

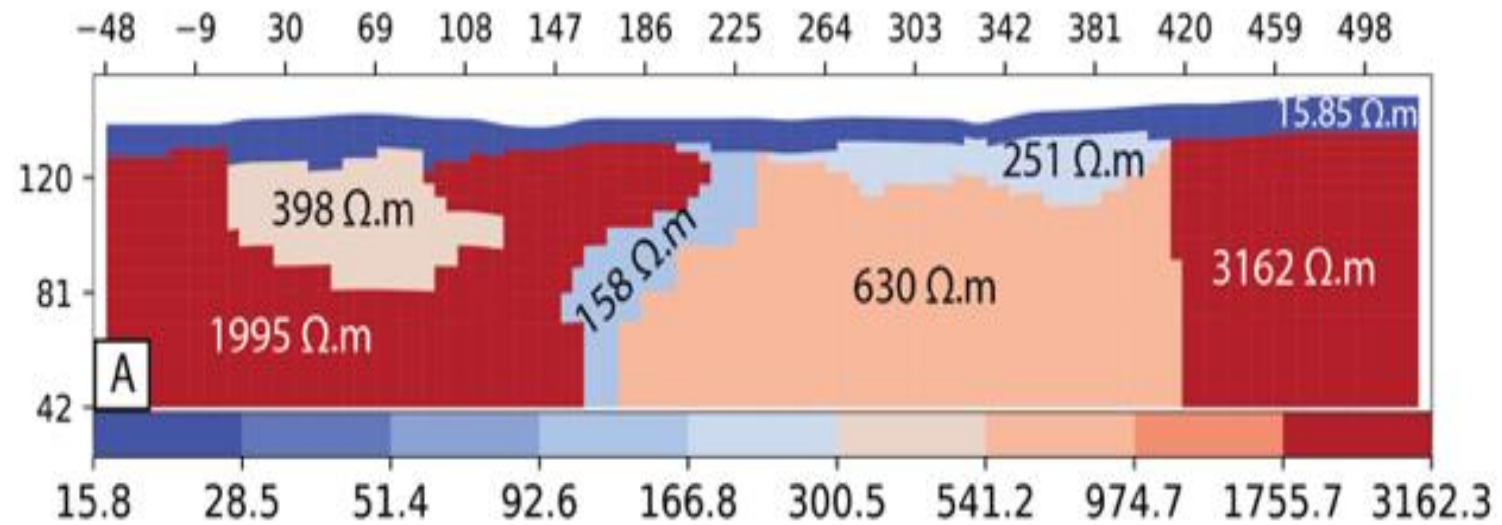
IMAGING THE SUBSURFACE TO INFORM HYDROLOGICAL MODELS: A GEOPHYSICIST'S PERSPECTIVE

Thomas Hermans, Hadrien Michel, Jorge Lopez-Alvis, Frédéric Nguyen

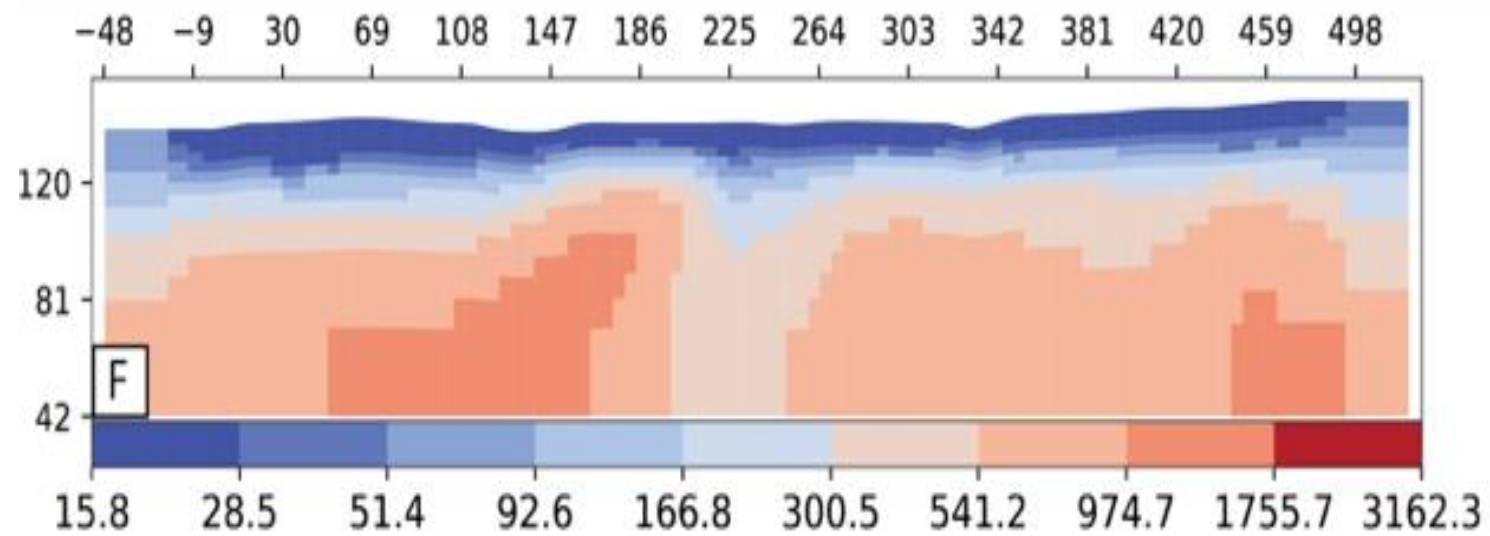
IMAGING THE SUBSURFACE WITH GEOPHYSICS

DETERMINISTIC GEOPHYSICAL INVERSION

Real geophysical parameter distribution $\mathbf{m}$

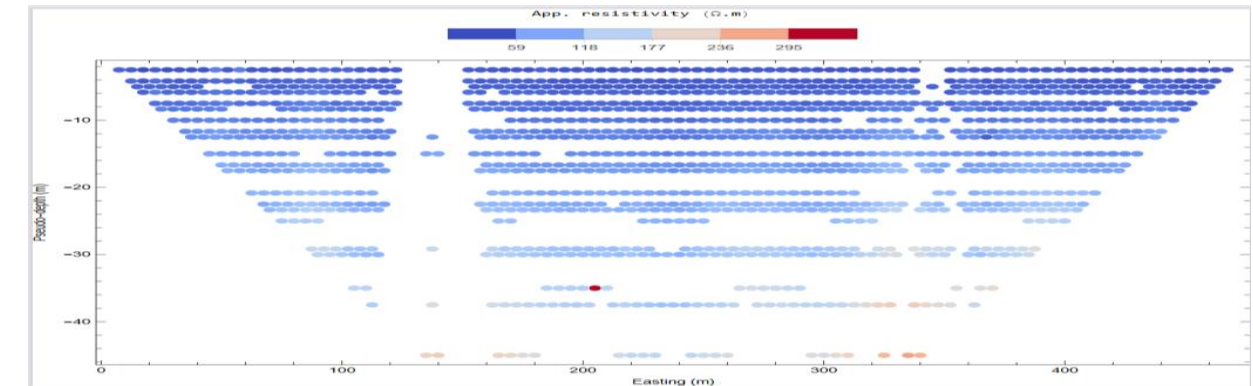


Estimated model parameter $\mathbf{m}_i$



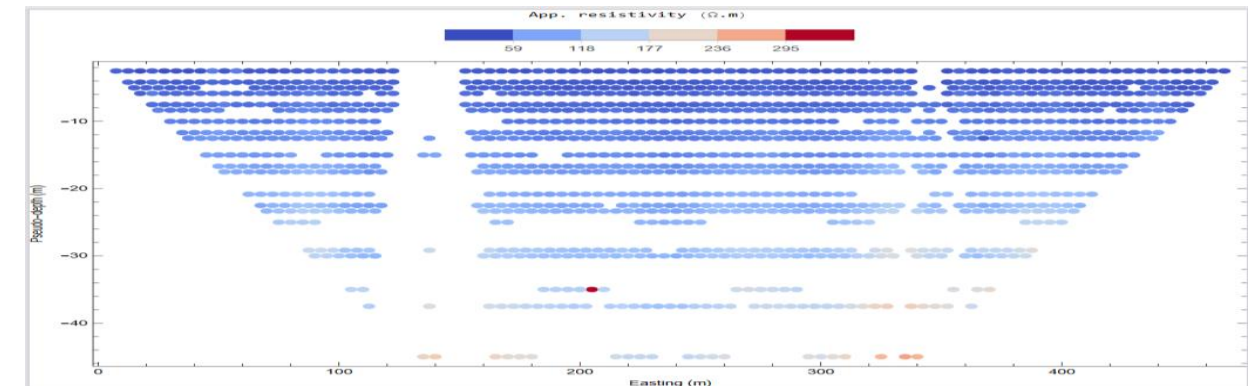
Field data collection

$$\text{data set } \mathbf{d}_{obs} = \mathbf{G}(\mathbf{m}) + \epsilon$$



Data misfit

$$\text{data set } \mathbf{d}_{calc} = \mathbf{G}(\mathbf{m}_i)$$



Forward model

Iterative updating

$$\mathbf{m}_i = \mathbf{m}_{i-1} + \Delta \mathbf{m}$$

→ Minimization of an objective function

DETERMINISTIC GEOPHYSICAL INVERSION

Standard deterministic approaches use regularization to stabilize the process

The objective function has a term characterizing the type of model expected

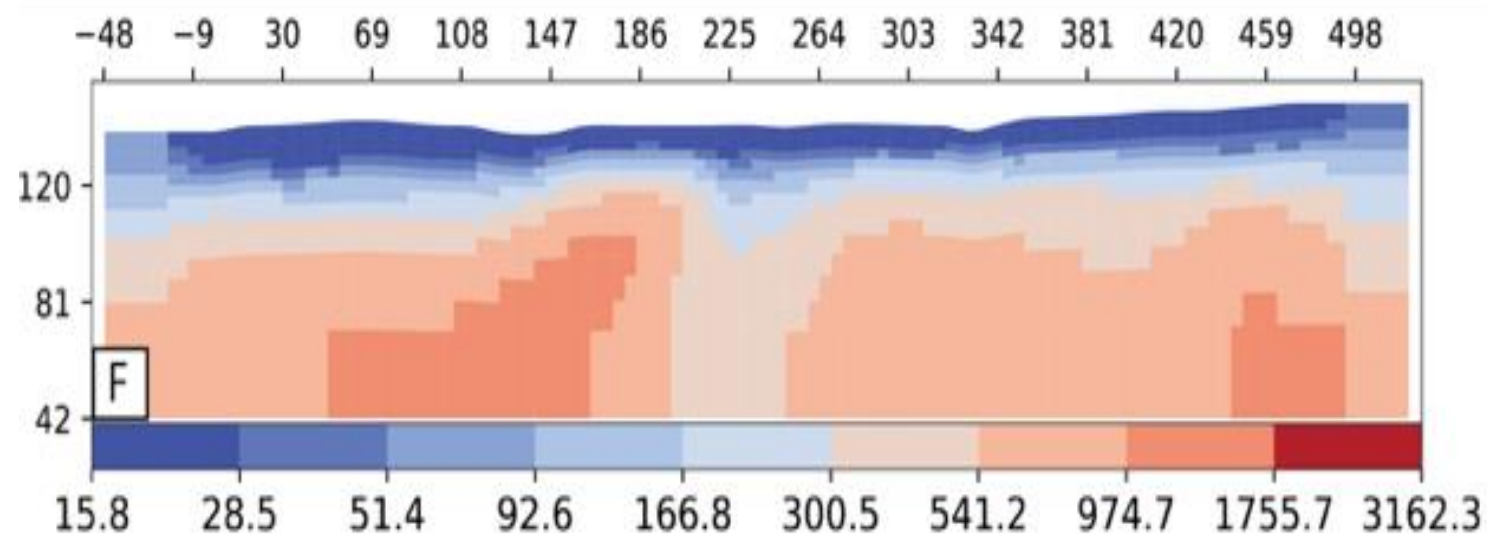
$$\phi(m) = || W_d (G(m) - d) ||^2 + \lambda || W_m m ||^2$$



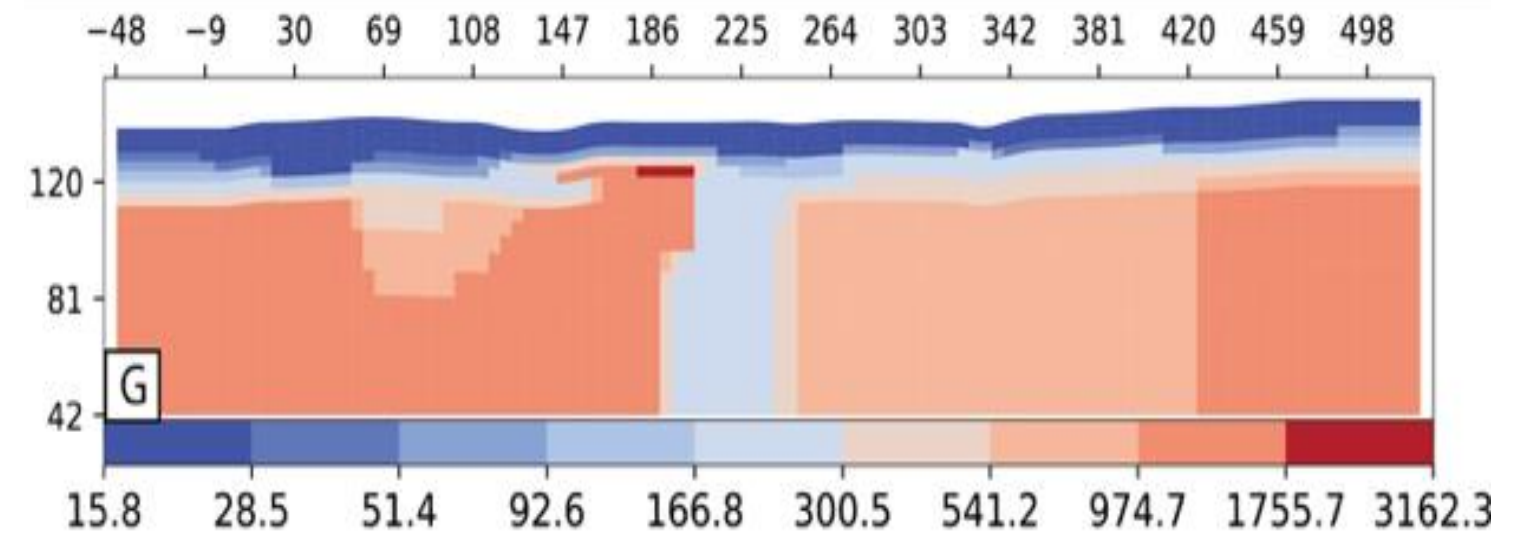
Data misfit



Model constraint



Smoothness constraint

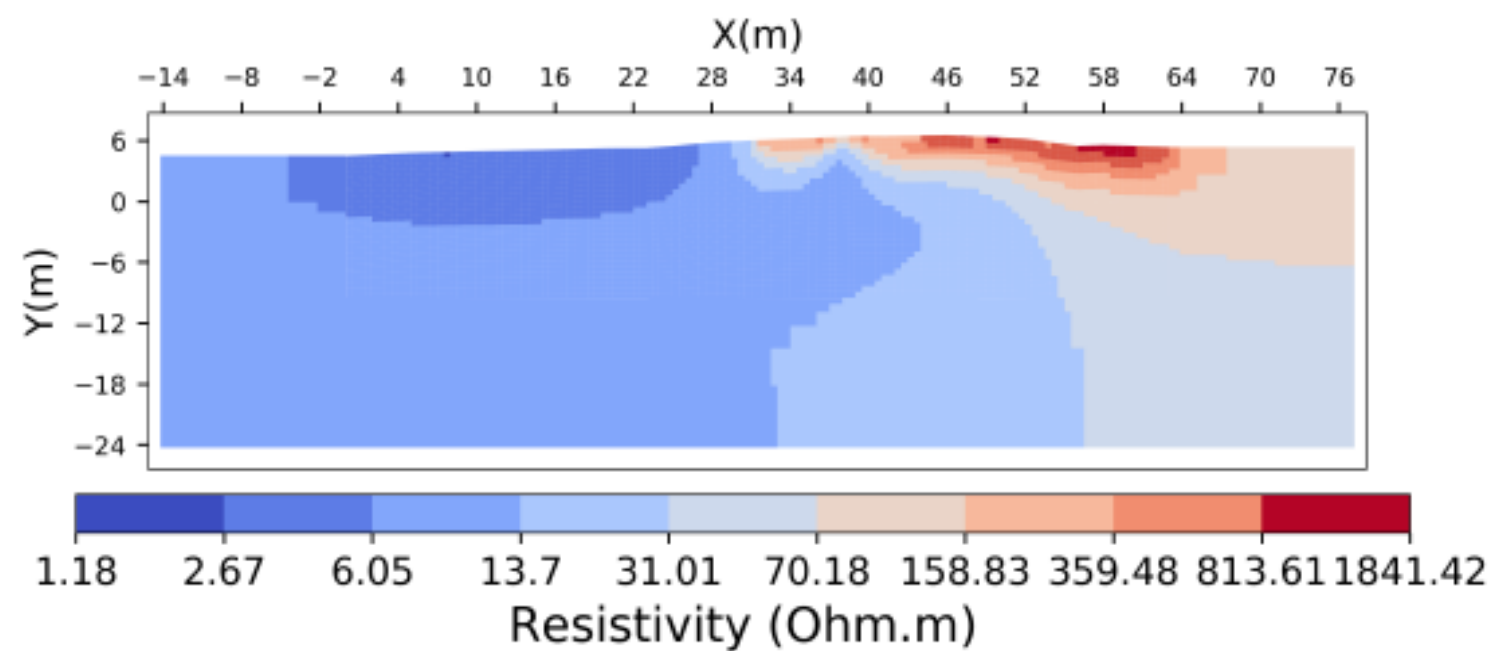


Minimum Gradient Support

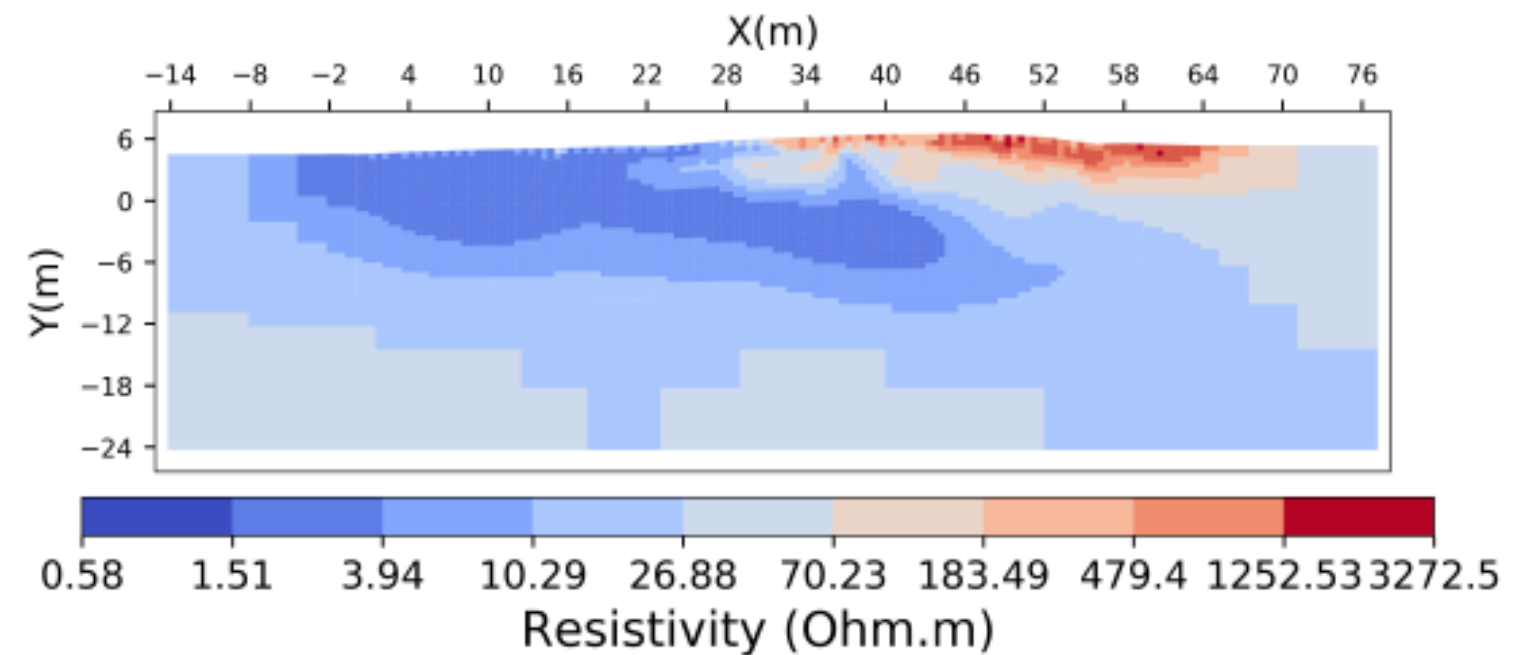
DEALING WITH NOISE

The data should be fitted within its estimated noise level

Risk of overfitting (artefacts) or oversmoothing



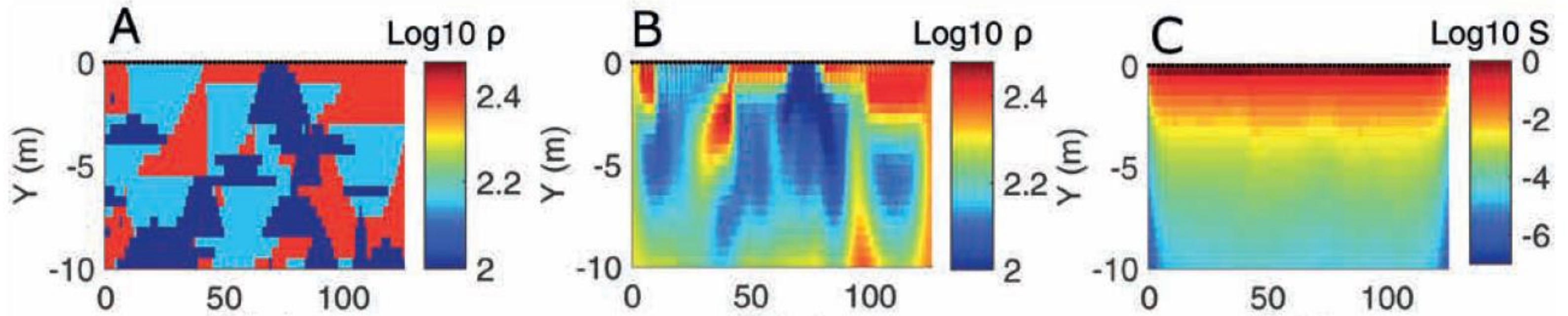
High estimated noise level



Low estimated noise level

IMAGING HETEROGENEITY

The resolution of geophysical data limits its ability to discriminate between different facies



The regularization is a filter, the final image is always uncertain

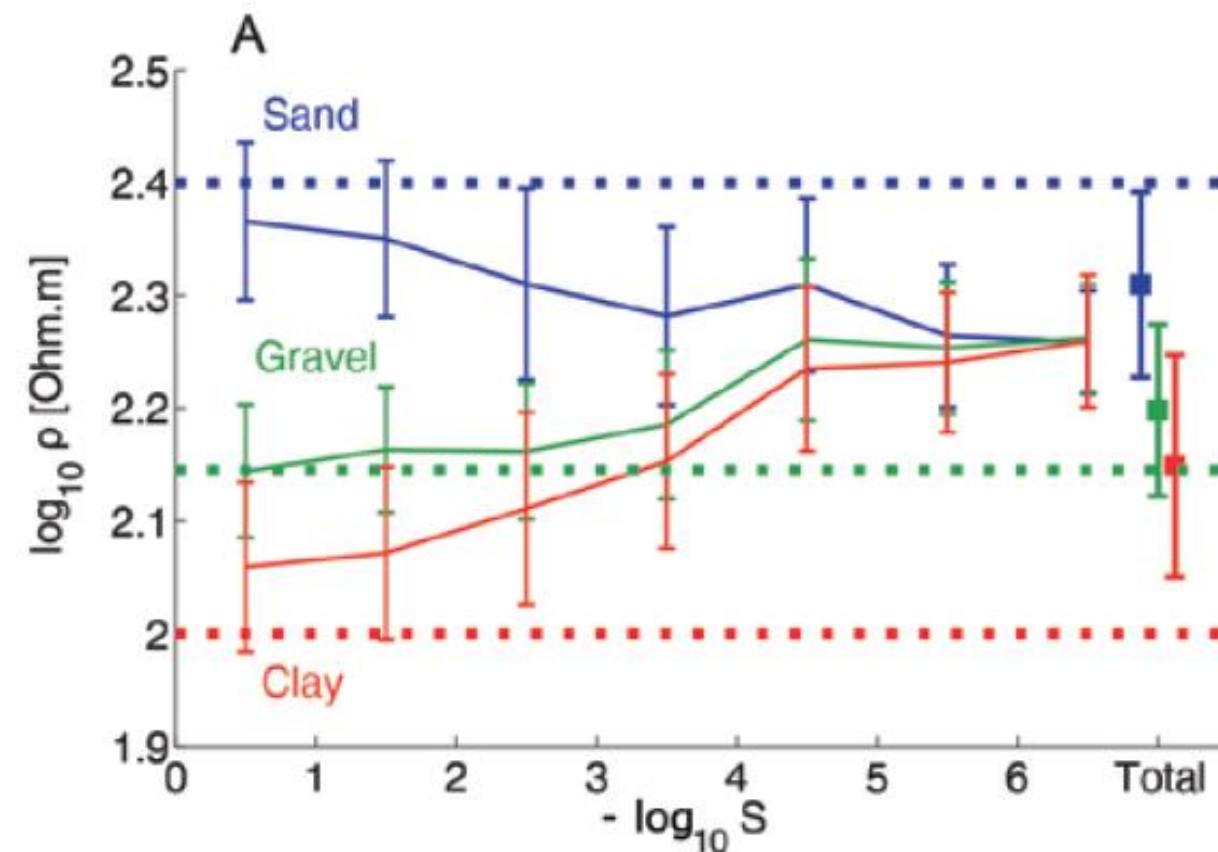
The sensitivity decreases with depth for surface data

(Hermans and Irving, NSG, 2017)

