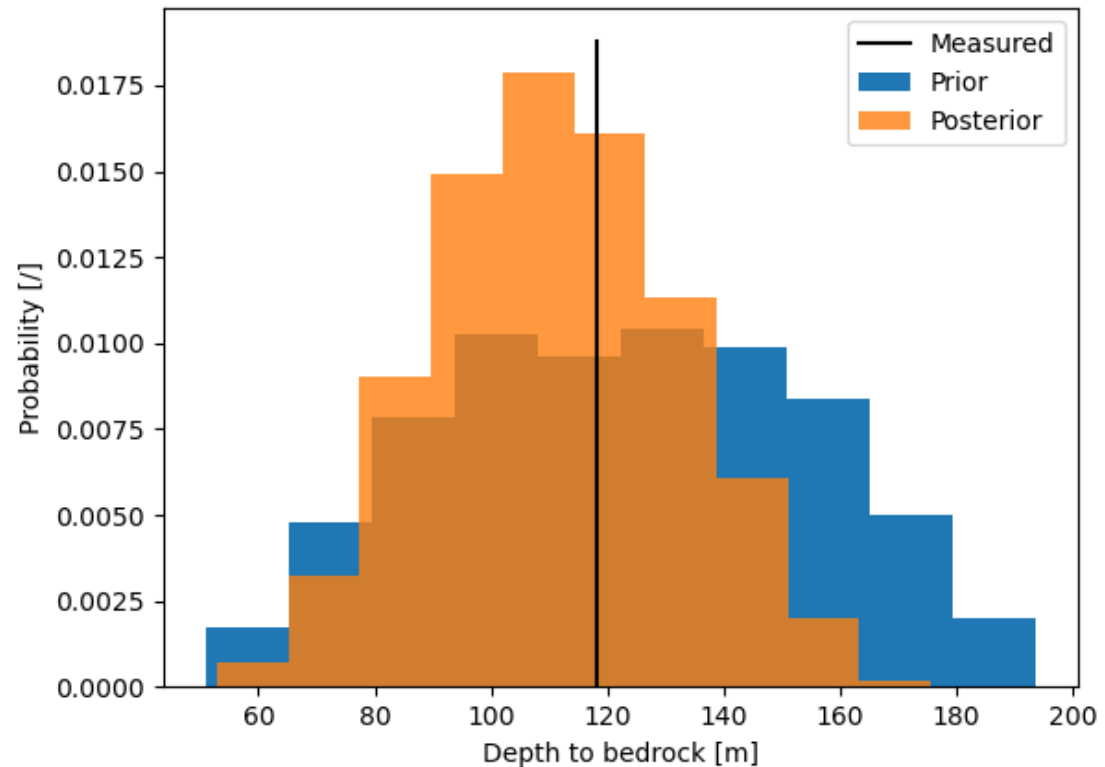
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23

# Conclusion and perspectives

## Work in progress – Surface waves preview

- Field benchmark available:  
Depth to the bedrock = 118m  
(Garofalo et al., 2016, SOIL DYN  
EARTHQ ENG)
- Accurately reproduced by BEL1D



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24

# Publication

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## 1D geological imaging of the subsurface from geophysical data with Bayesian Evidential Learning

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25





# Thanks for your attention!



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26

# Conclusion and perspectives

- BEL1D combined with IPR is:
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  - Efficient (CPU time)
  - Easy to tune to convergence
- Significant improvement over BEL1D without iterations
- Currently developing other use case (MASW, EM)
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