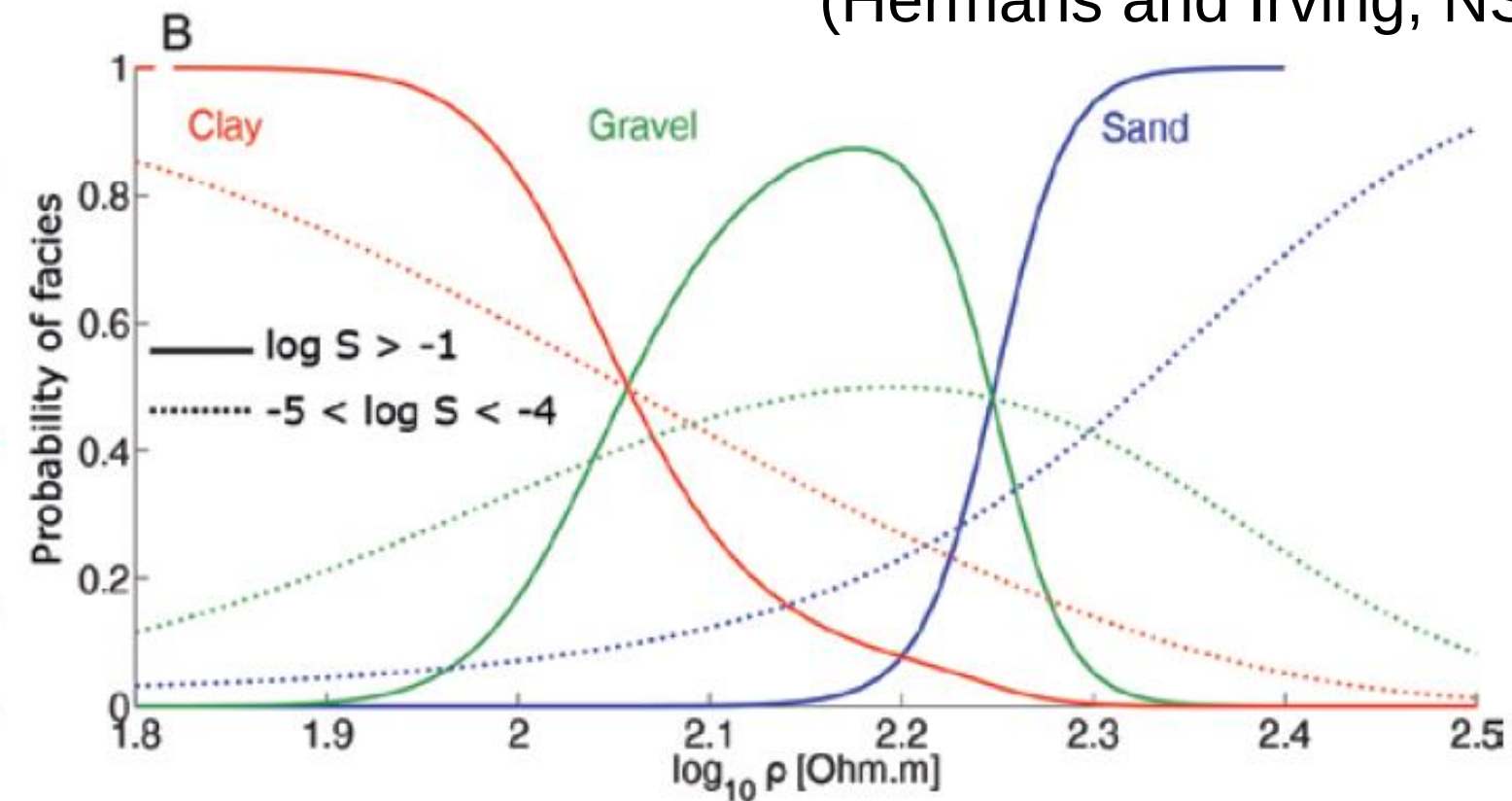
IMAGING HETEROGENEITY

If a model with constant properties is inverted, there is an overlap in the value after inversion, and the overlap depends on the sensitivity ! It can be quantified using conditional probabilities

(Hermans and Irving, NSG, 2017)



Distribution of resistivity for different sensitivity classes after inversion, the dotted line shows the true value



Conditional probability of the different facies based on the inverted resistivity values for different sensitivity classes

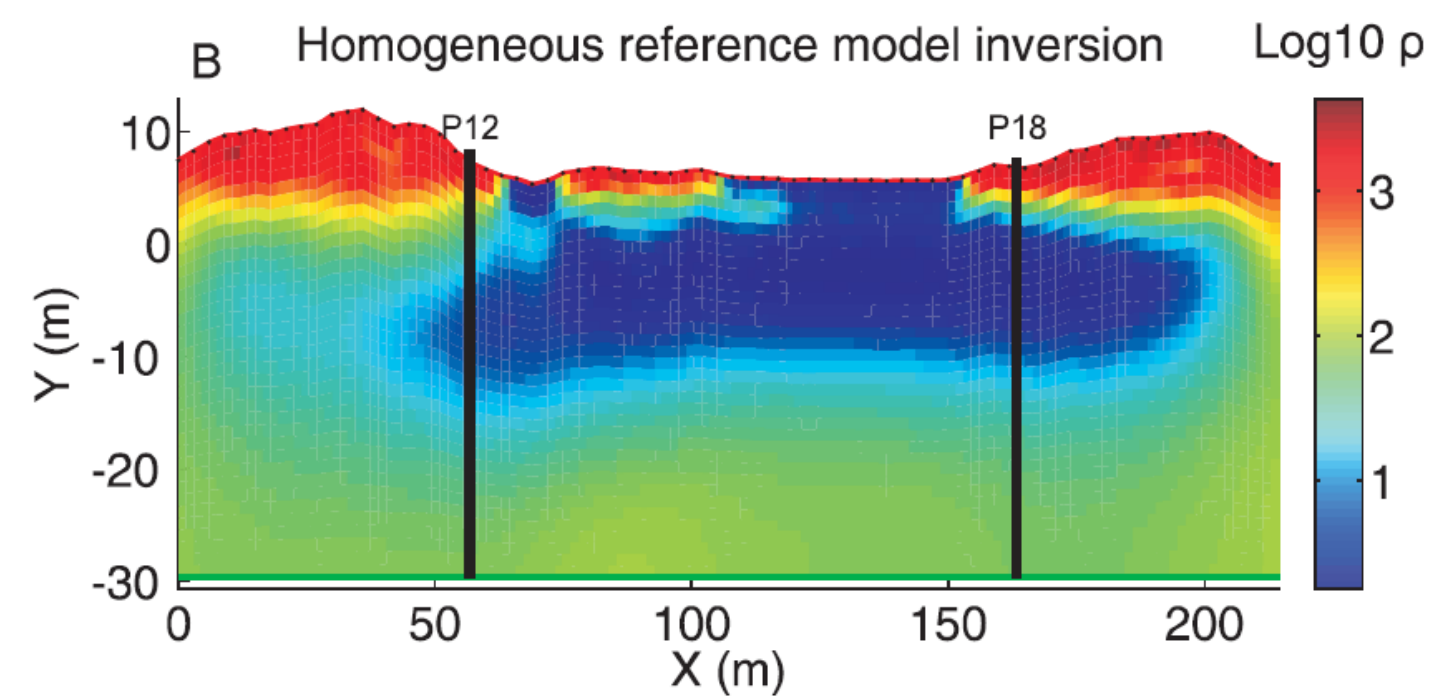
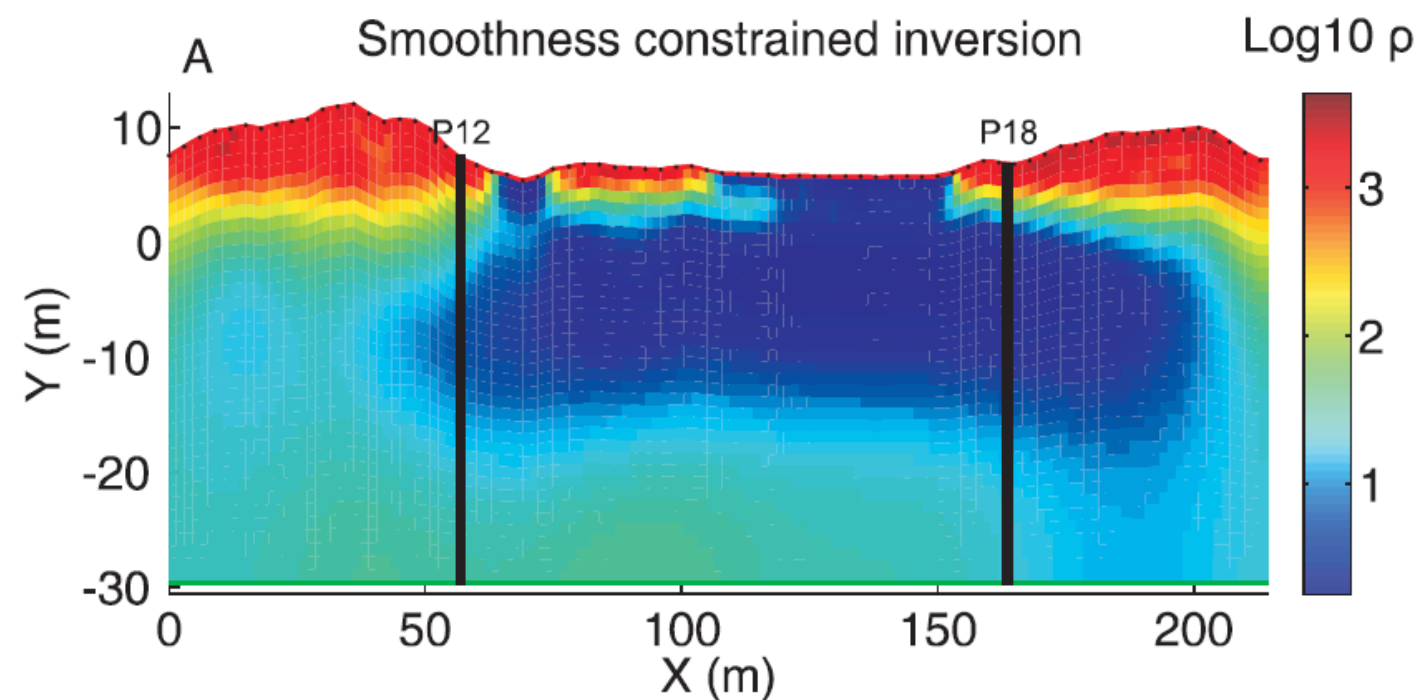
How can we improve this ? By adding prior information during the inversion

ADDING A REFERENCE MODEL

$$\phi(m) = \underbrace{\|W_d(G(m) - d)\|^2}_{\text{Data misfit}} + \underbrace{\lambda(\|W_m(m - m_{ref})\|^2)}_{\text{Model constraint}} + \alpha(m) \|m - m_{ref}\|^2$$

Data misfit

Model constraint



For example from borehole data

Possibility to adapt the weight cell by cell

Improve the final image, mainly in low sensitivity zones

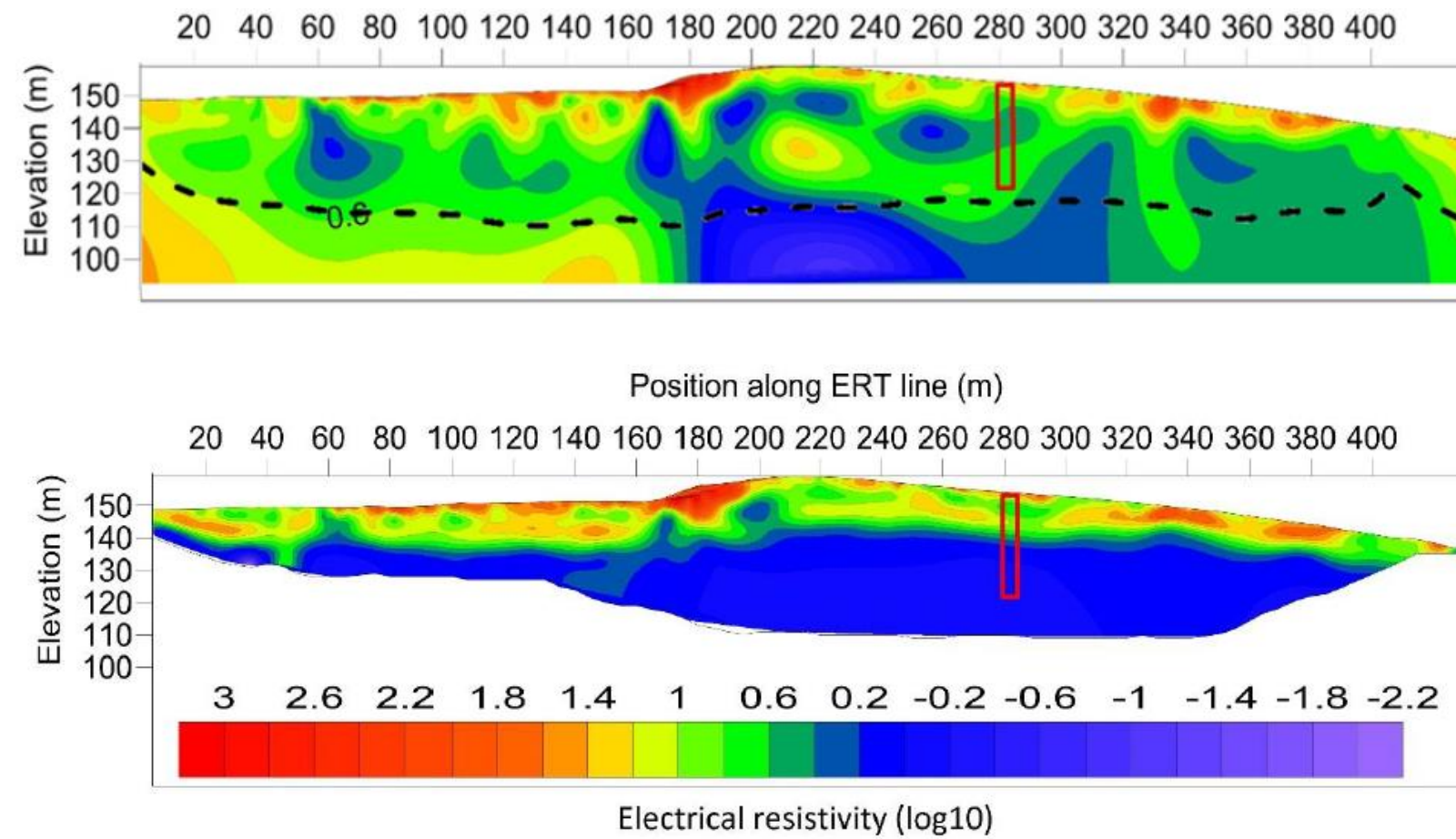
(Hermans et al. JoH, 2012)

ADDING A REFERENCE MODEL

$$\phi(m) = \underbrace{\|W_d(G(m) - d)\|^2}_{\text{Data misfit}} + \underbrace{\lambda(\|W_m(m - m_{ref})\|^2)}_{\text{Model constraint}} + \alpha(m) \|m - m_{ref}\|^2$$

Data misfit

Model constraint



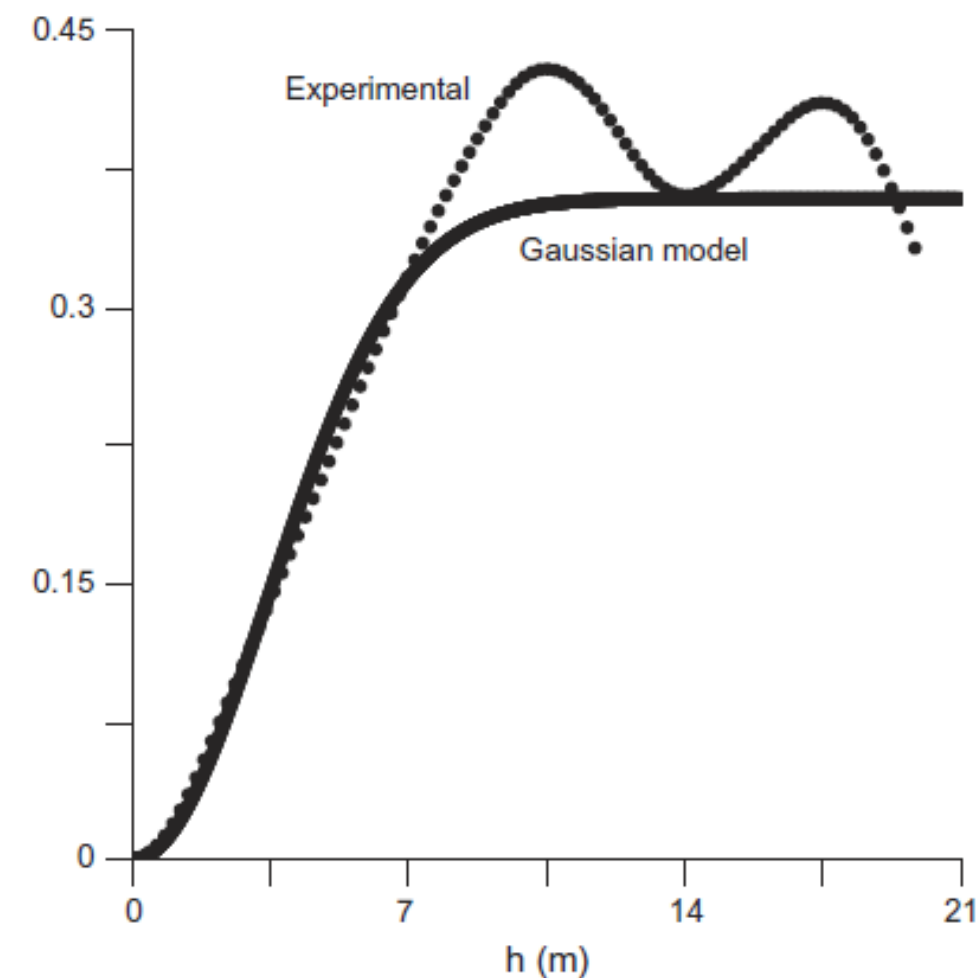
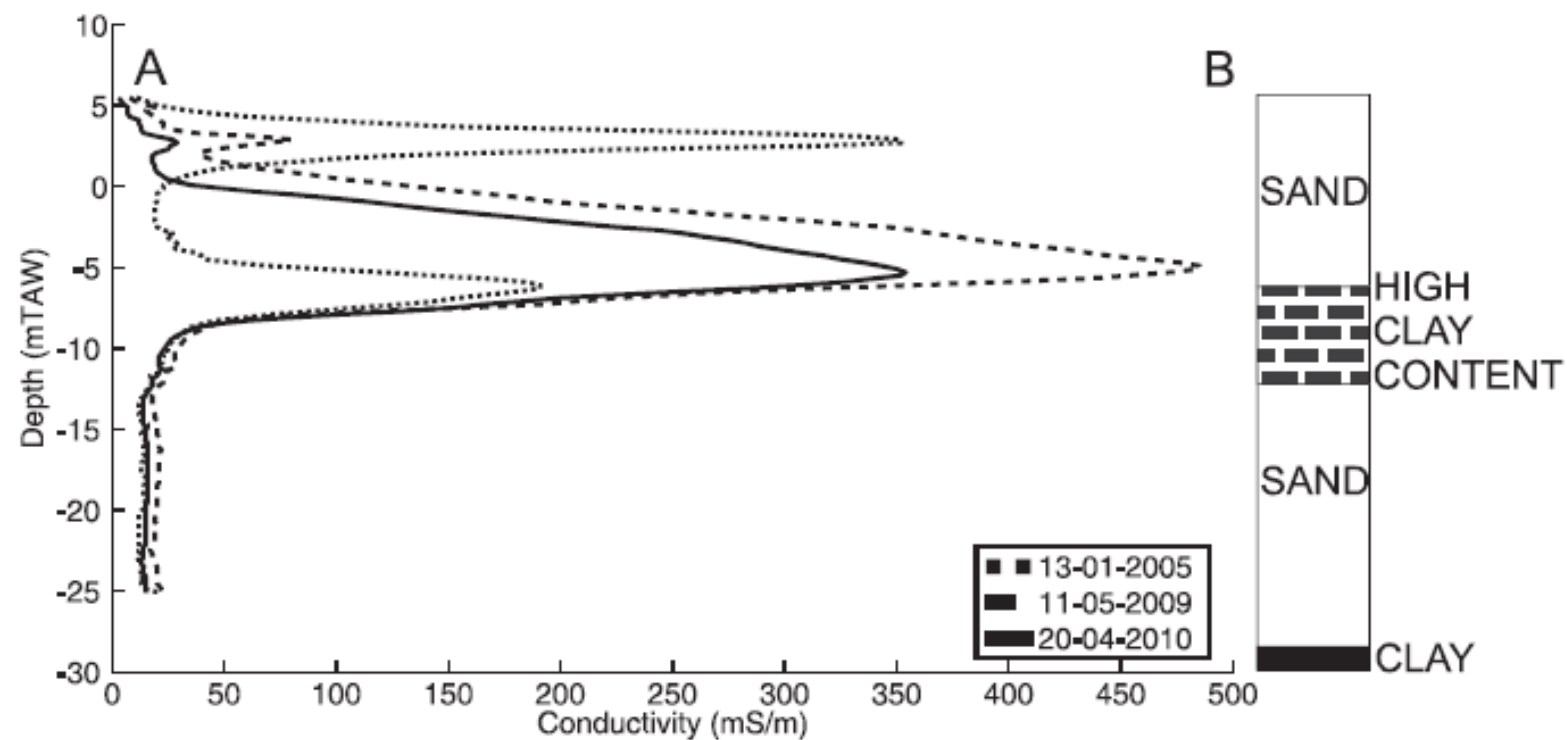
CHANGING THE SMOOTHING OPERATOR

$$\phi(m) = ||W_d(G(m) - d)||^2 + \lambda(||C_m^{-0.5}(m - m_{ref})||^2)$$

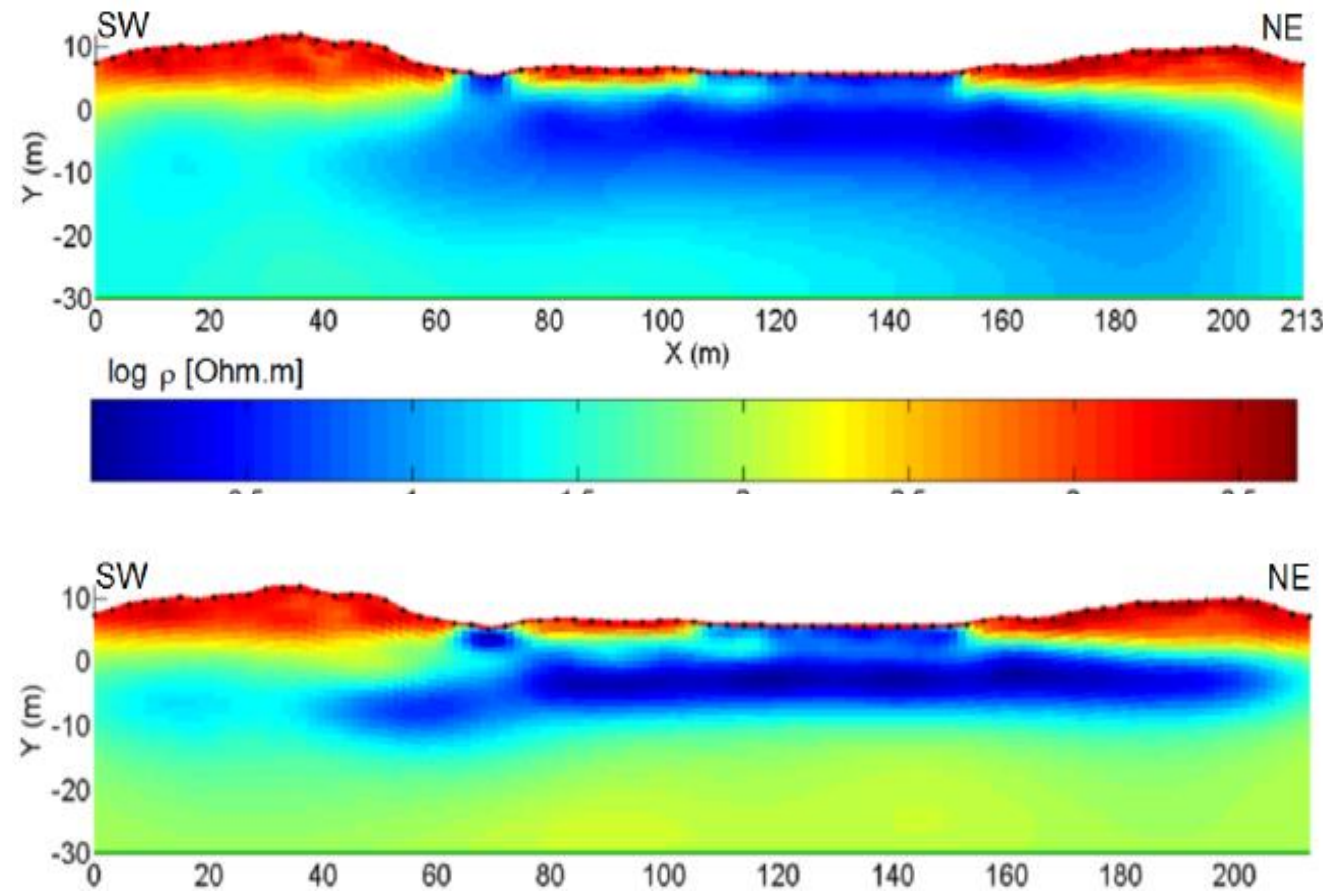
↓
Data misfit

↓
Model constraint
How do we get this matrix?

Using a covariance matrix, for example deduced from borehole logging data



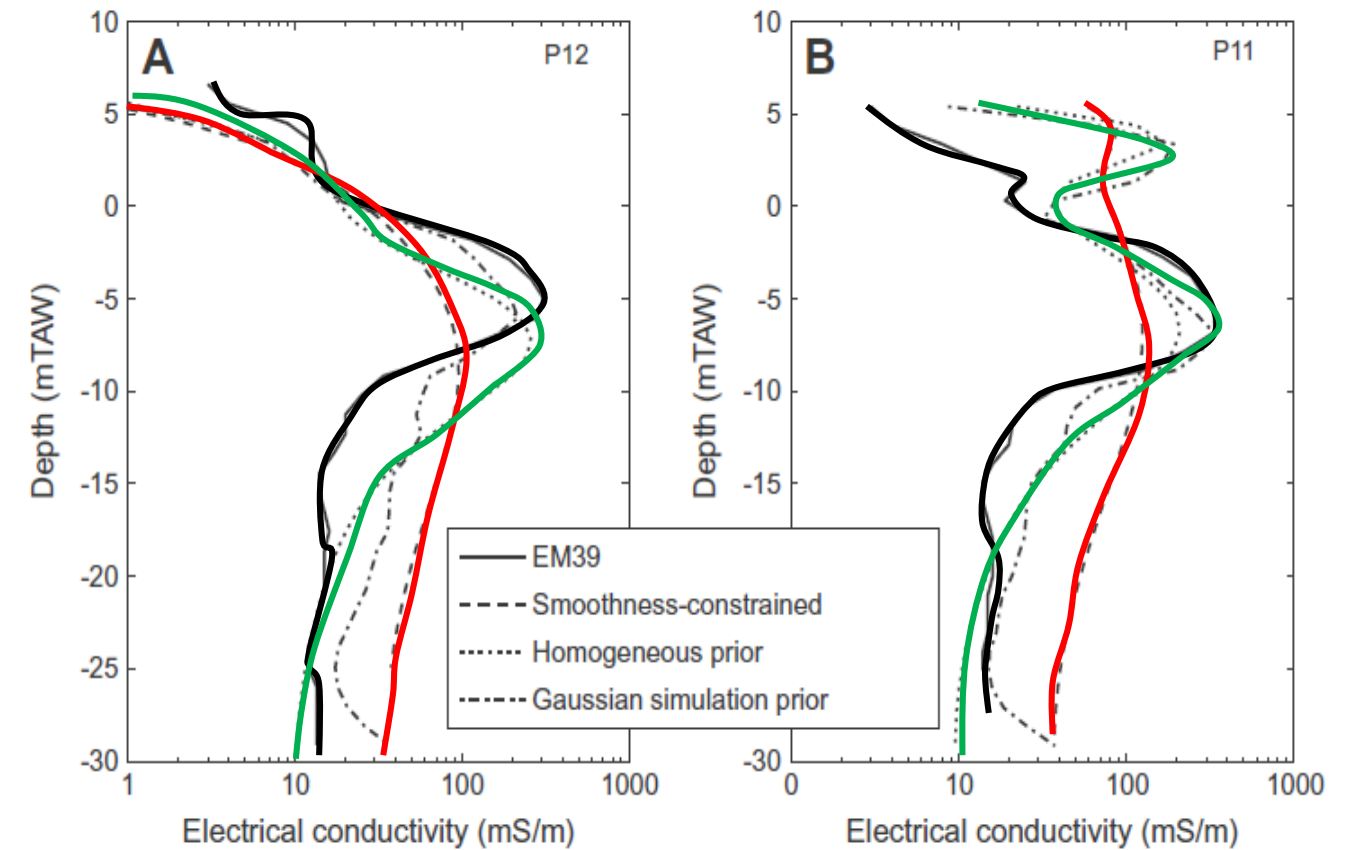
CHANGING THE SMOOTHING OPERATOR



(Hermans et al. JoH, 2012)

(Caterina, Hermans & Nguyen, 2014, NSG)

Hermans et al. (JoH, 2012)



- True conductivity
- SC Inverted conductivity
- Improved Inverted conductivity

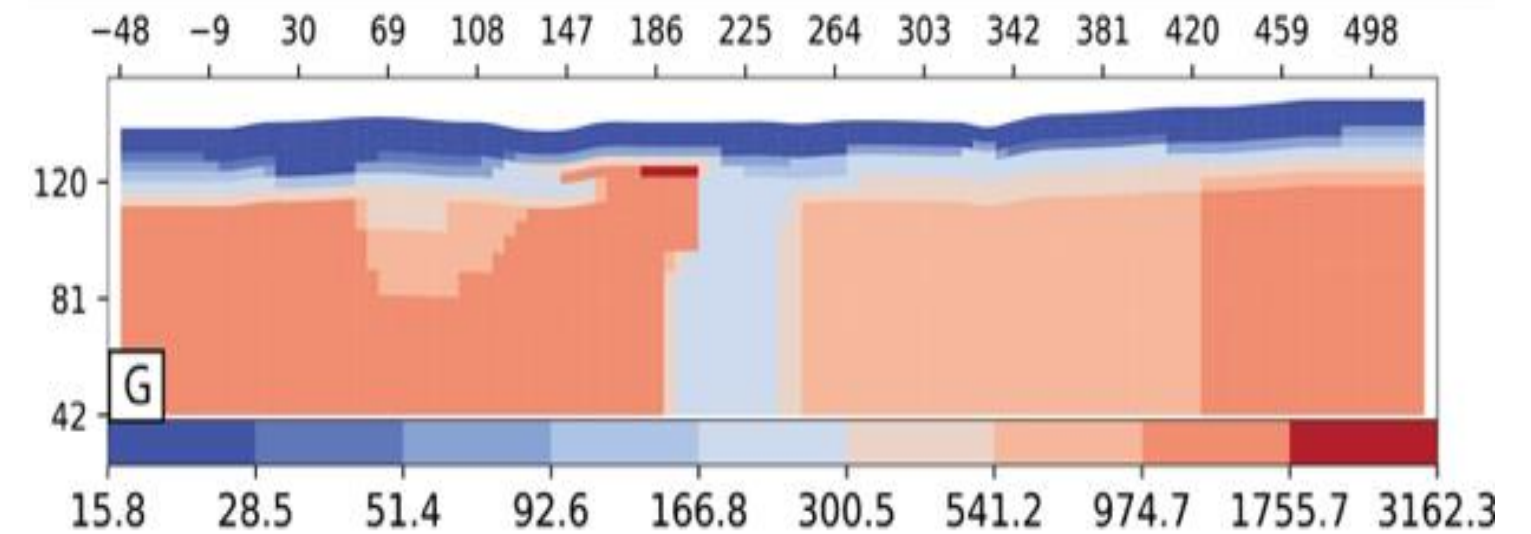
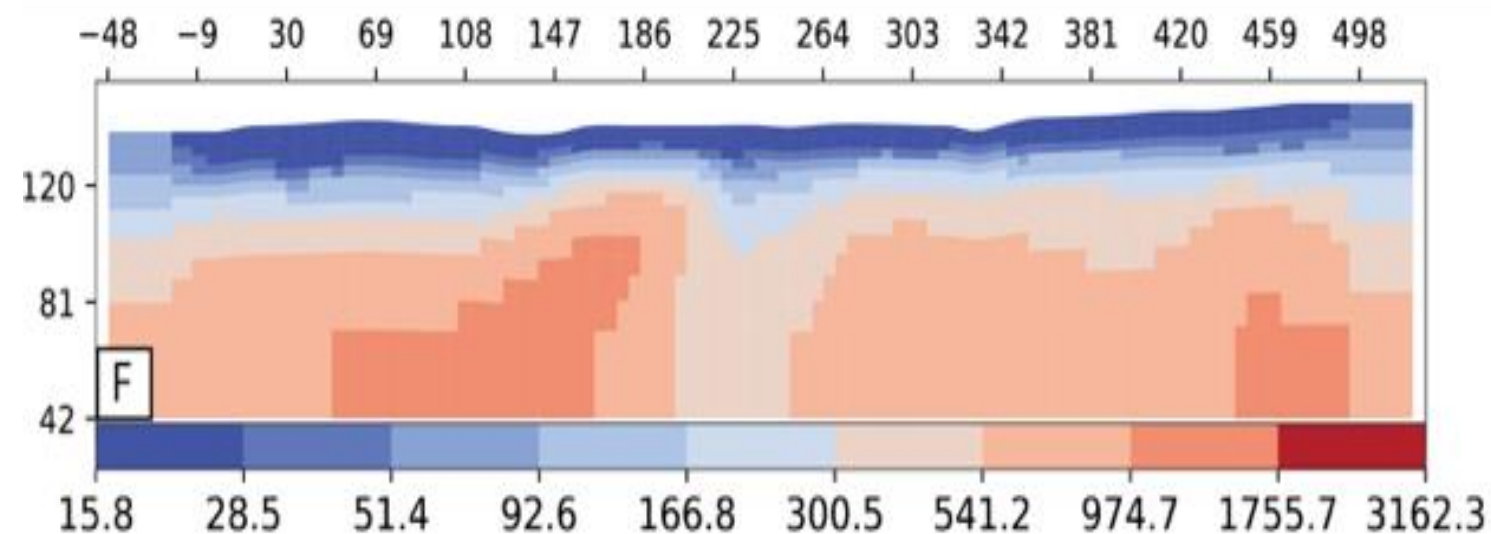
CHANGING THE SMOOTHING OPERATOR

$$W_m = \int_V \frac{\nabla m \nabla m}{\nabla m \nabla m + \beta^2} dv \text{ favors sharp contrasts if } \beta \rightarrow 0$$

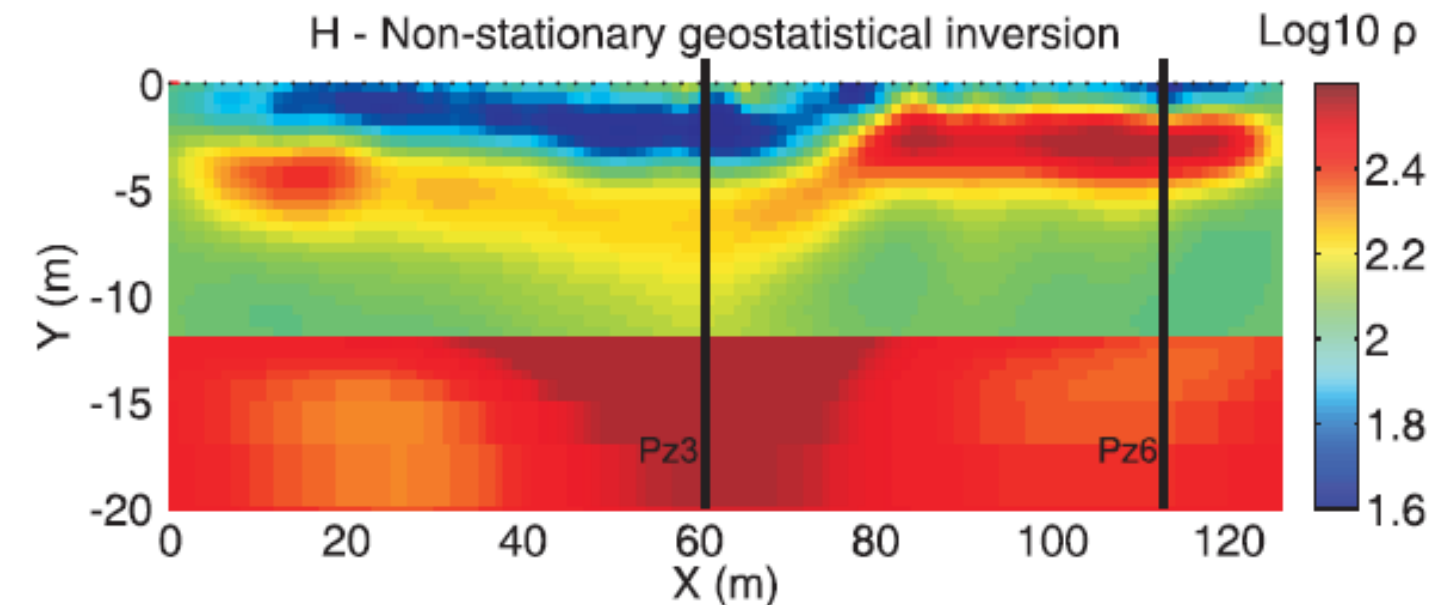
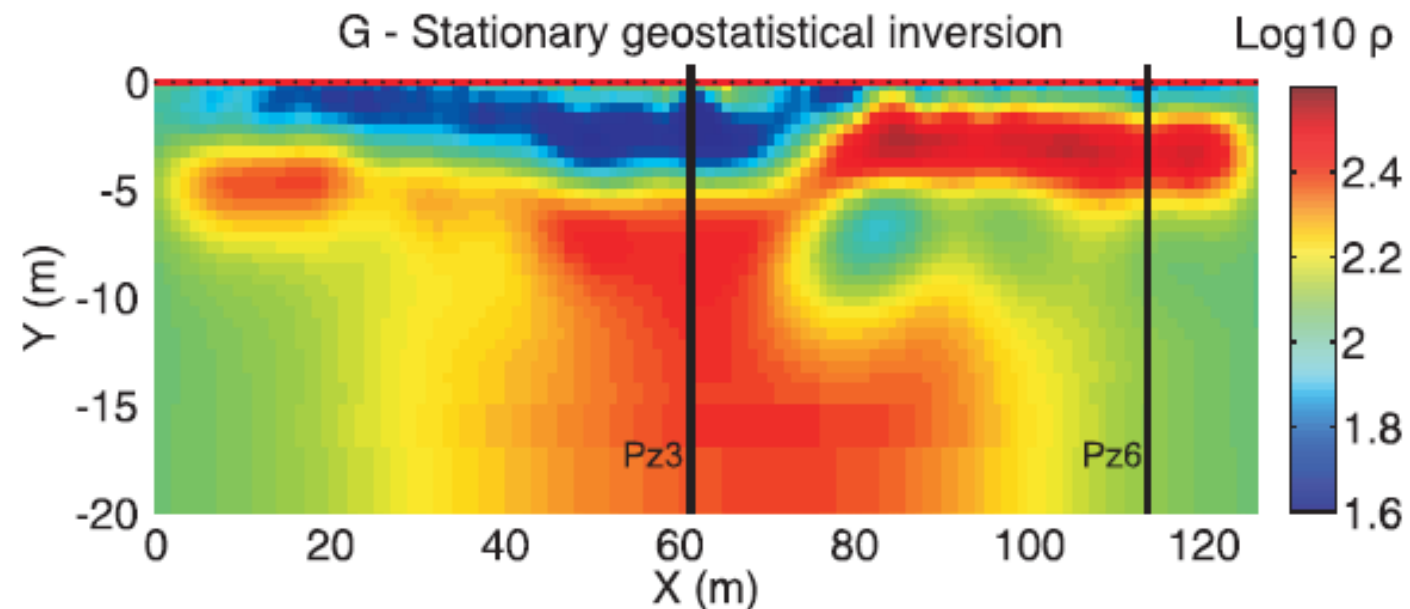
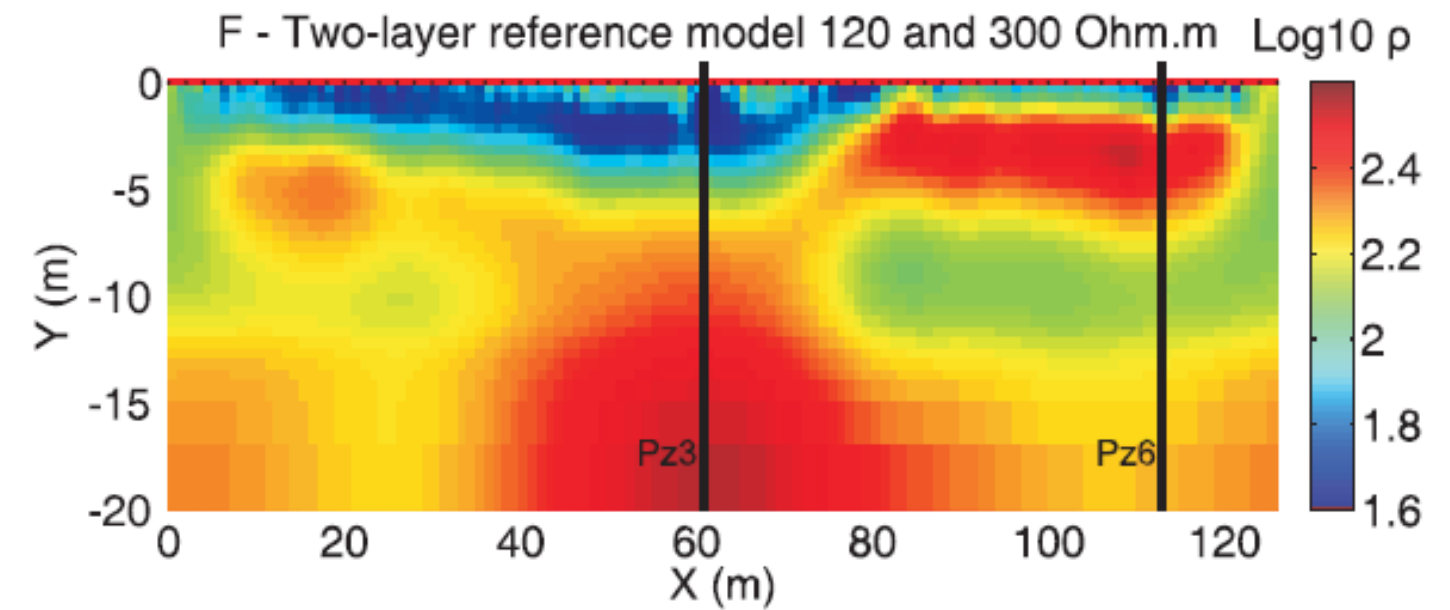
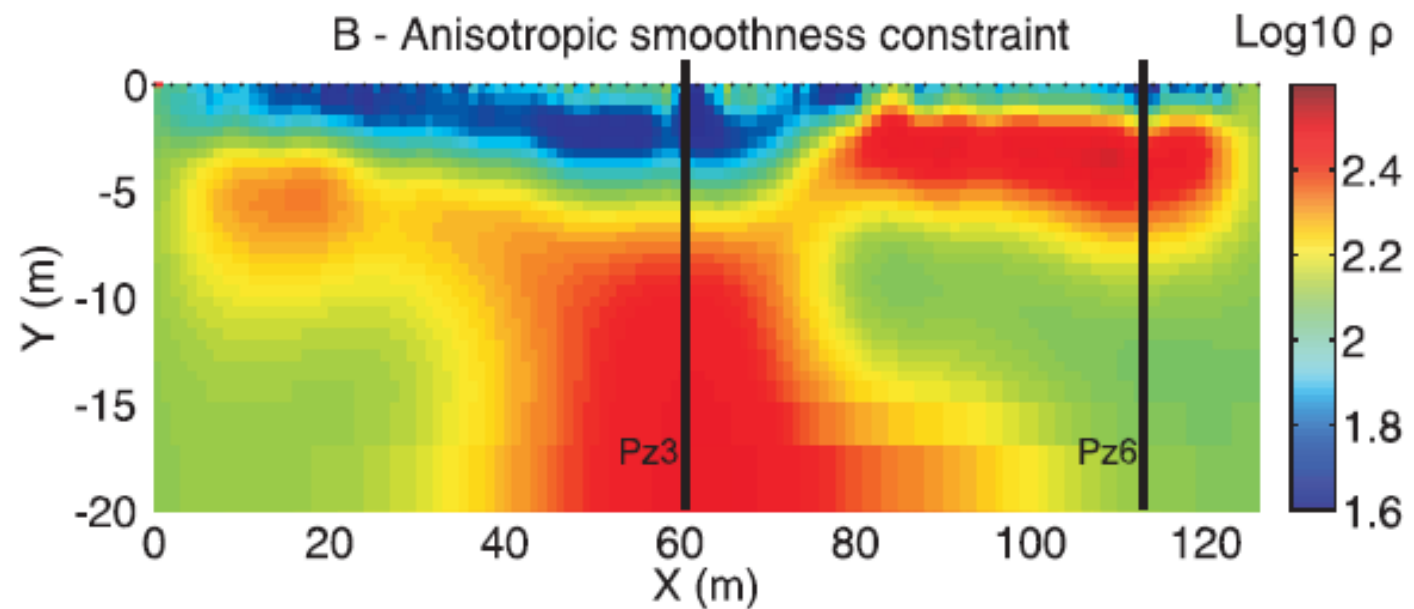
Minimum Gradient support

To retrieve sharp boundaries instead of smoothing them out

Geologically more realistic ? It depends on the local heterogeneity !

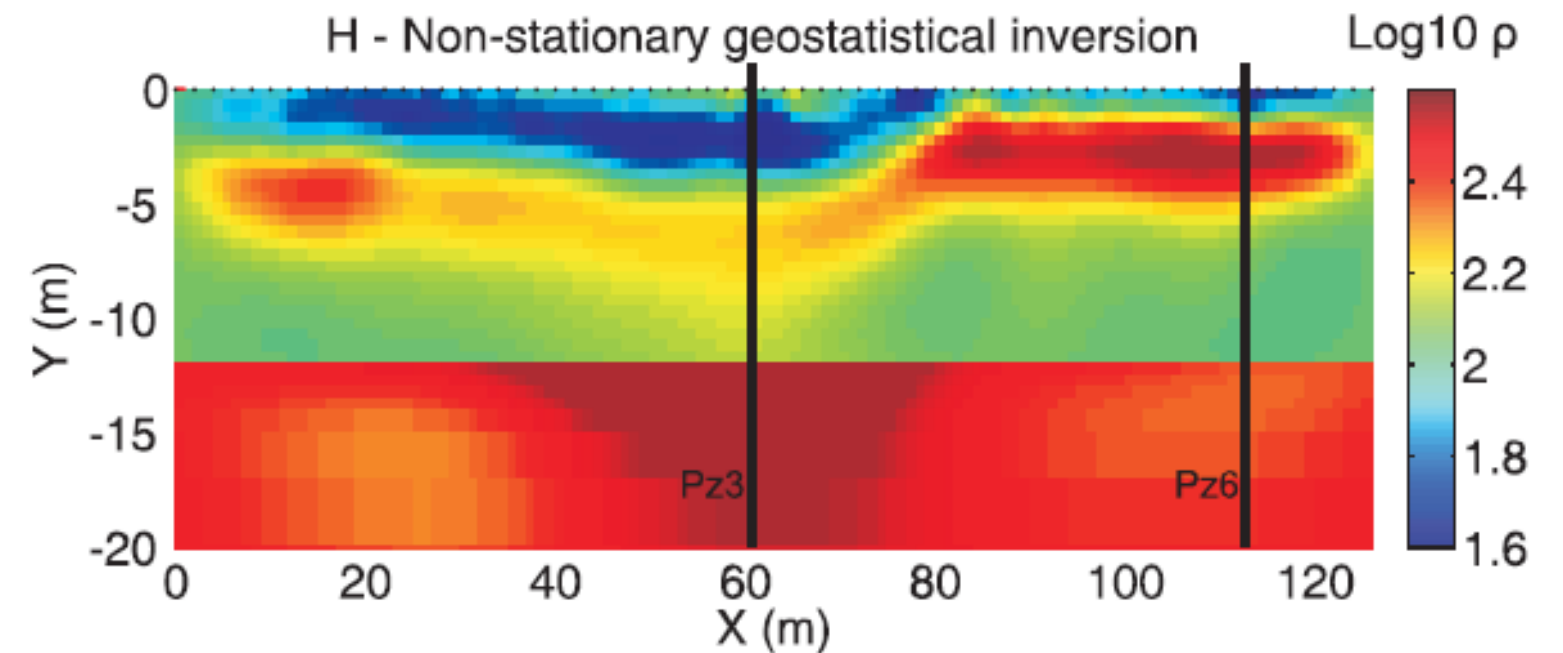
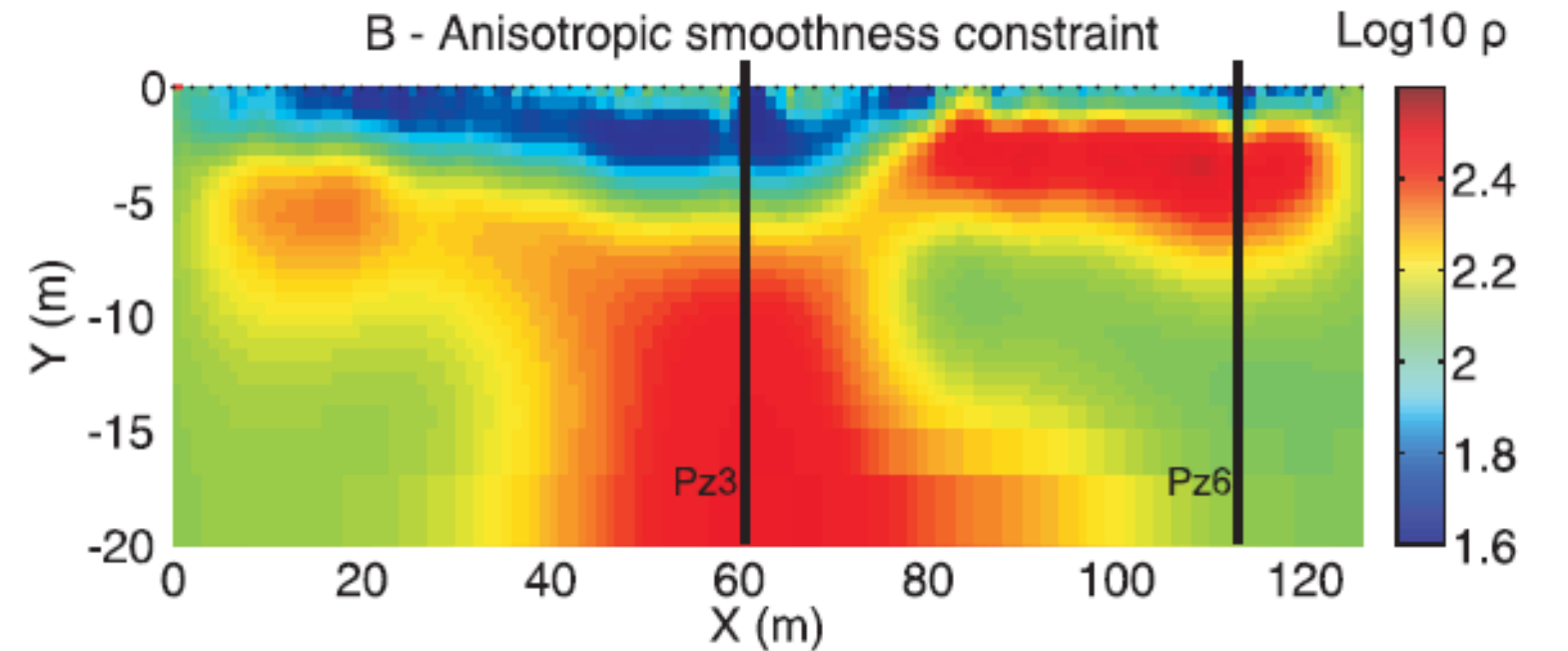
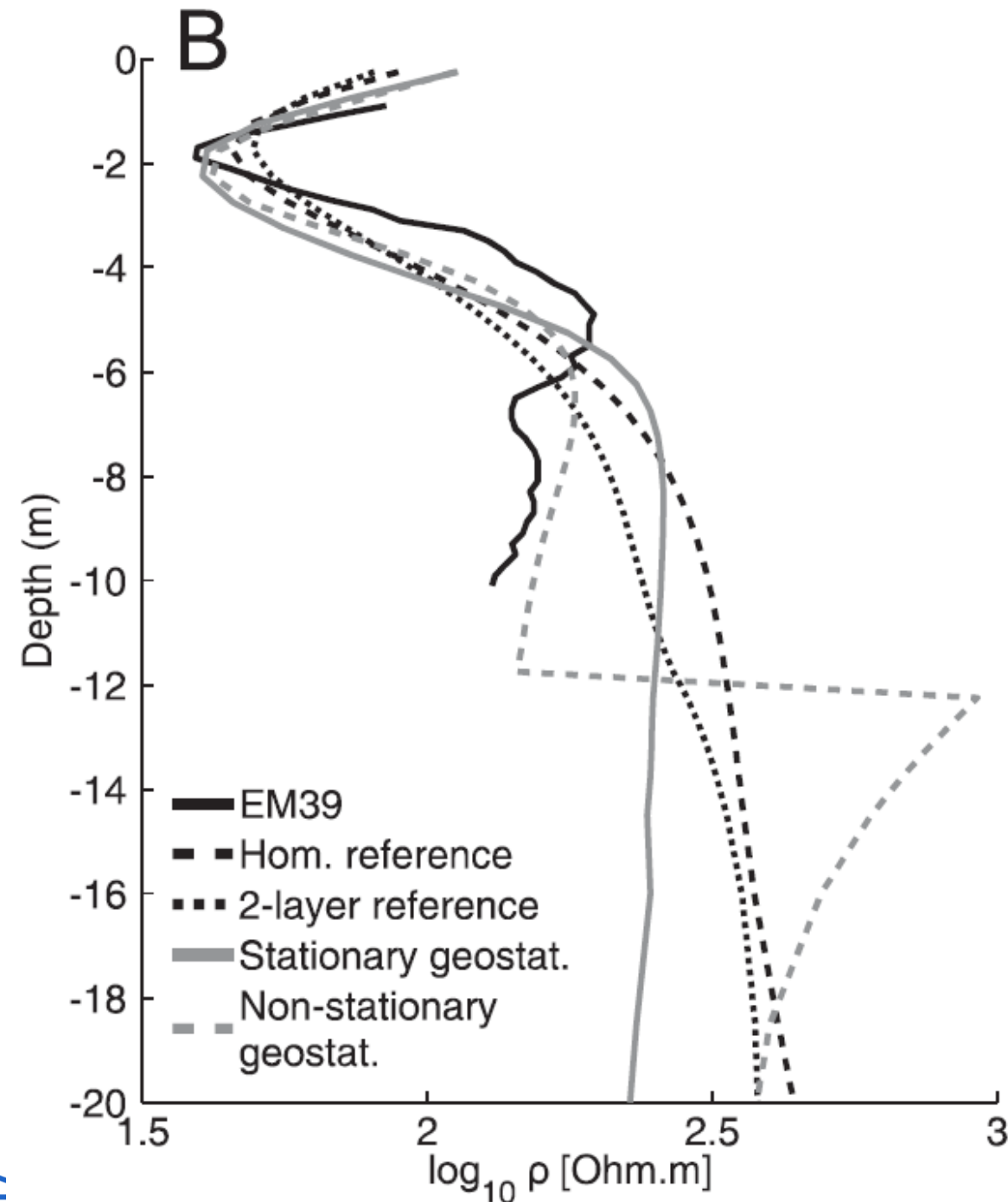


COMBINING APPROACHES



All the models above are fitting the same data set $\rightarrow$ non-uniqueness of the solution

COMBINING APPROACHES



Including appropriate prior information can strongly increase the accuracy of inversion

ADVANCED APPROACH: MACHINE LEARNING

The limited resolution of geophysical data limits the imaging capability

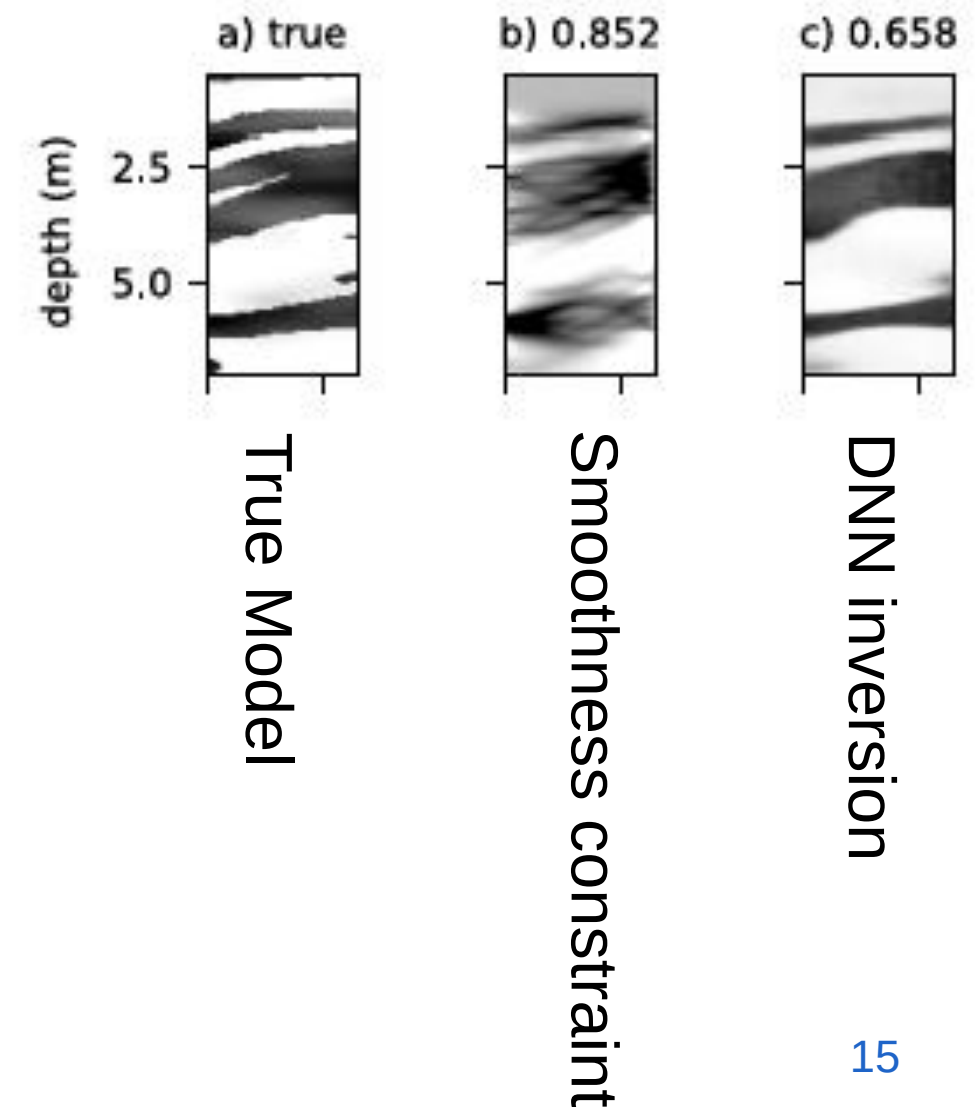
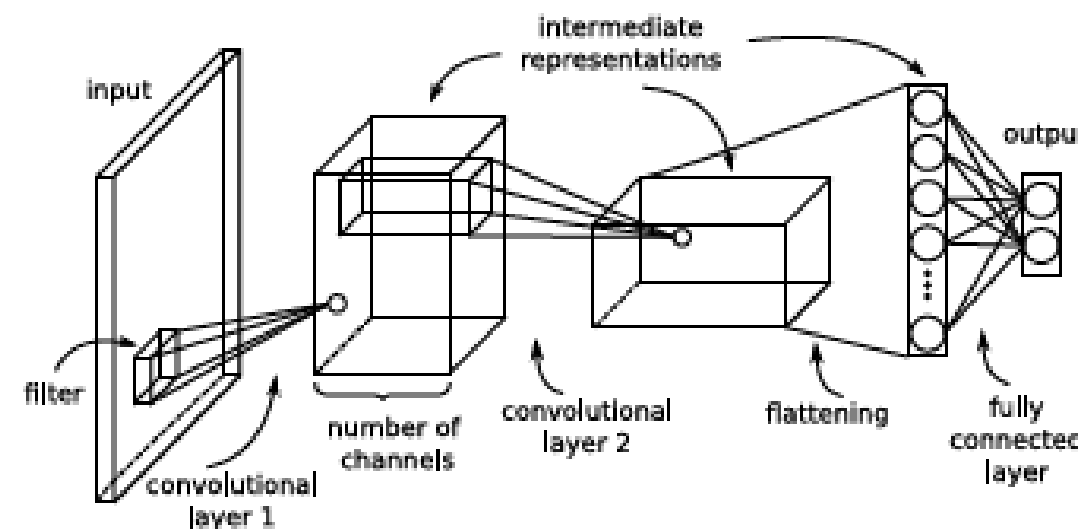
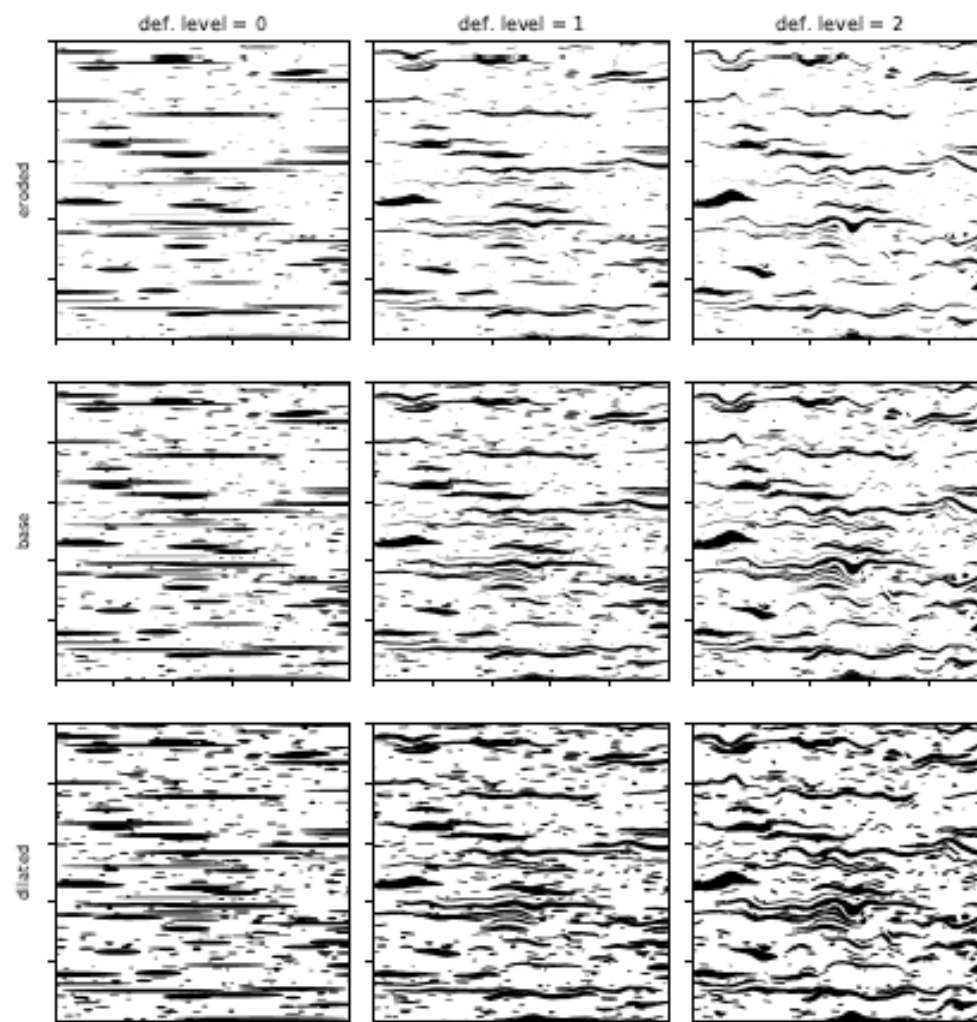
Machine learning approaches offer new ways to deal with geophysical inversion

Using Deep Neural Network

1) Training images depicting the expected heterogeneity of the site

2) Encoding the complex patterns in a low dimensional latent space using Deep neural networks

3) Inverting in the latent space



Lopez Alvis et al., 2021, Comp. & Geos.
Lopez Alvis et al., JGRSE, submitted

ADVANCED APPROACH: MACHINE LEARNING

The limited resolution of geophysical data limits the imaging capability

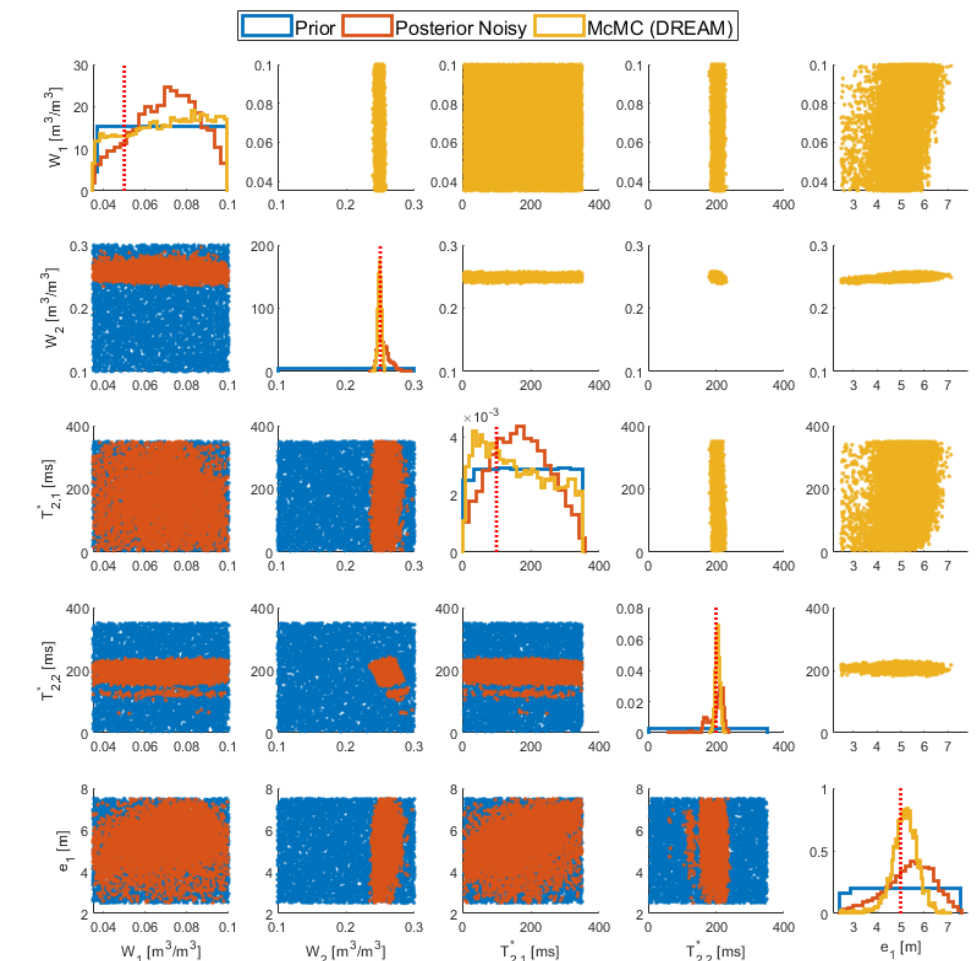
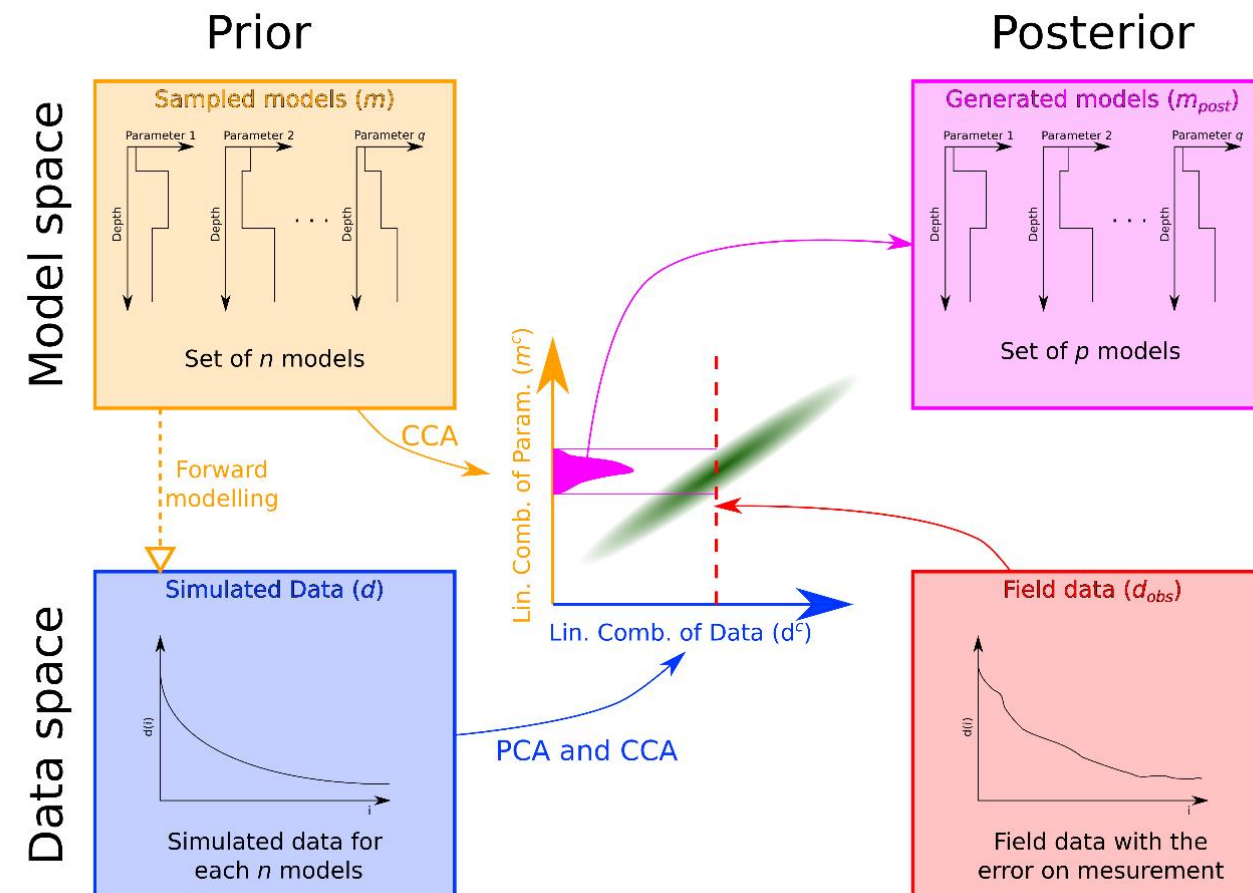
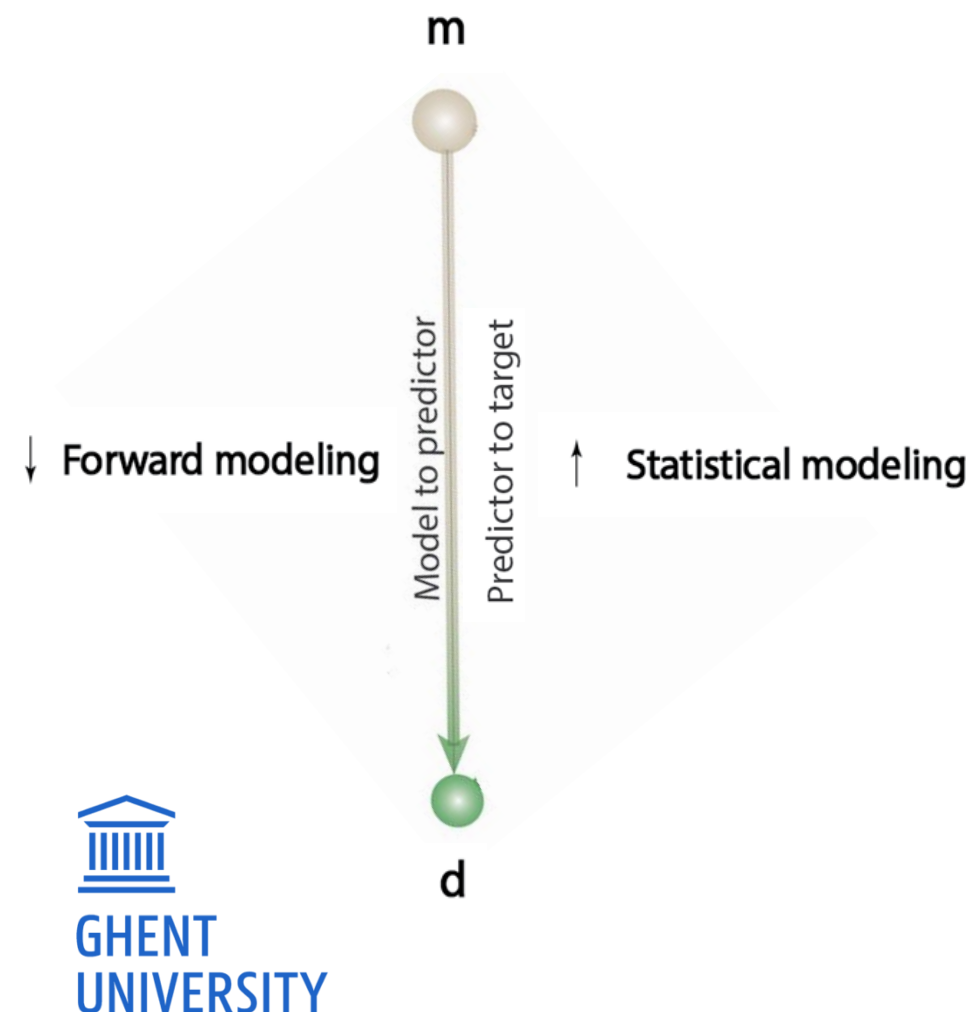
Machine learning approaches offer new ways to deal with geophysical inversion

Bayesian Evidential Learning (Michel et al., Comp. & Geos., 2020)

Inversion is replaced by statistical learning

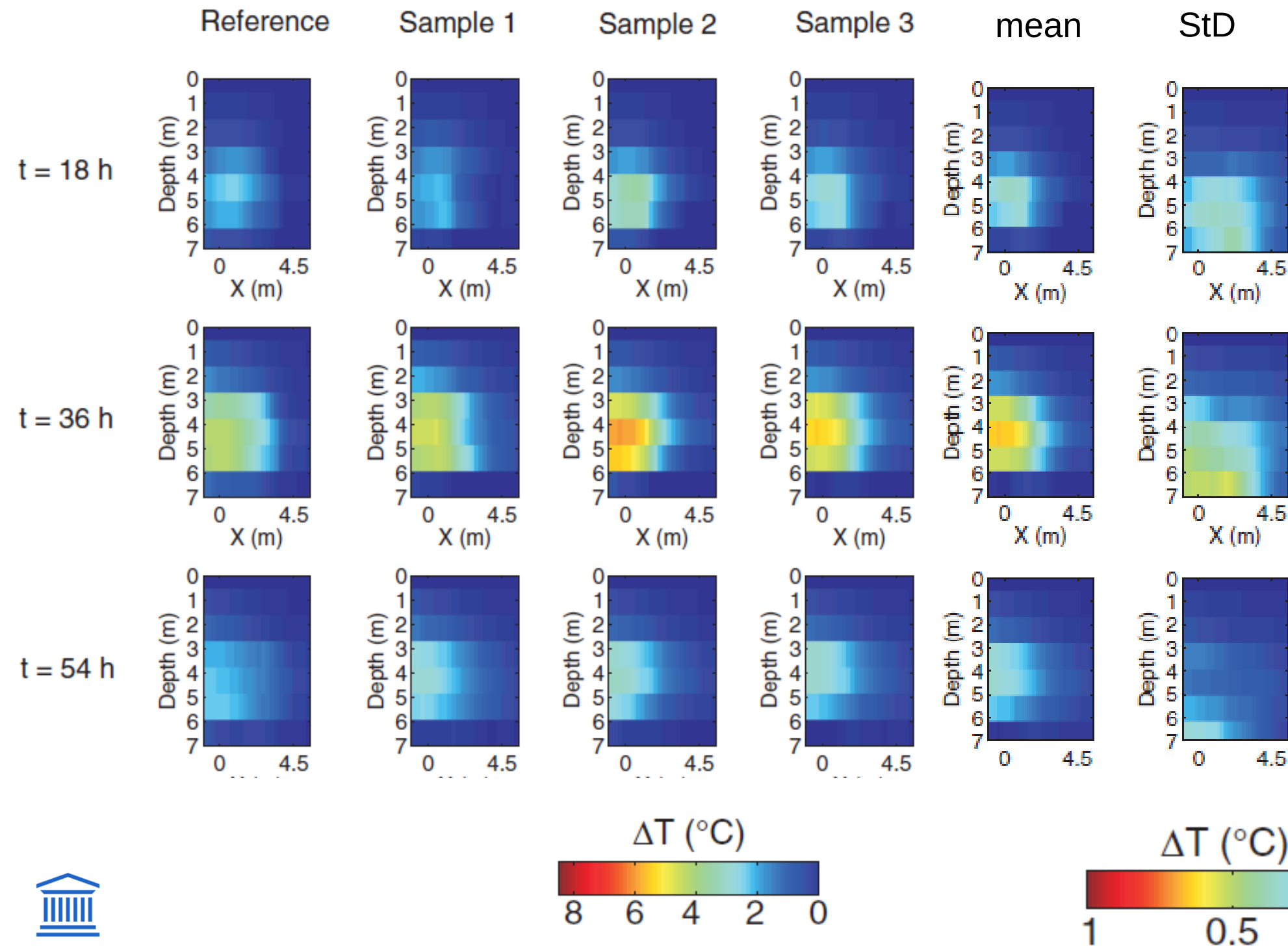
1) Synthetic models are used to learn the statistical relationship (based on the definition of a prior model space)

2) The posterior distribution is deduced from the field observed data

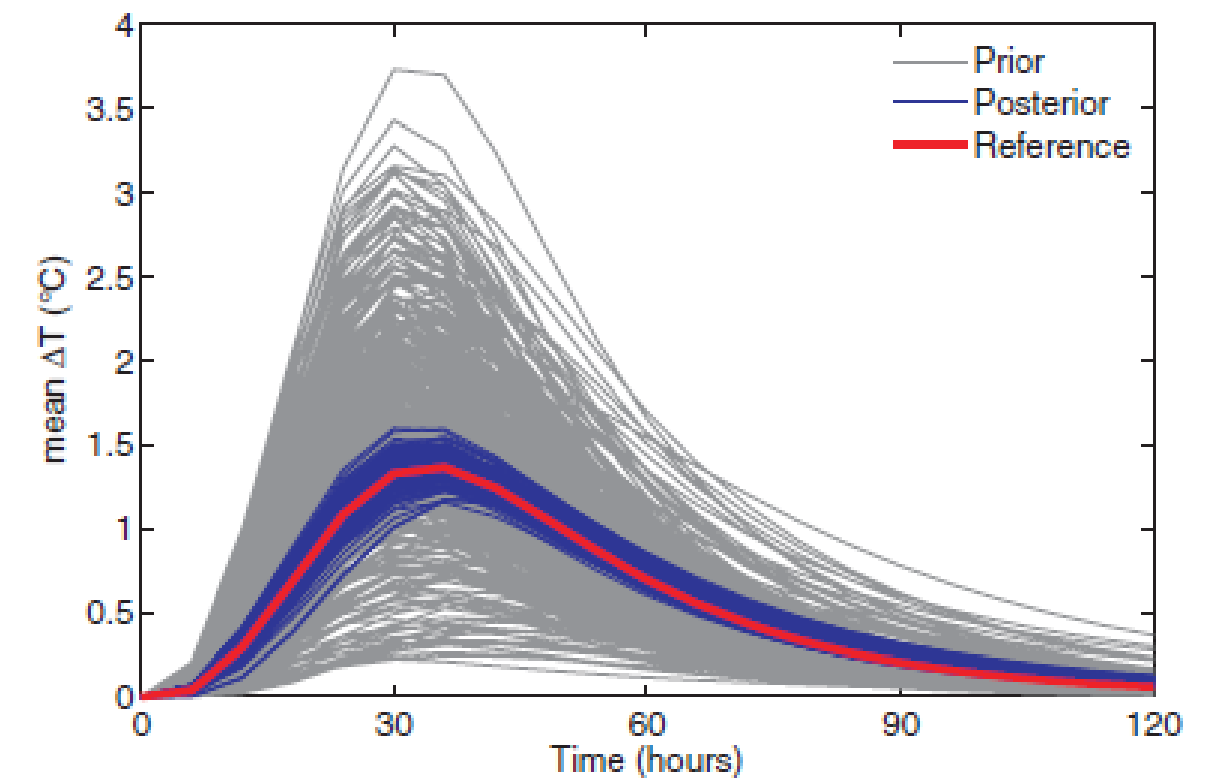


BEL EXAMPLE

Synthetic example: heat tracing experiment



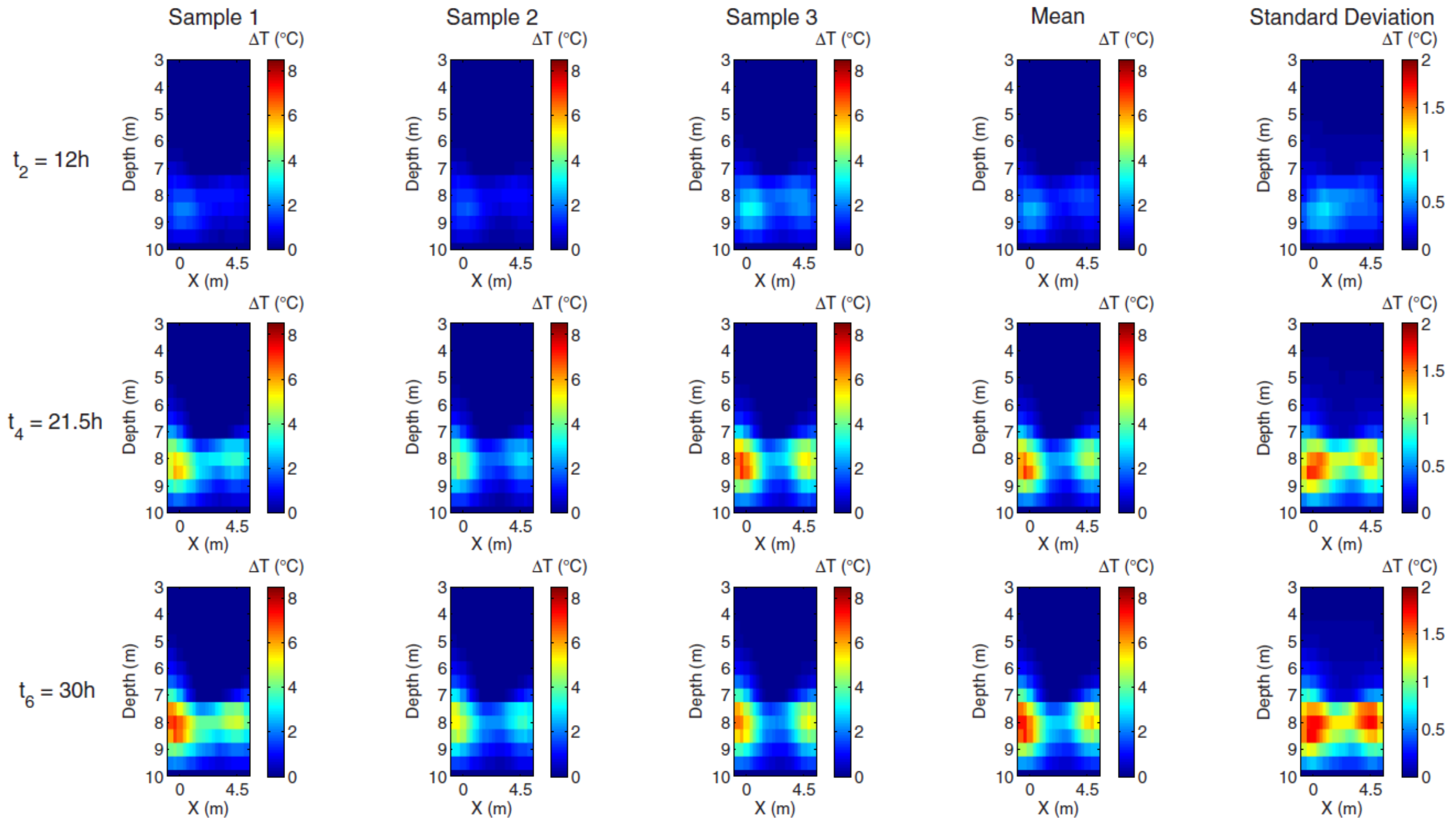
(Hermans et al., 2016, WRR)



BEL EXAMPLE

Field example: heat tracing experiment

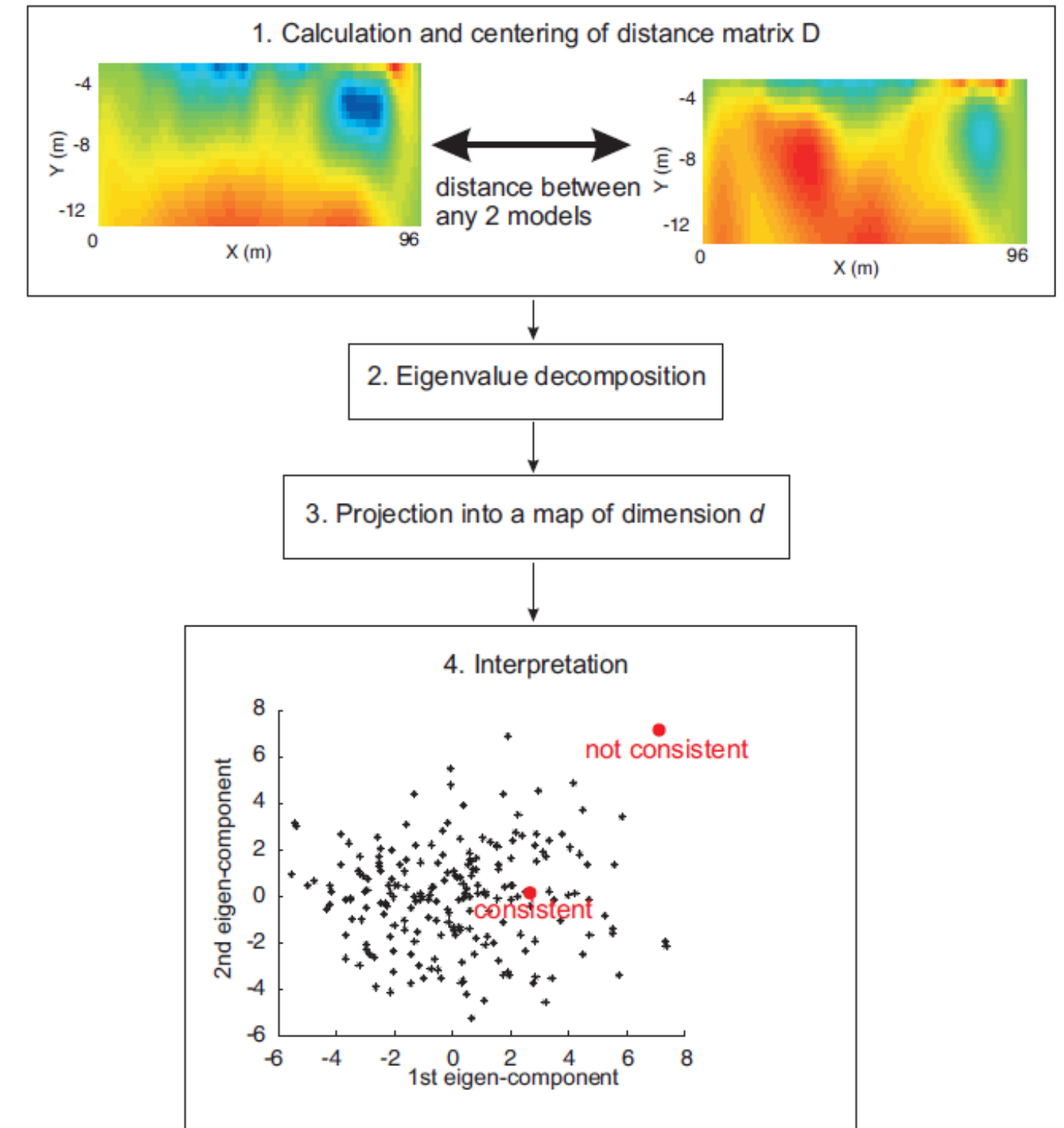
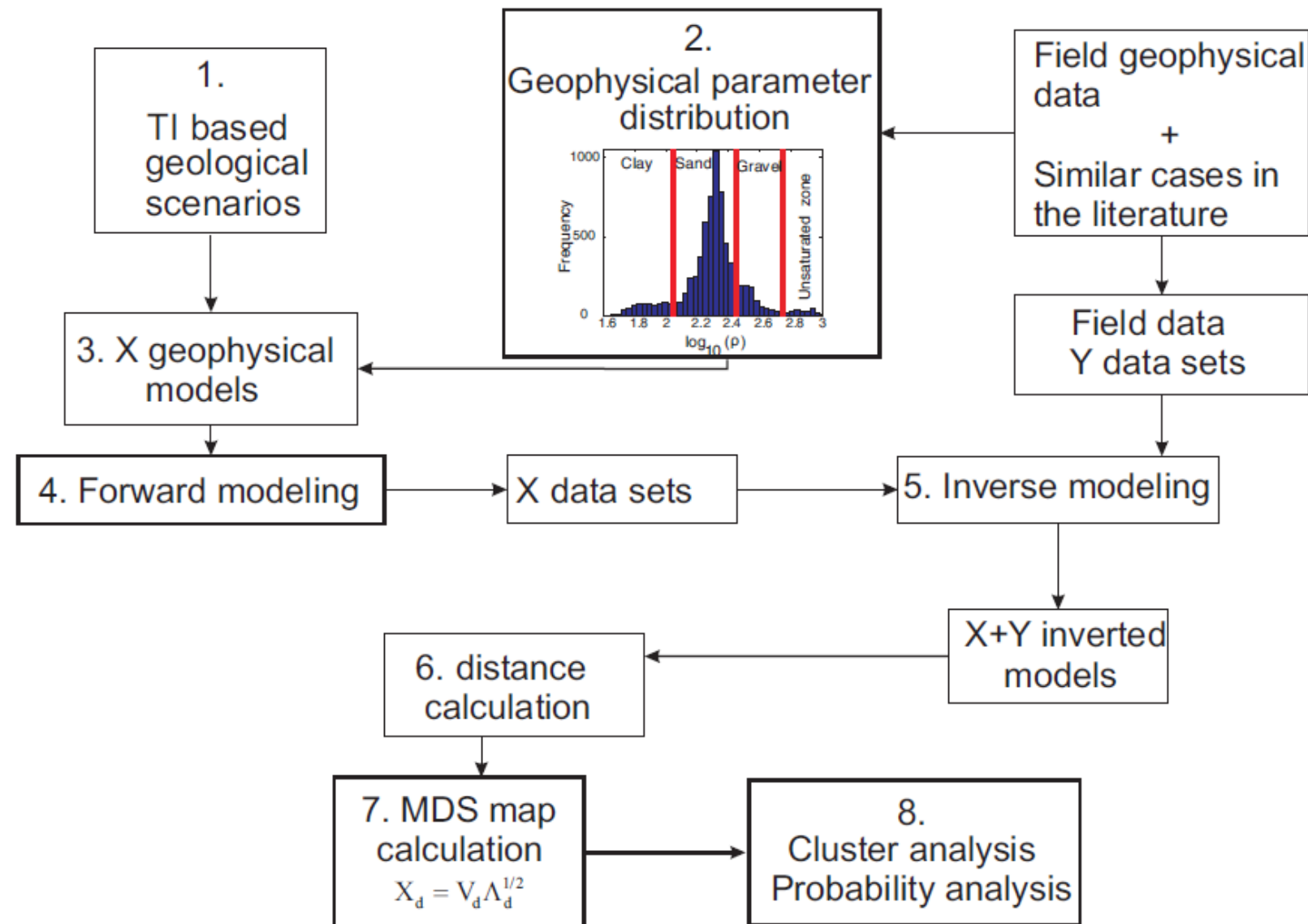
(Hermans et al., 2018, WRR)



INTEGRATING GEOPHYSICAL DATA IN HYDROLOGICAL MODELS

SELECTING GEOLOGICAL SCENARIOS

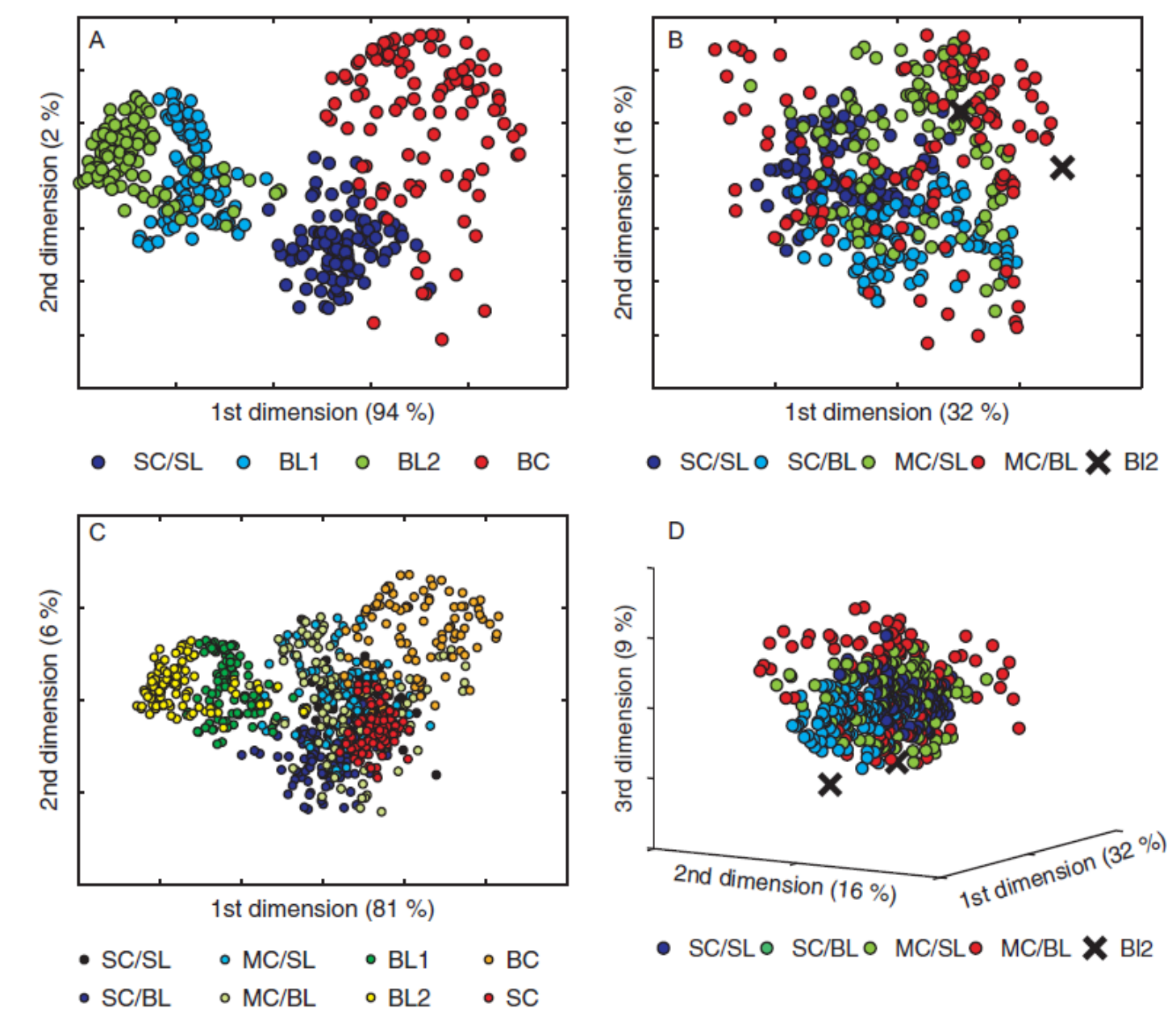
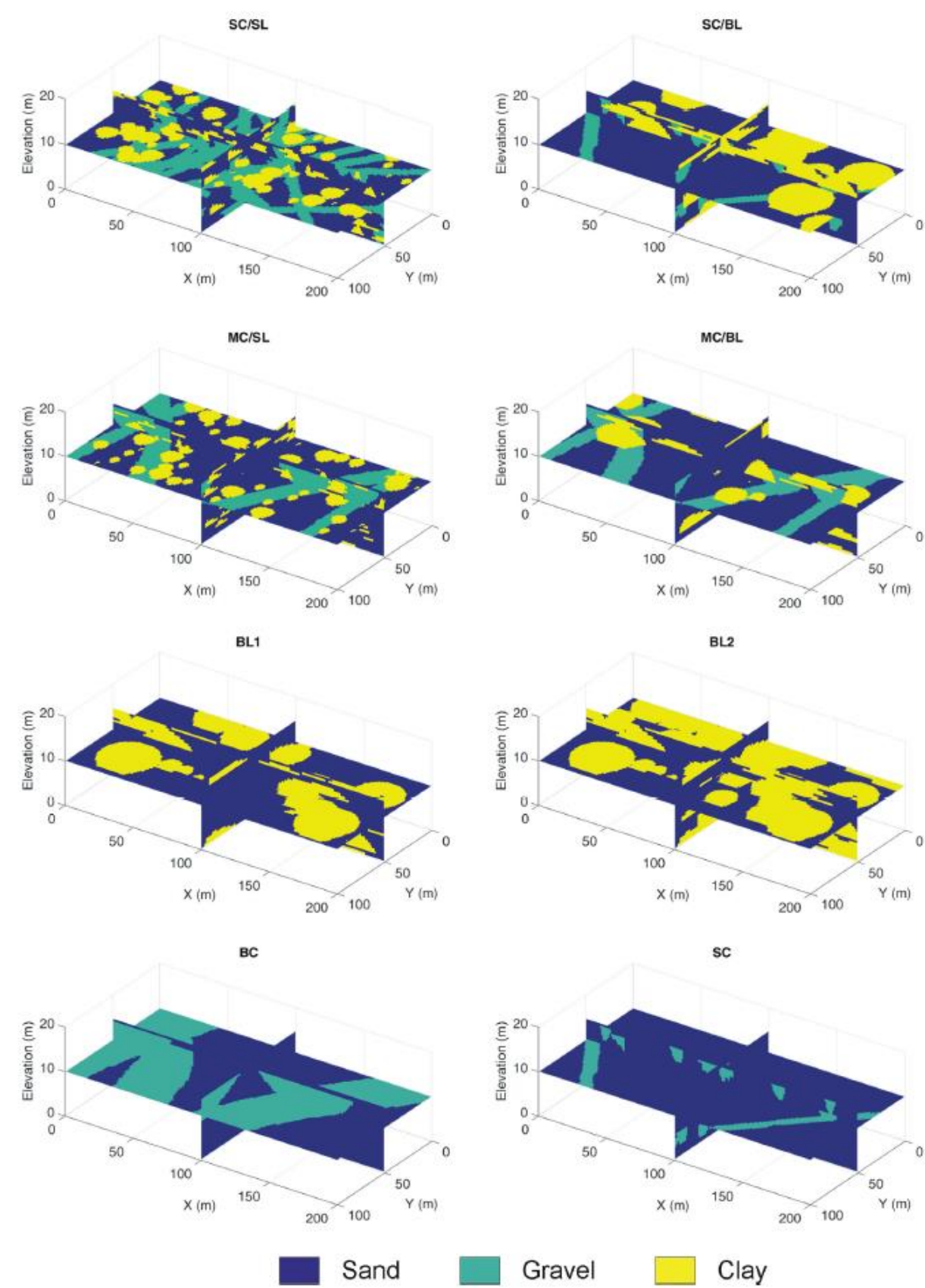
Flowchart to estimate scenario probability using geophysical data through building prior scenarios and generating synthetic data from samples



MDS = Multidimensional scaling, based on the distance between model/data

SELECTING GEOLOGICAL SCENARIOS

8 possible scenarios → Acquisition of geophysical data → Identification of probability of scenarios using MDS

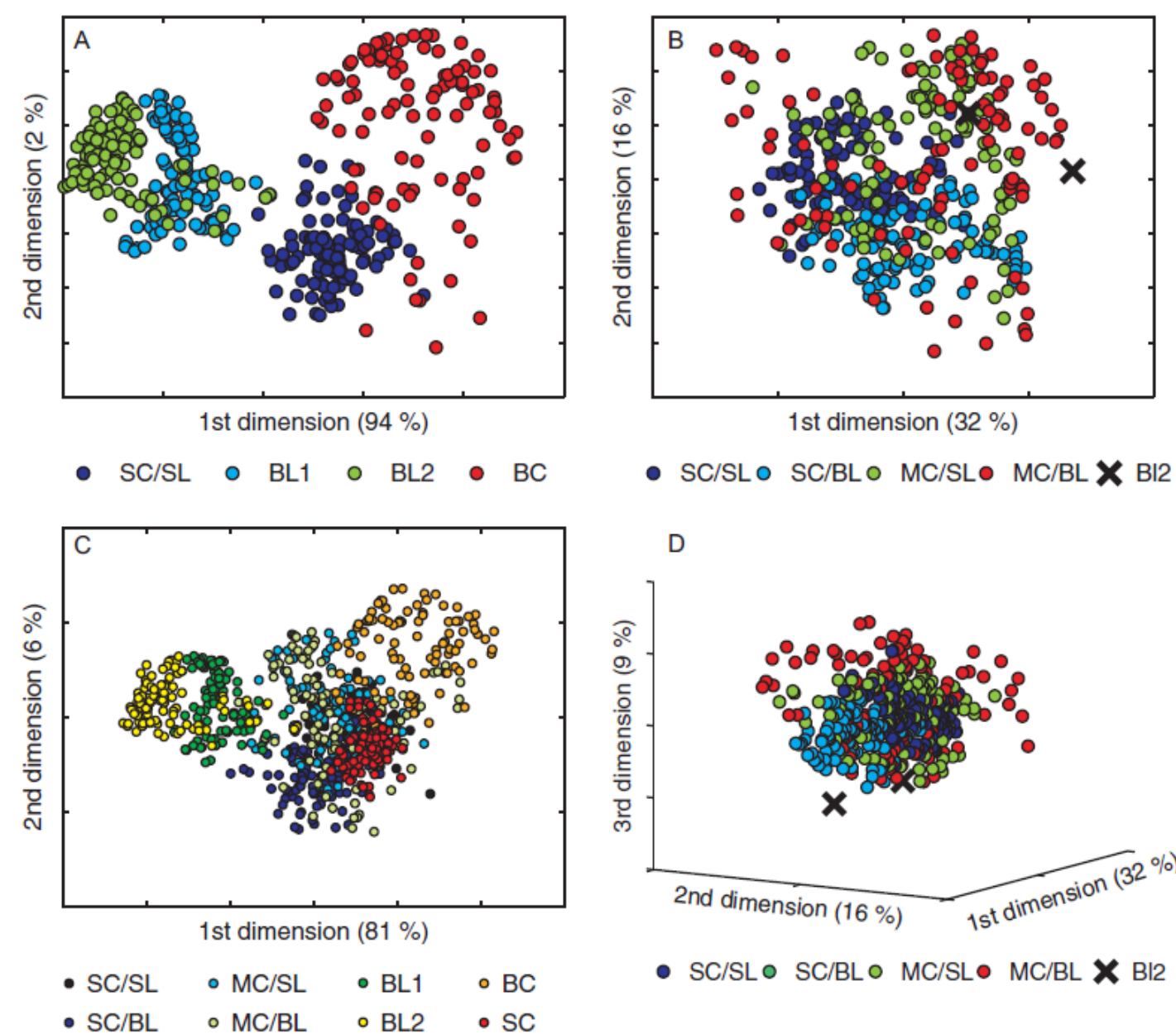


(Hermans et al., WRR, 2015)

SELECTING GEOLOGICAL SCENARIOS

8 possible scenarios → Acquisition of geophysical data → Identification of probability of scenarios using MDS

MDS maps allows to compute probabilities based on Kernal Density Estimation



Scenario	Confusion Matrix (%)				Mean Updated Probability (%)			
	SC/SL	BL1	BL2	BC	$P(SC/SL ref)$	$P(BL1 ref)$	$P(BL2 ref)$	$P(BC ref)$
SC/SL	100	0	0	0	88.3	1.8	0.8	9.1
BL1	3	96	1	0	3	75.1	21.7	0.2
BL2	3	15	82	0	1.7	21.6	76.6	0.1
BC	14	0	0	86	14.5	0.1	0	85.4

Scenario	Confusion Matrix (%)				Mean Updated Probability (%)			
	SC/SL	SC/BL	MC/SL	MC/BL	$P(SC/SL ref)$	$P(SC/BL ref)$	$P(MC/SL ref)$	$P(MC/BL ref)$
SC/SL	93	4	2	1	62.9	18.2	15.4	3.5
SC/BL	11	88	1	0	18.3	68.2	10.6	2.9
MC/SL	29	10	51	10	24.2	12	42.7	21.1
MC/BL	8	6	19	67	9.9	6.1	30	54

Scenario	SC/SL	SC/BL	MC/SL	MC/BL	BL1	BL2	BC	SC
Classification								
With SC/SL	70	2	4	1	0	0	0	23
Without SC/SL		4	32	1	0	0	0	63
Mean Updated Probability								
With SC/SL	46.2	7.7	14.7	7	0.8	0.4	2.2	21
Without SC/SL		17	26.7	8.3	2	1.4	4	40.6

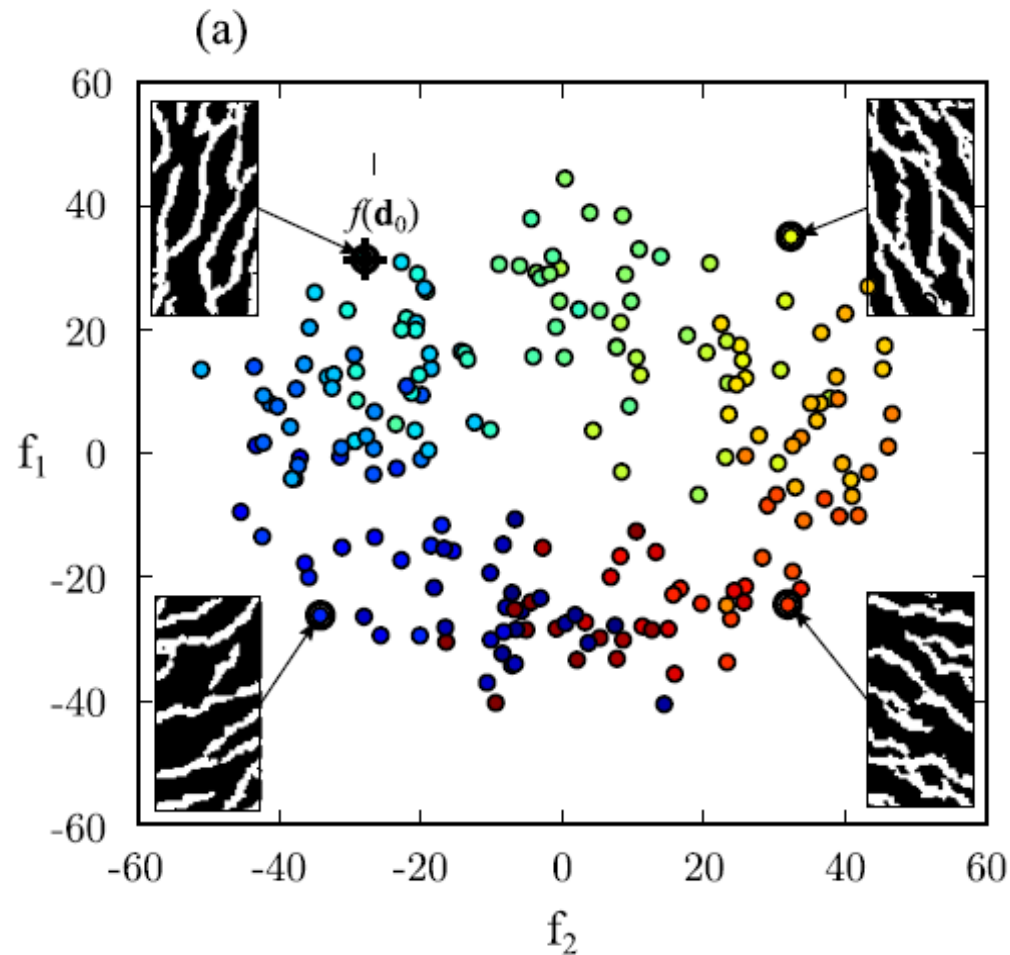
Confusion matrix = how many times a model is correctly classified
Updated probability = how certain are we about the classification ?

SELECTING GEOLOGICAL SCENARIOS

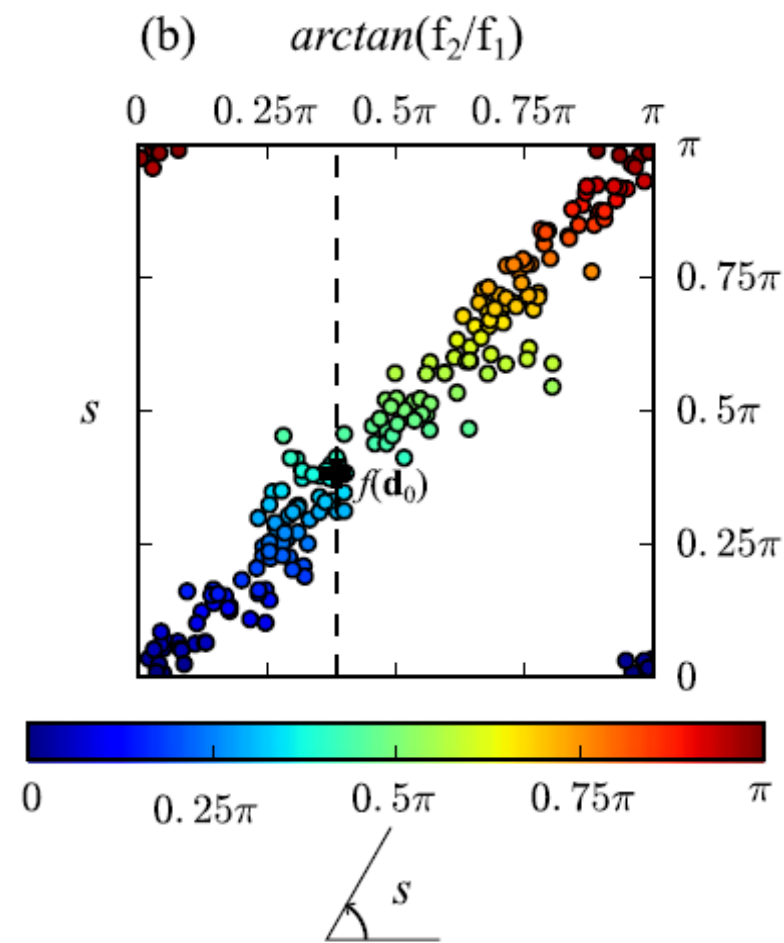
Also possible to retrieve continuous parameters

Estimating the orientation of channels

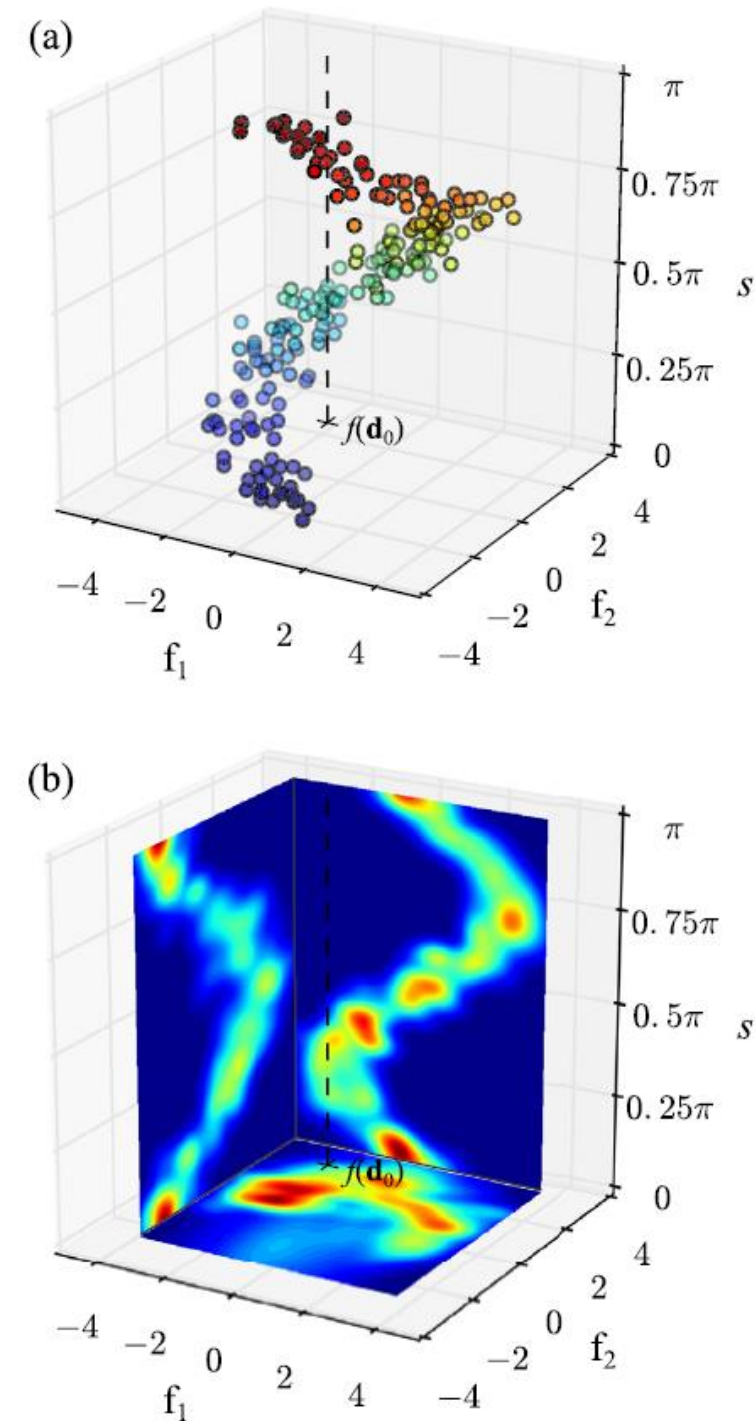
MDS map



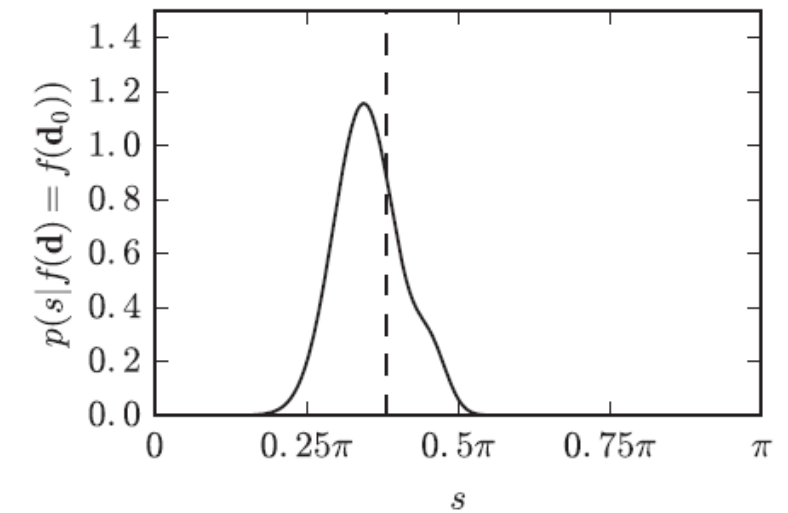
Correlation



KDE

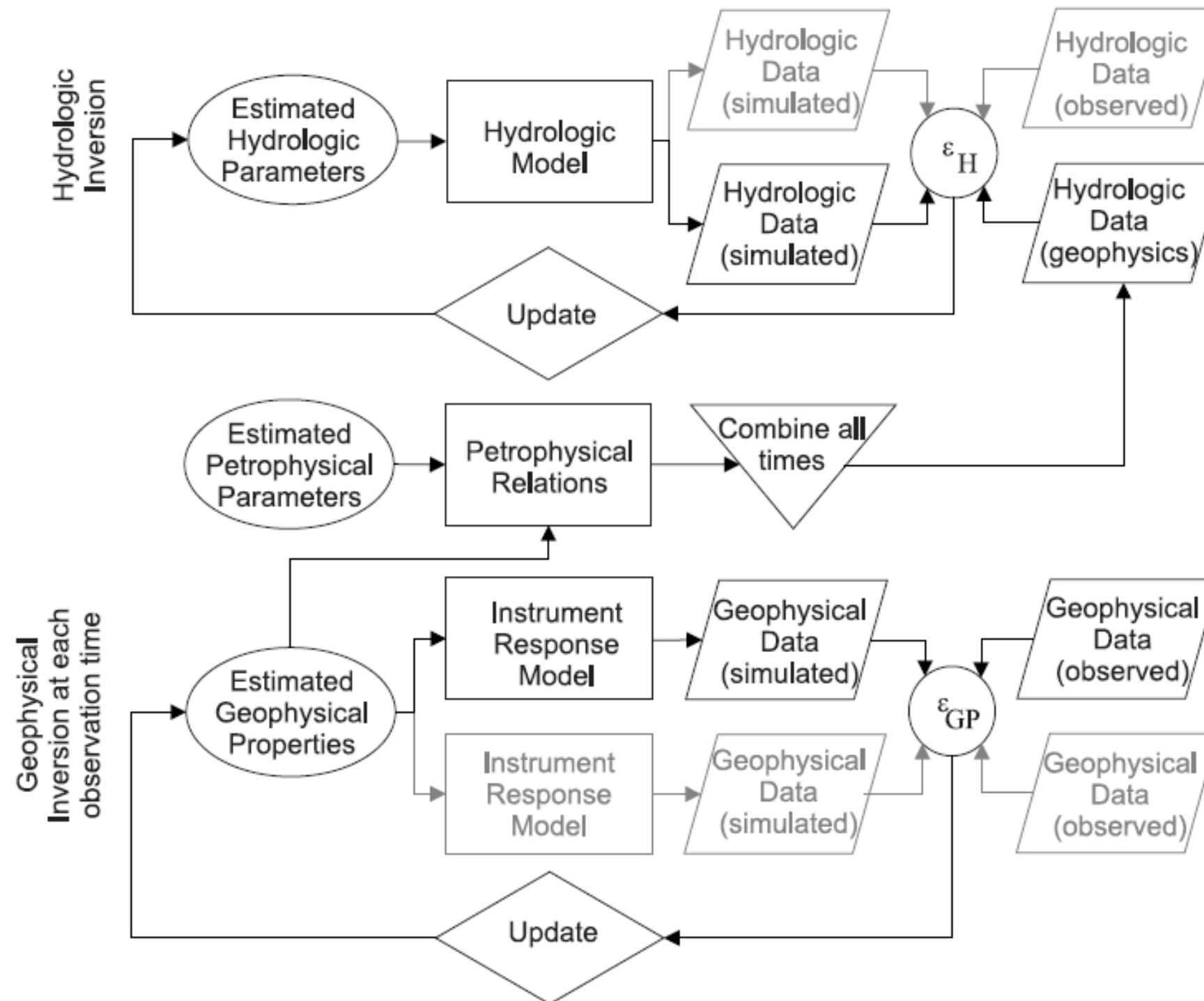


Posterior probability



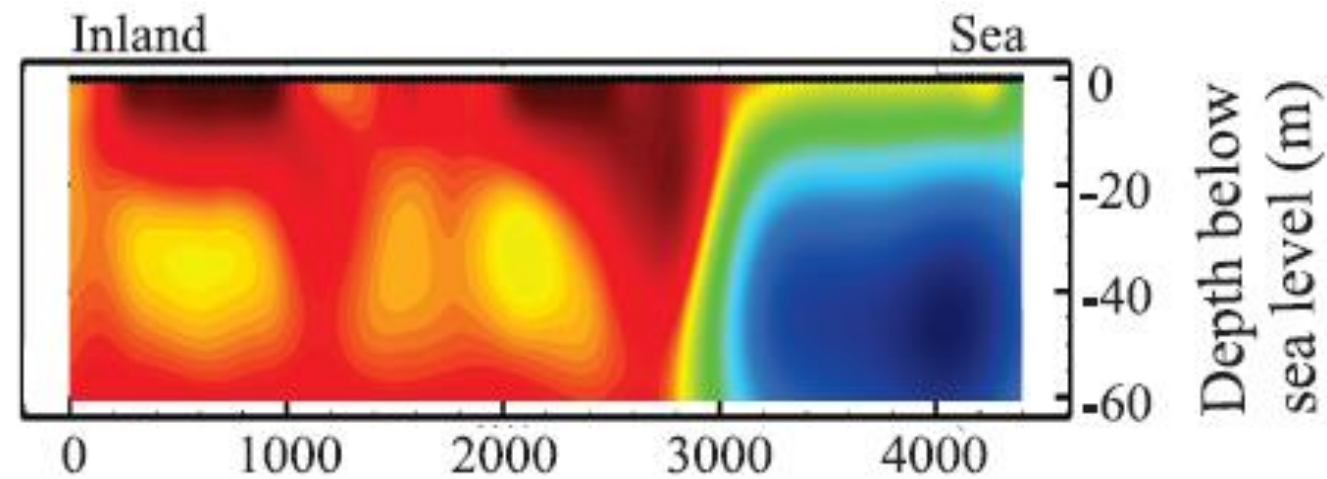
INTEGRATION OF GEOPHYSICAL DATA

Uncoupled (sequential) and coupled approaches (Beaujean, PhD Thesis, 2015)

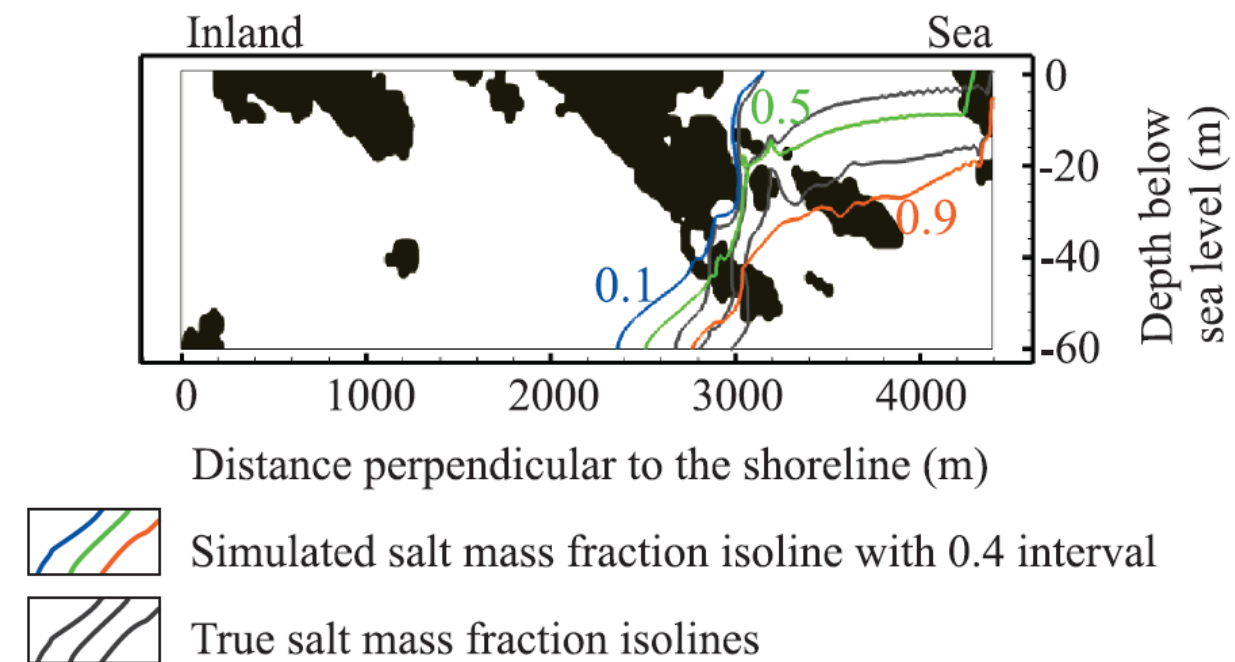


UNCOUPLED APPROACH

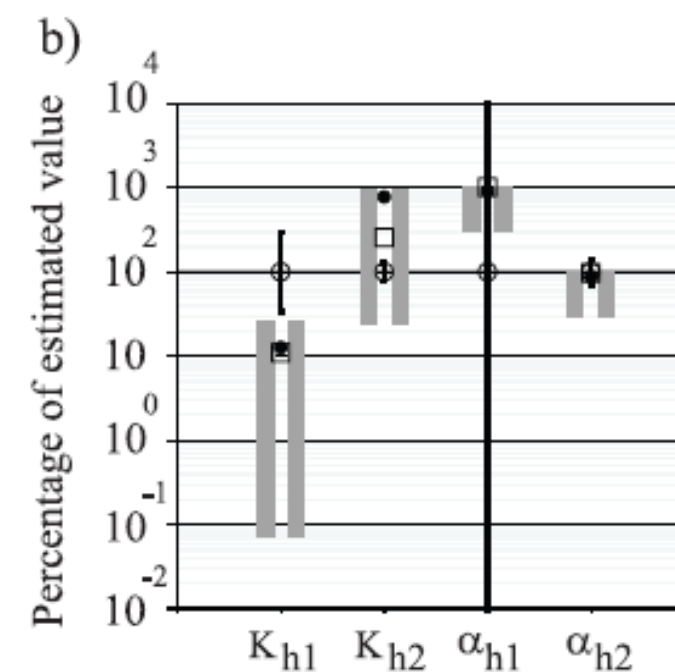
Geophysical Inversion



Extraction of salt mass fraction from ERT for inversion

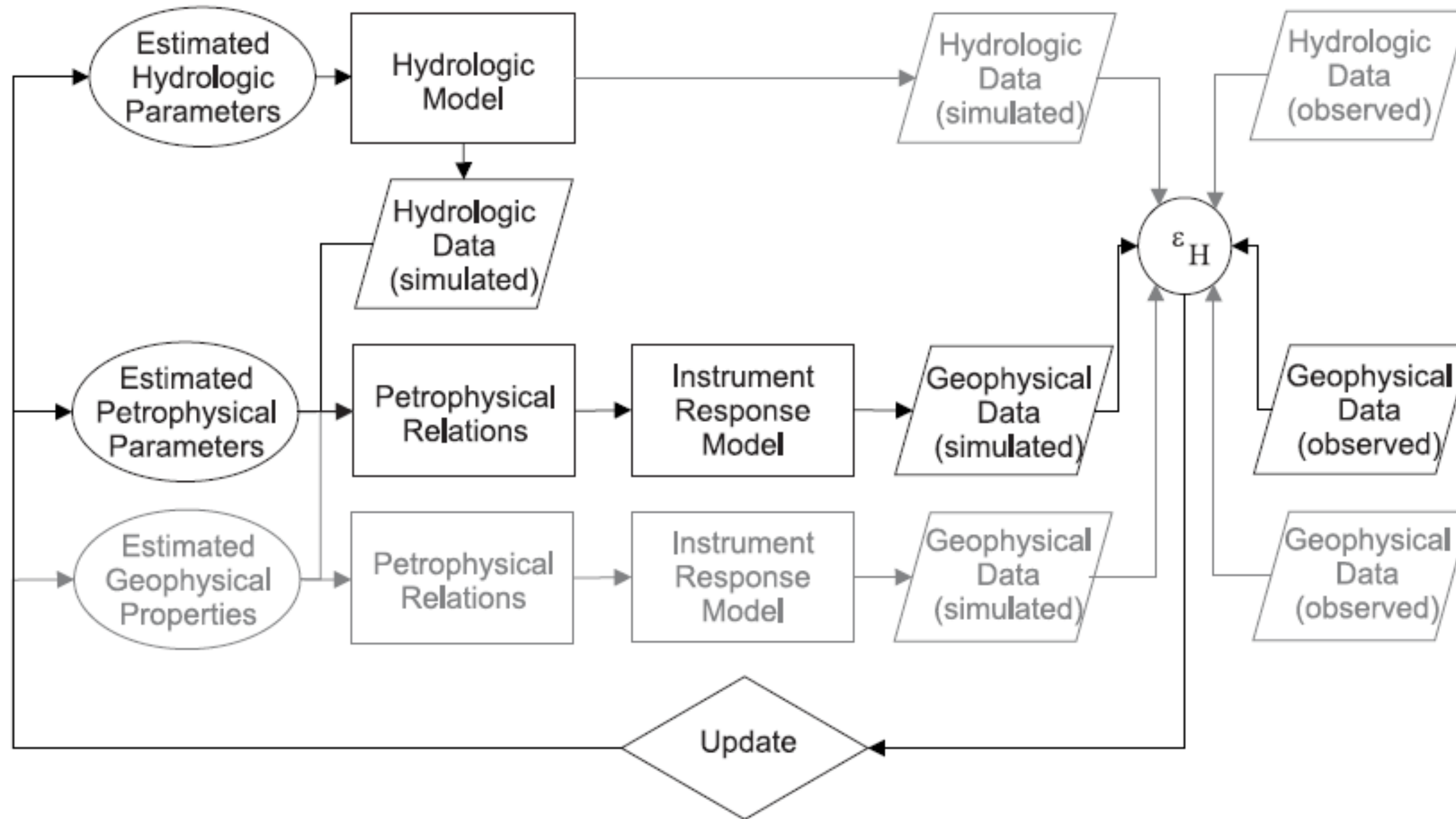


Estimation of hydrogeological parameters
Hydraulic conductivity
Longitudinal dispersivity



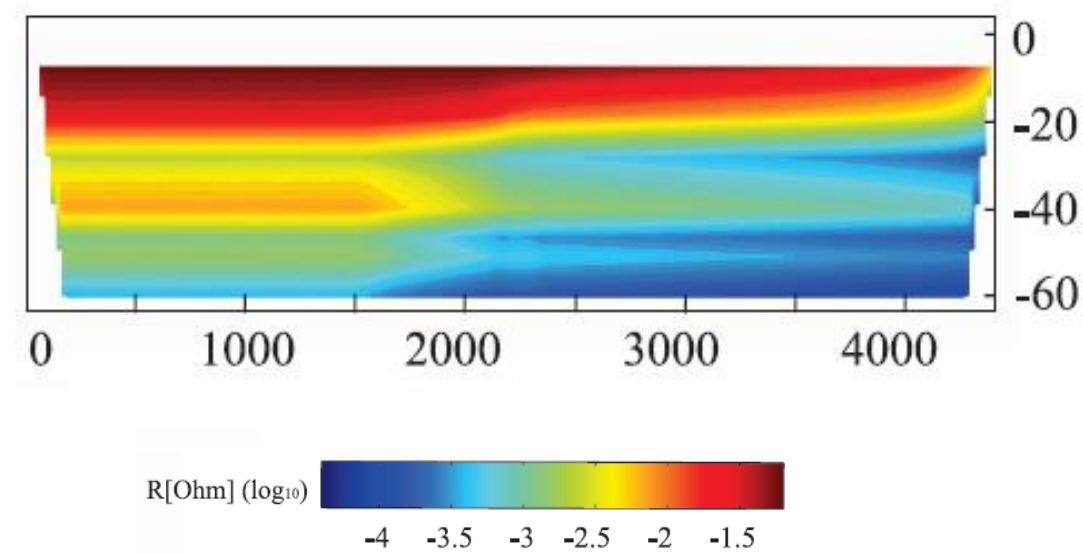
INTEGRATION OF GEOPHYSICAL DATA

Uncoupled (sequential) and **coupled** approaches (Beaujean, PhD Thesis, 2015)

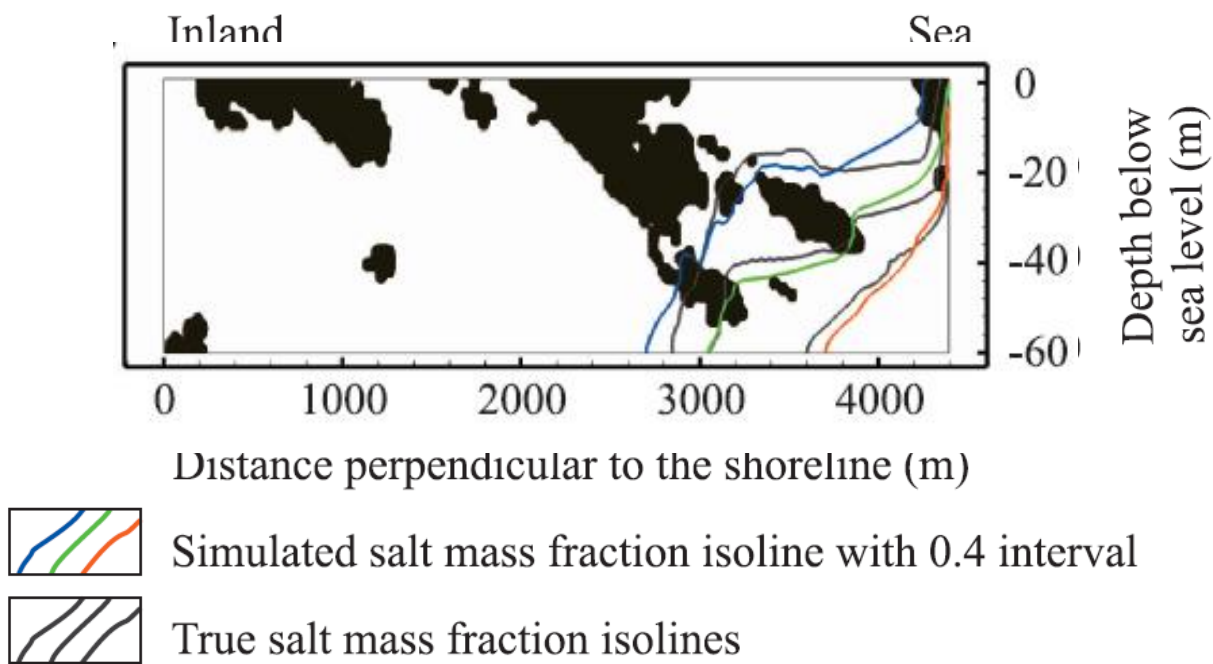


COUPLED APPROACH

Geophysical data (resistance)



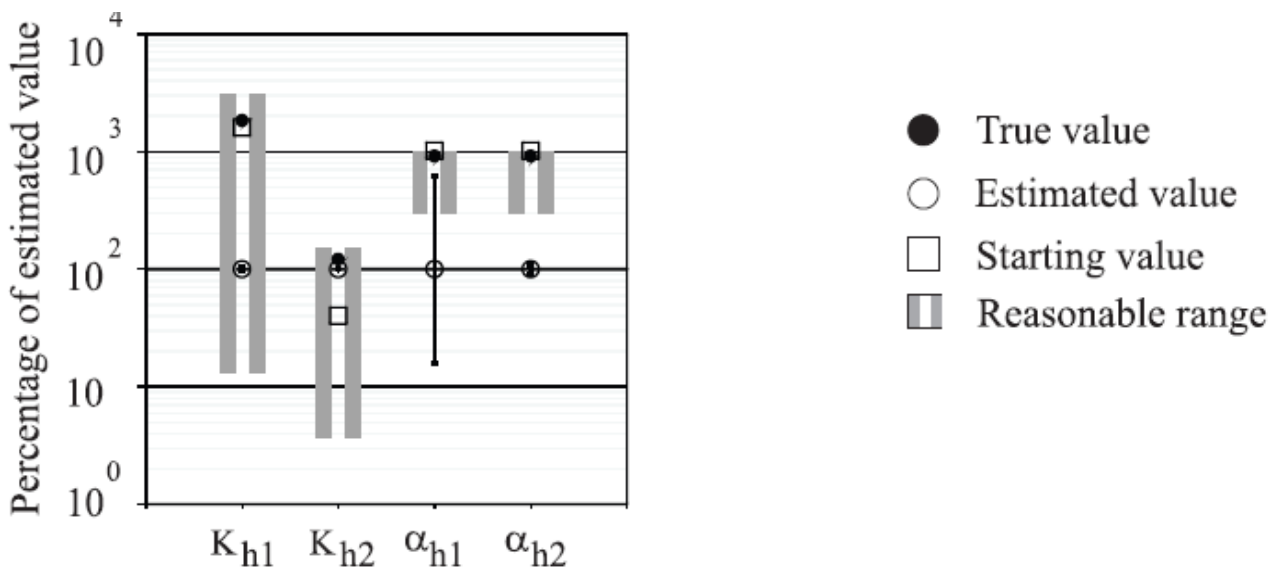
Simulation of salt mass fraction and ERT forward model (fitting resistance data)



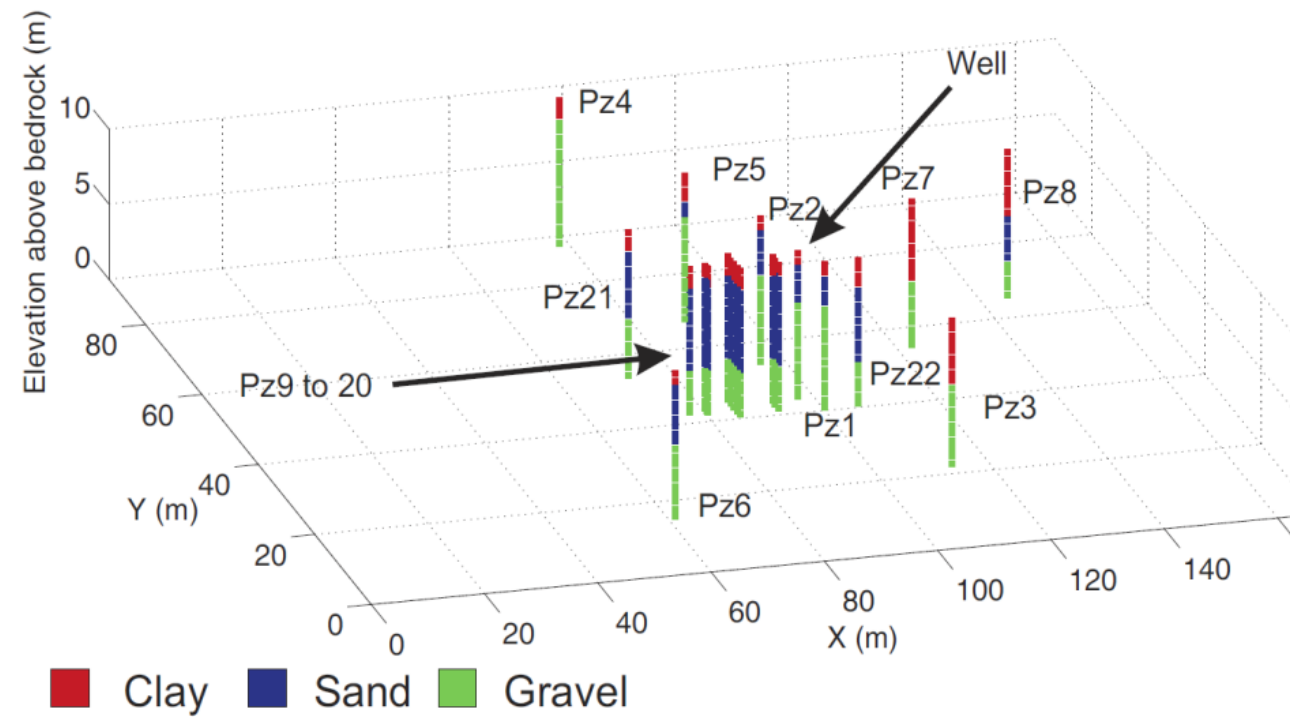
Estimation of hydrogeological parameters

Hydraulic conductivity

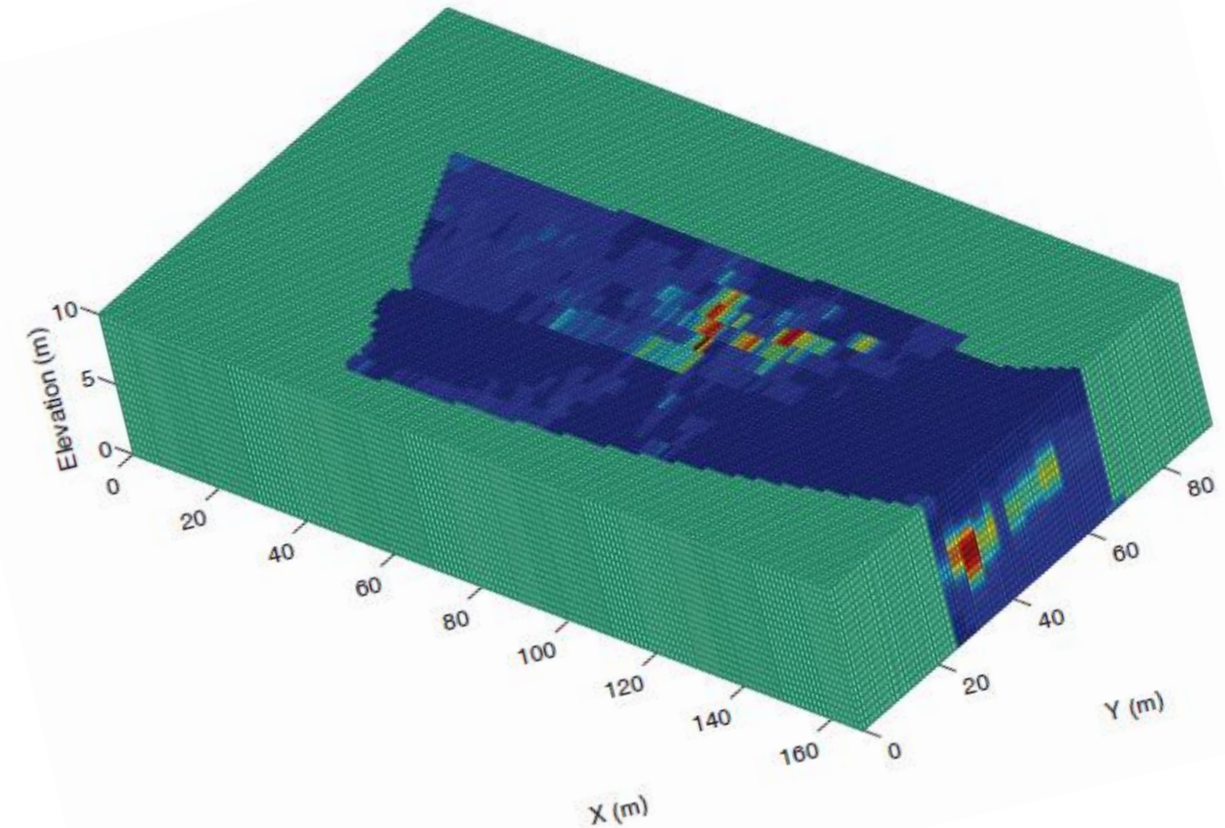
Longitudinal dispersivity



PROBABILISTIC APPROACH



Hydrogeological interpretation of boreholes

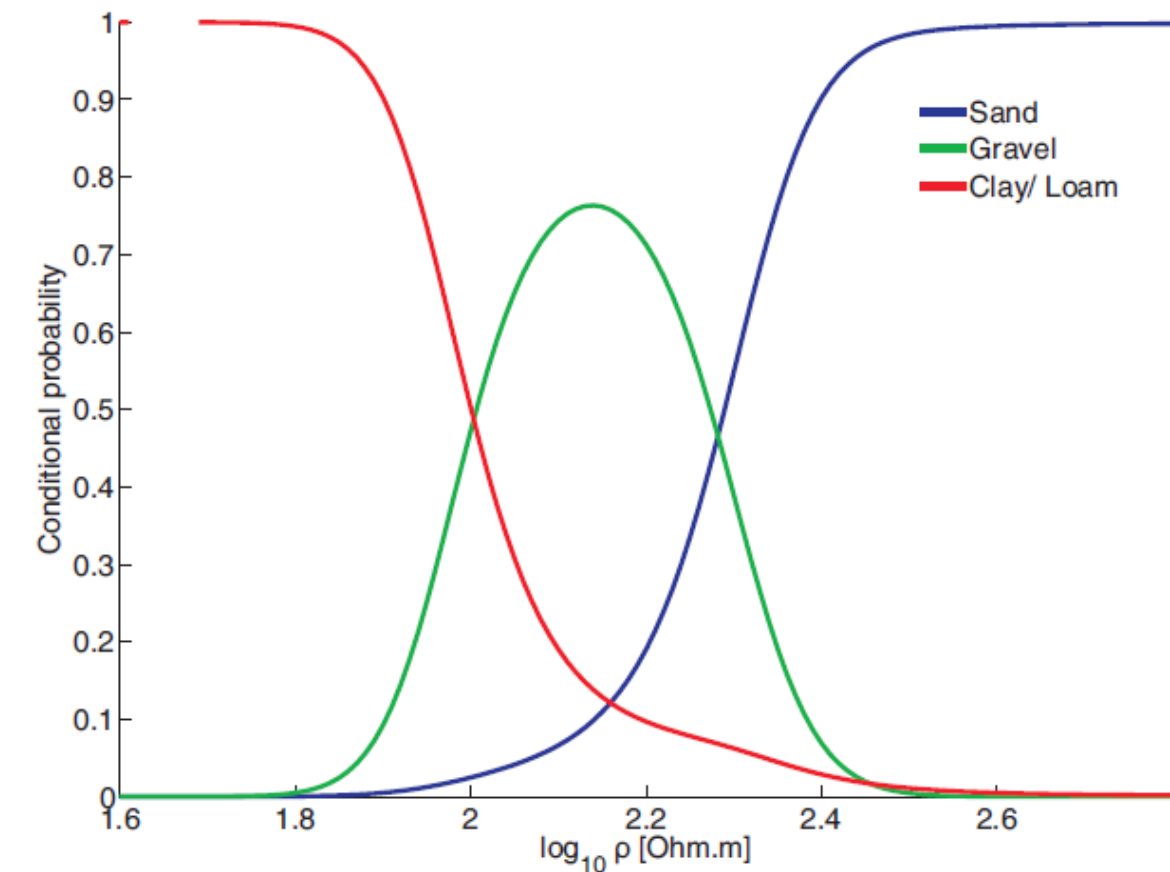
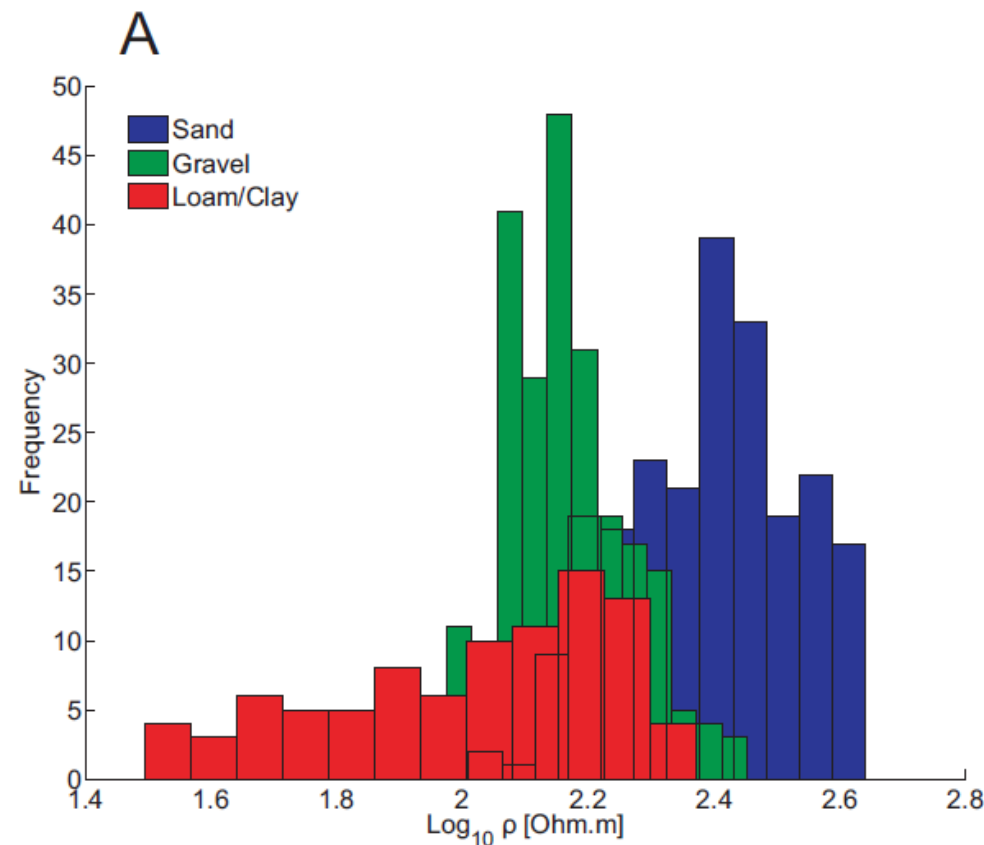


Resistivity distribution

ERT profiles and borehole data (classified into hydrofacies)

Accounting for uncertainty in ERT inversion using co-located data

PROBABILISTIC APPROACH



Hydrogeophysical interpretation of boreholes

Conditional probability

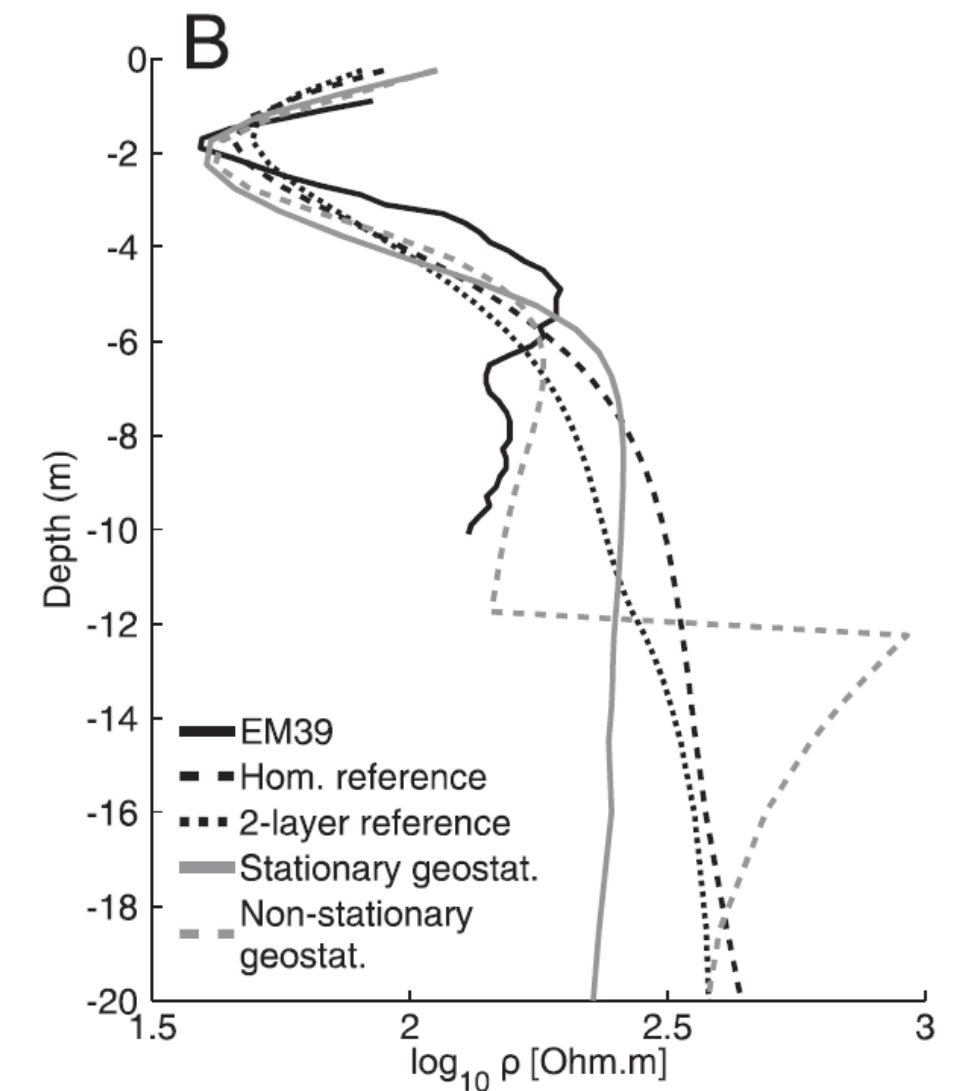
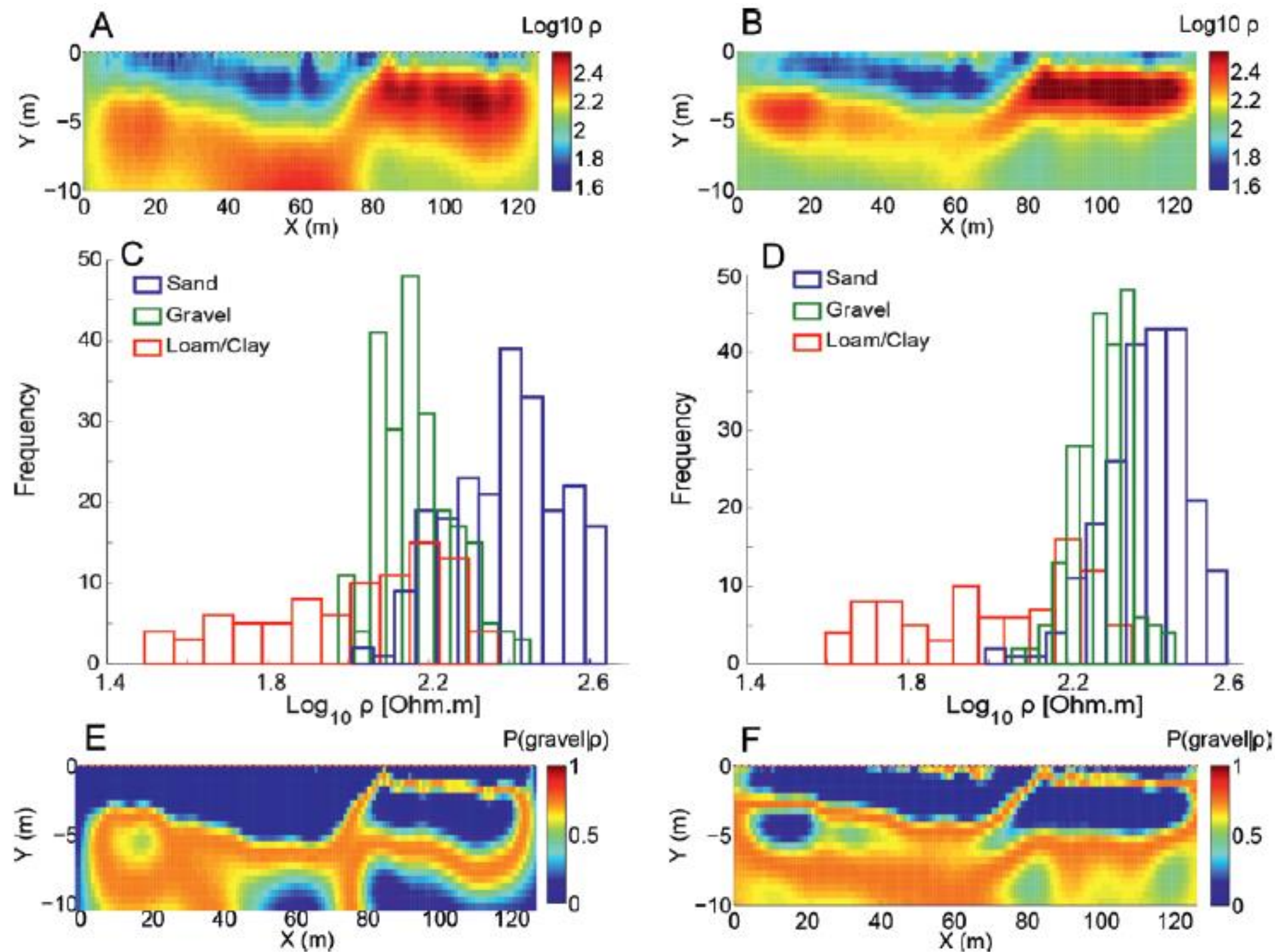
Resistivity **after inversion** for each hydrofacies

Proportion of each facies from borehole data

→ Conditional probability of facies from resistivity

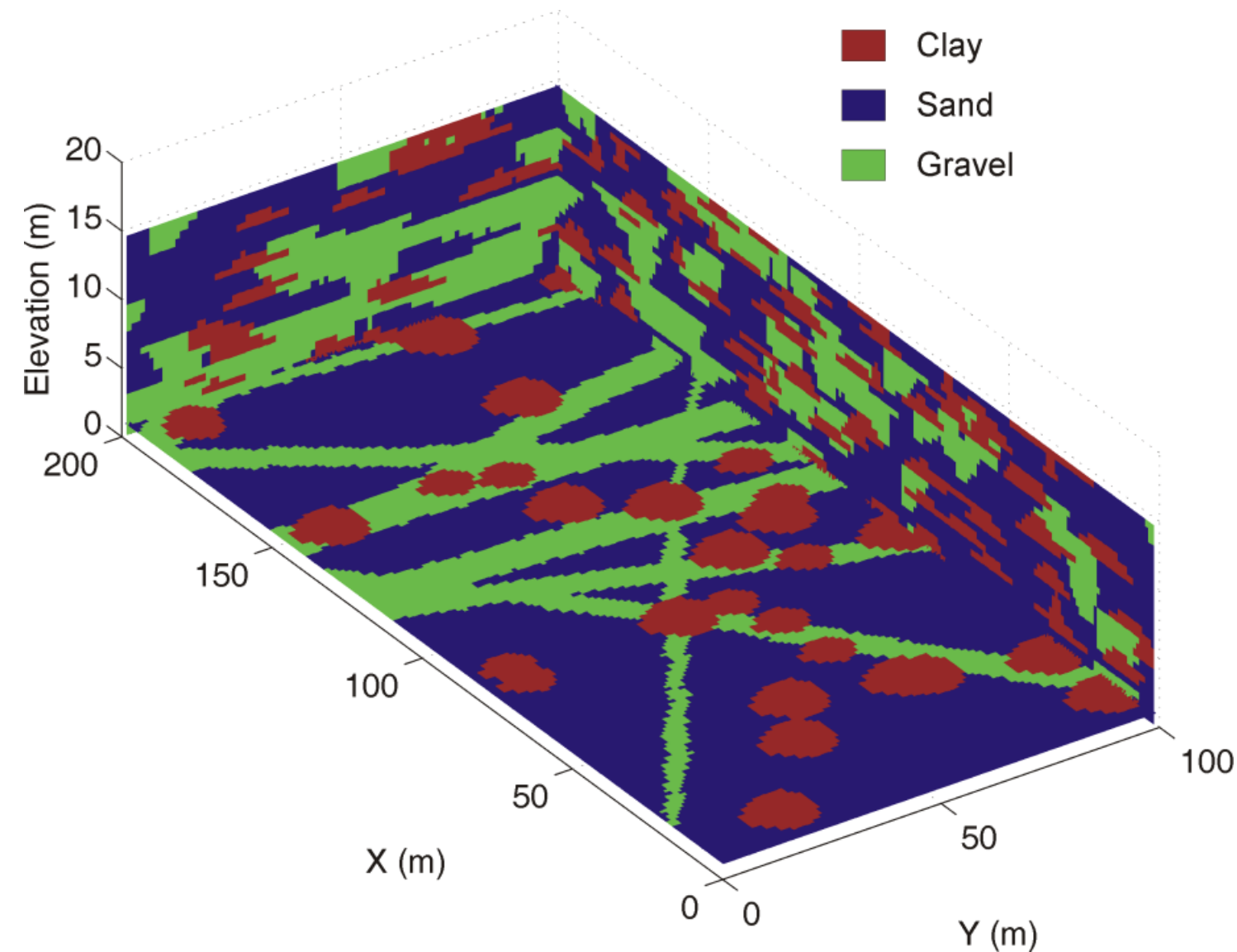
PROBABILISTIC APPROACH

Choosing the adapted inversion approach helps to correctly identified the heterogeneity of the subsurface and use more appropriate conditional probabilities !

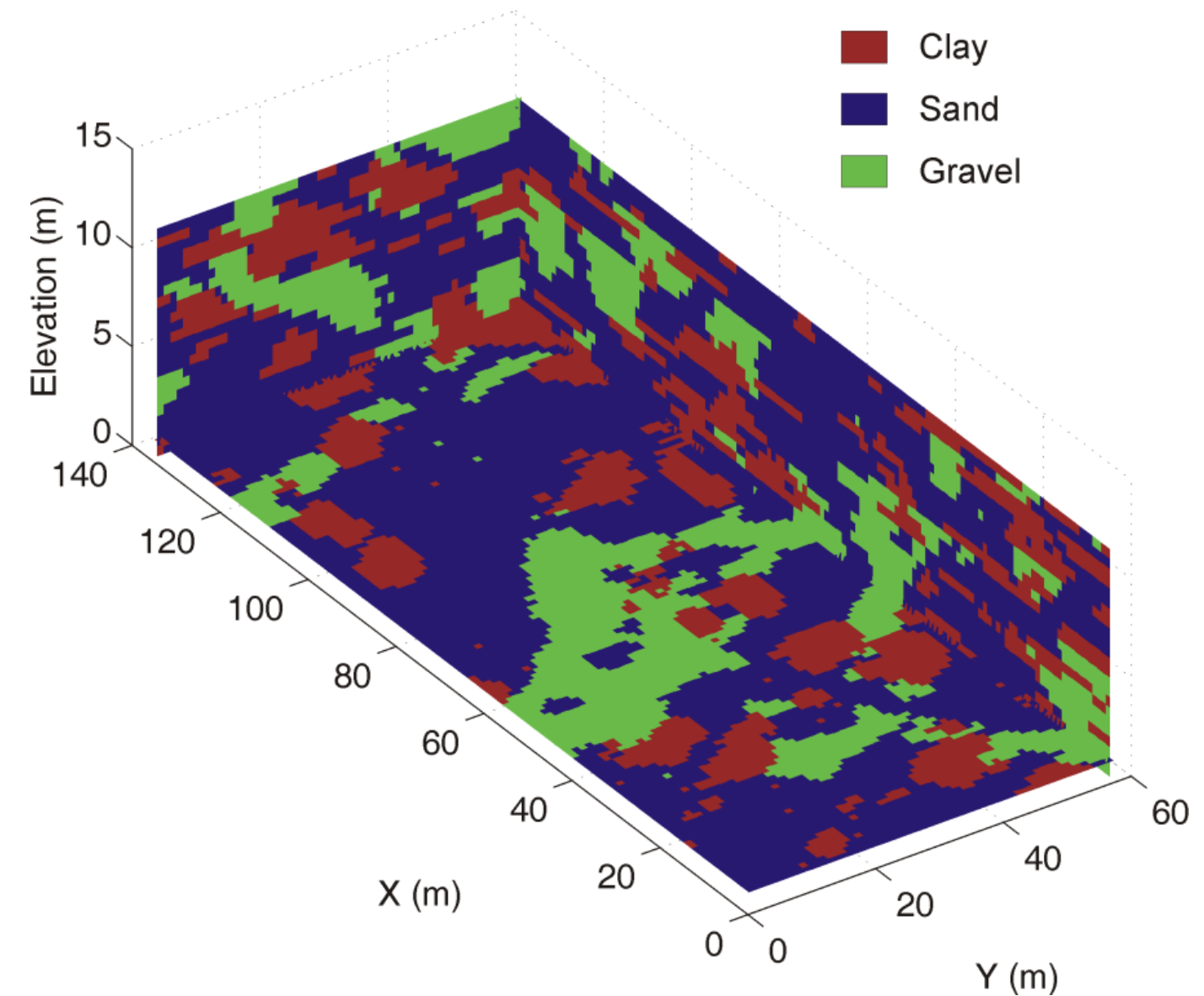


(Hermans & Irving, NSG, 2017)

PROBABILISTIC APPROACH



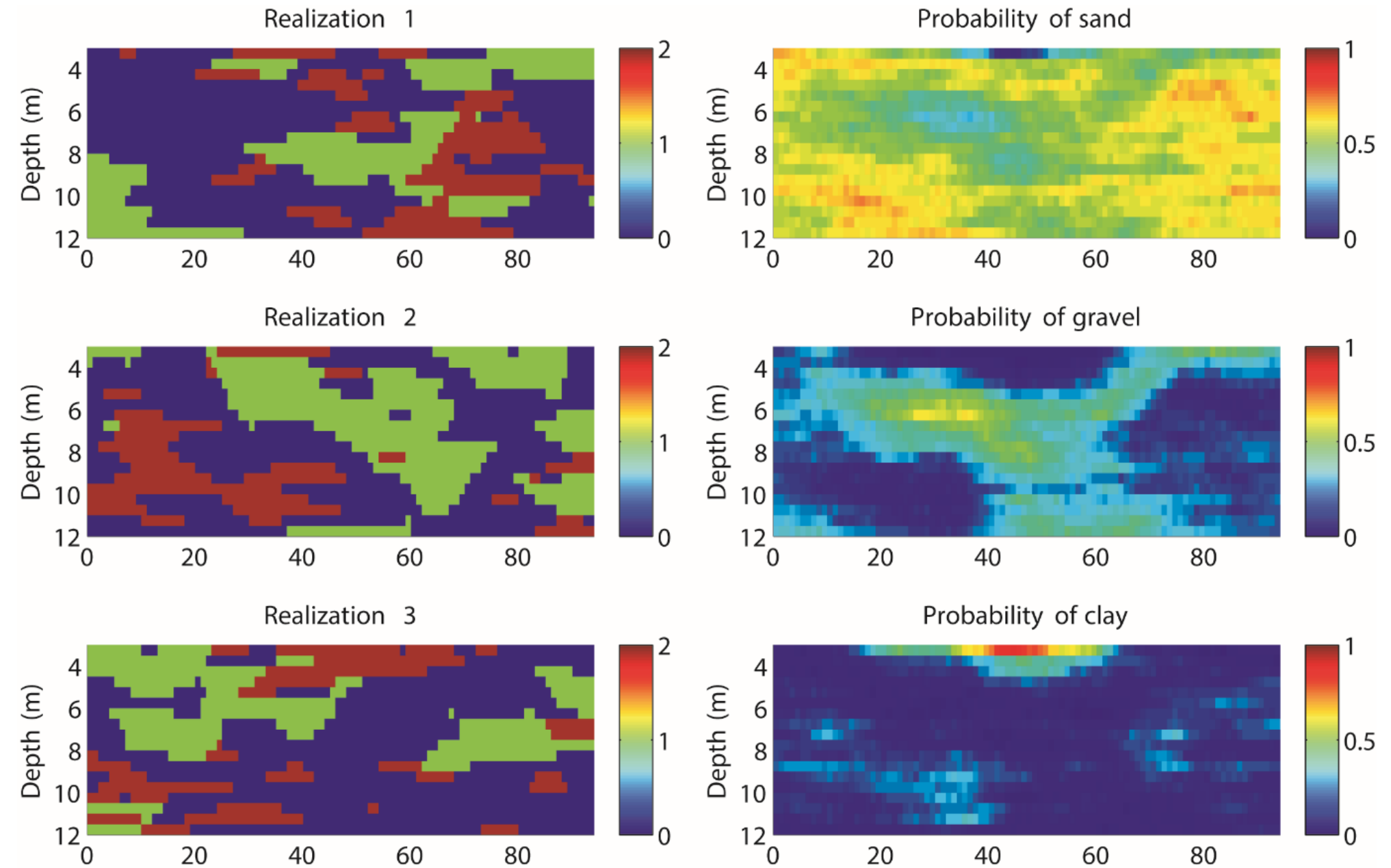
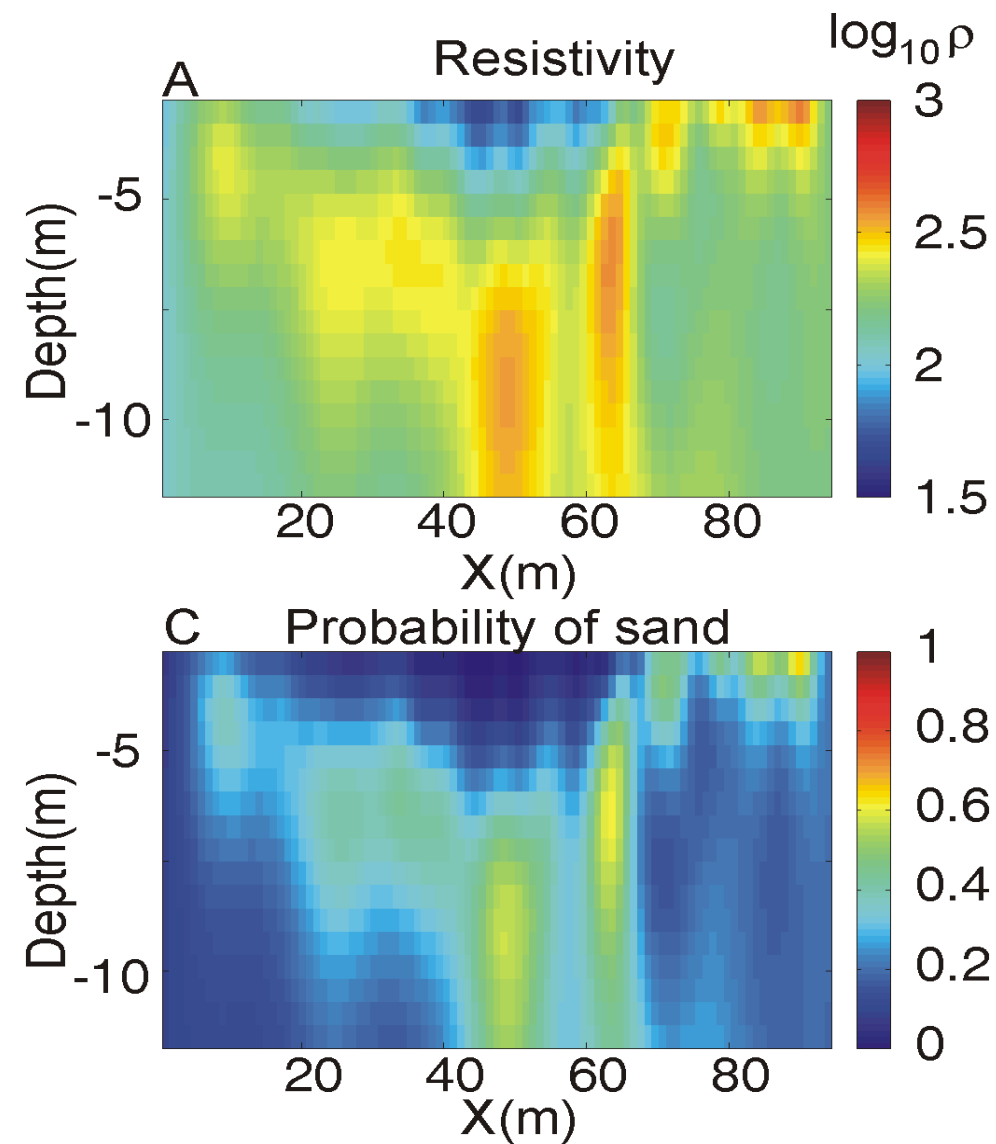
Training image



Simulation

Conceptual representation of the heterogeneity using a Training Image
Multiple-point geostatistics simulation to simulate the aquifer

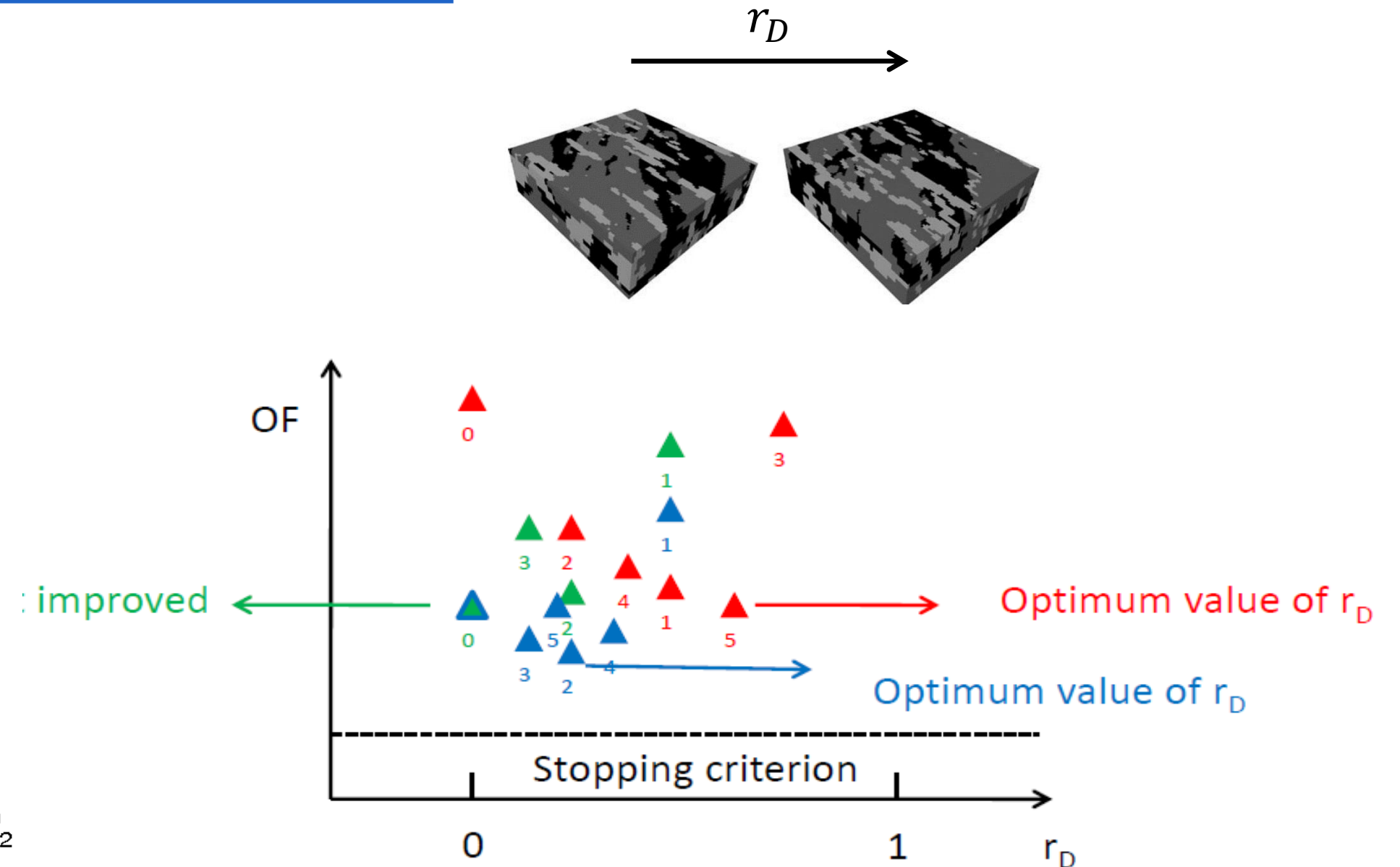
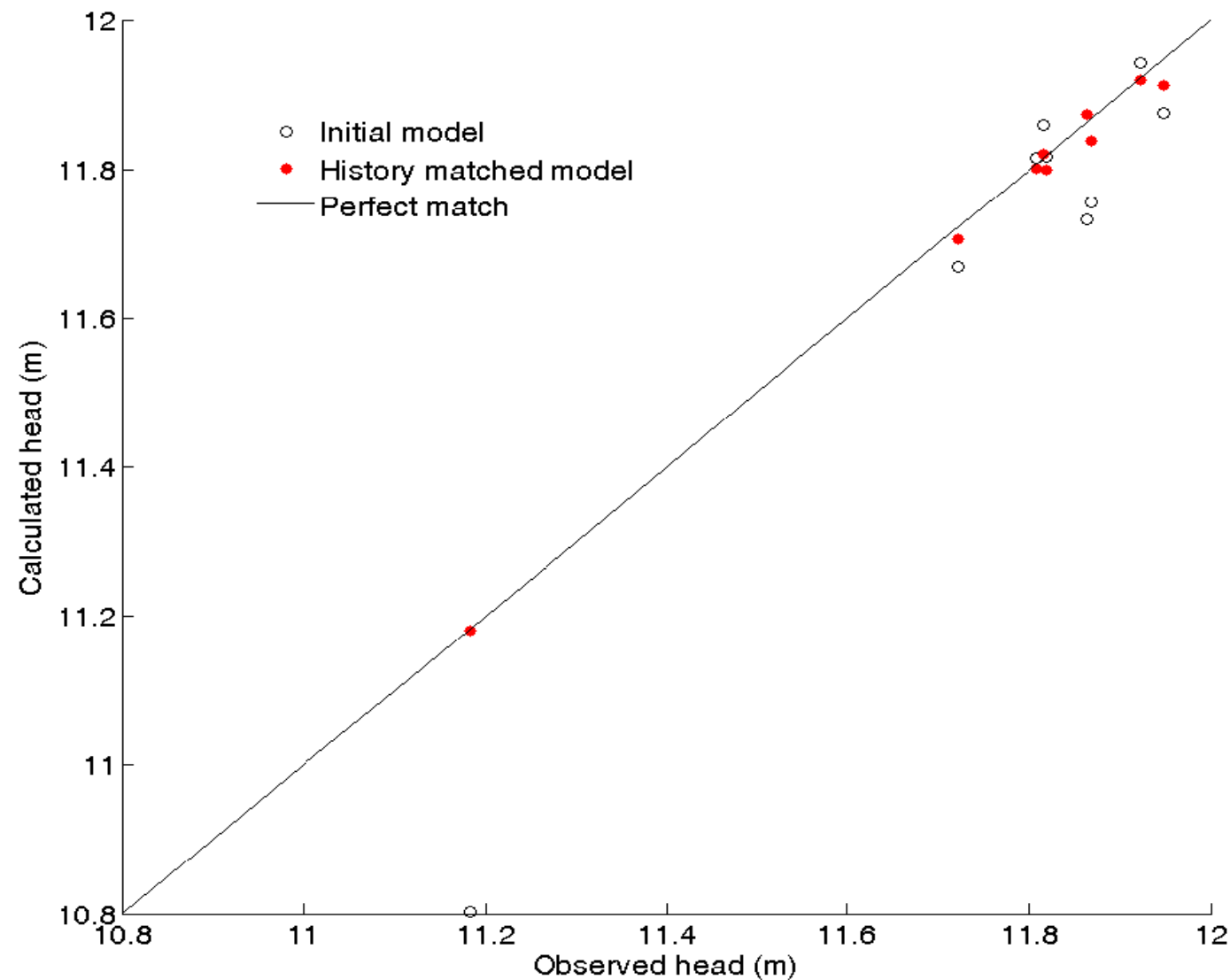
PROBABILISTIC APPROACH



(Hermans, 2014, PhD thesis)

Constraining MPS simulations using geophysical data as soft data through the conditional probabilities derived from co-located data

PROBABILISTIC APPROACH

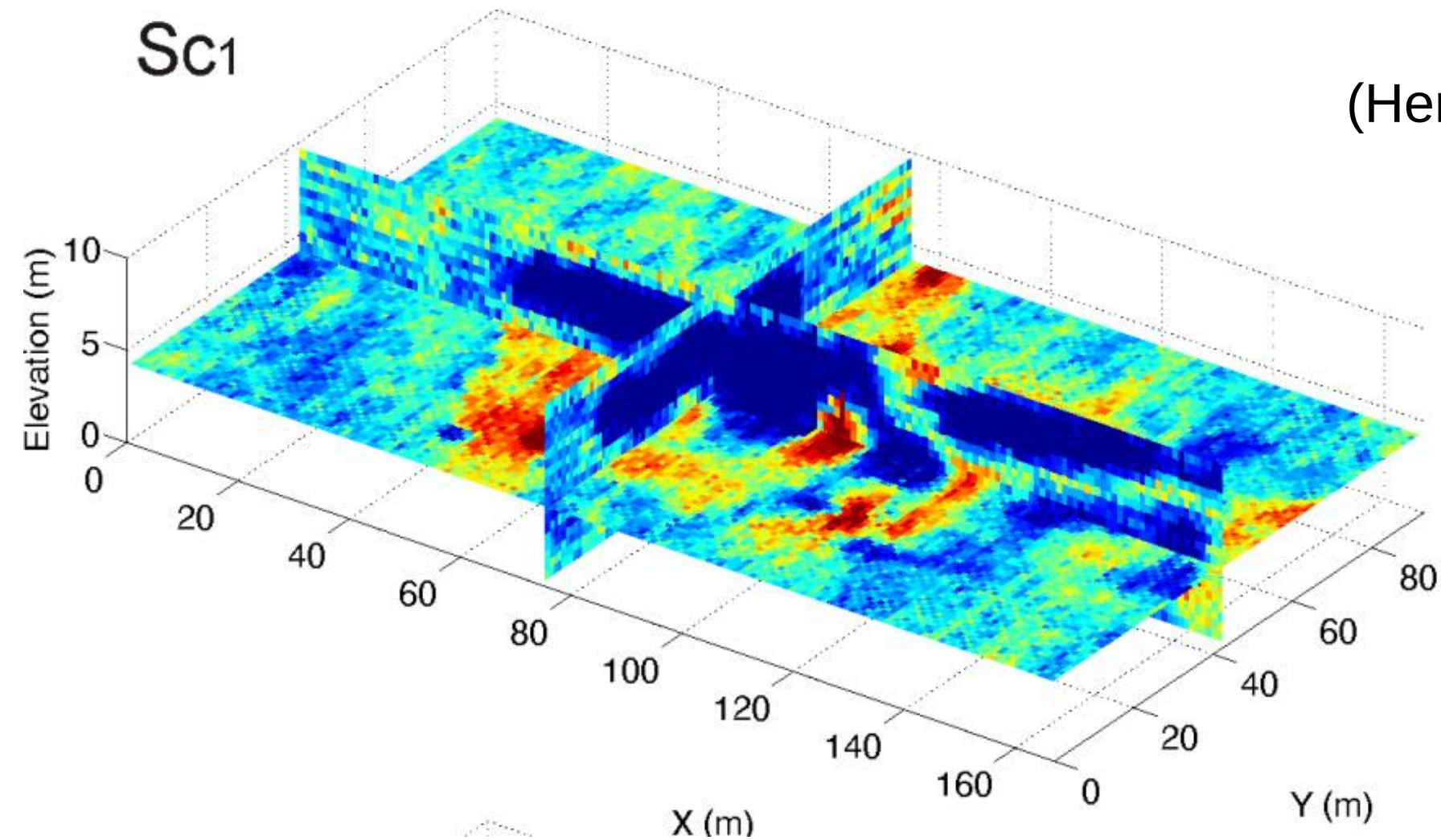


(Hermans et al., 2015, WRR)

The principle is to transform the realization into another one still consistent with the existing data to converge towards a calibrated model (fitting hydro data)

The approach can be repeated with another starting model to produce alternative solutions

PROBABILISTIC APPROACH



(Hermans et al., 2015, WRR)

If enough iterations are performed, we obtain an estimation of the posterior distribution

Here the solution is expressed as the posterior probability of gravel (blue = 0, red = 1)

PROBABILISTIC APPROACH

(Hermans et al., 2015, WRR)

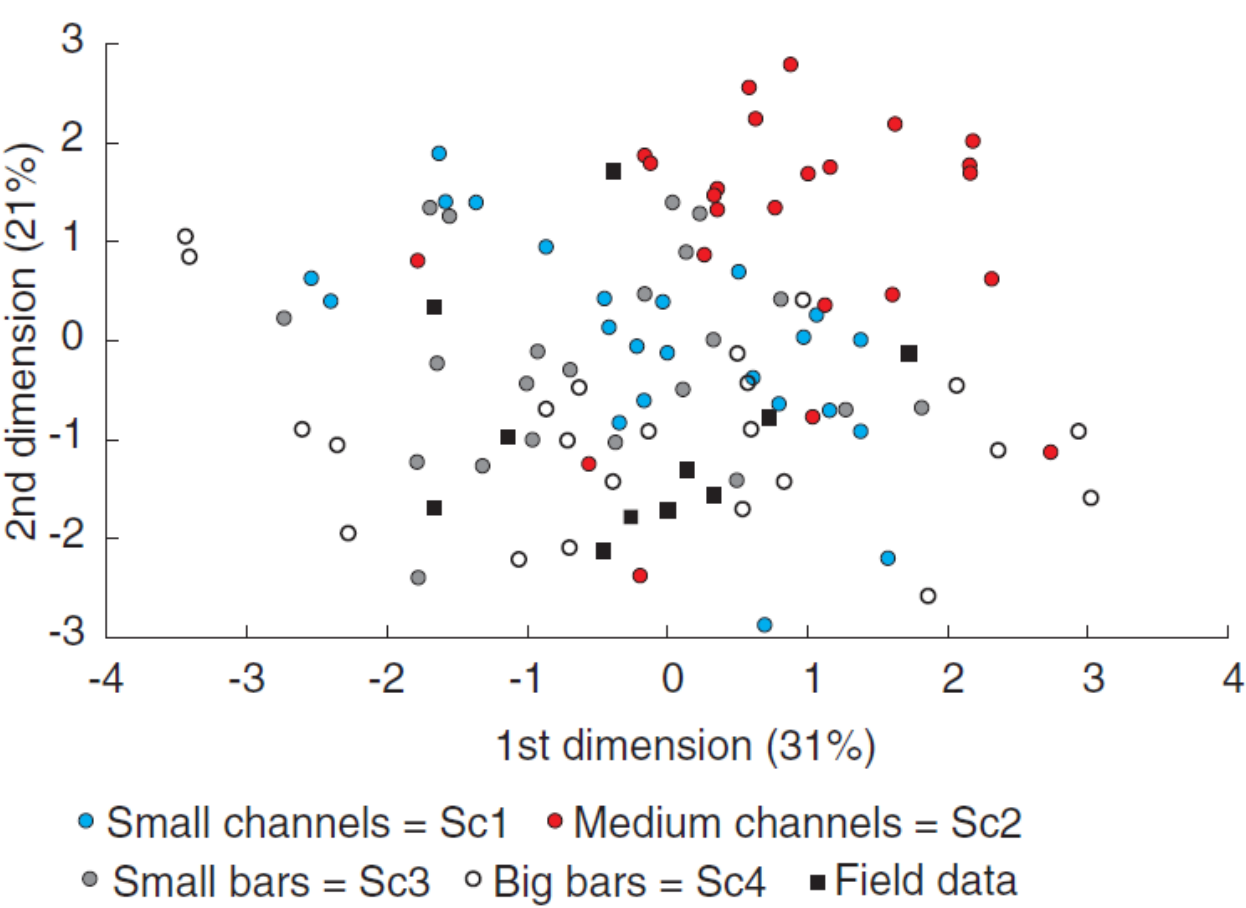
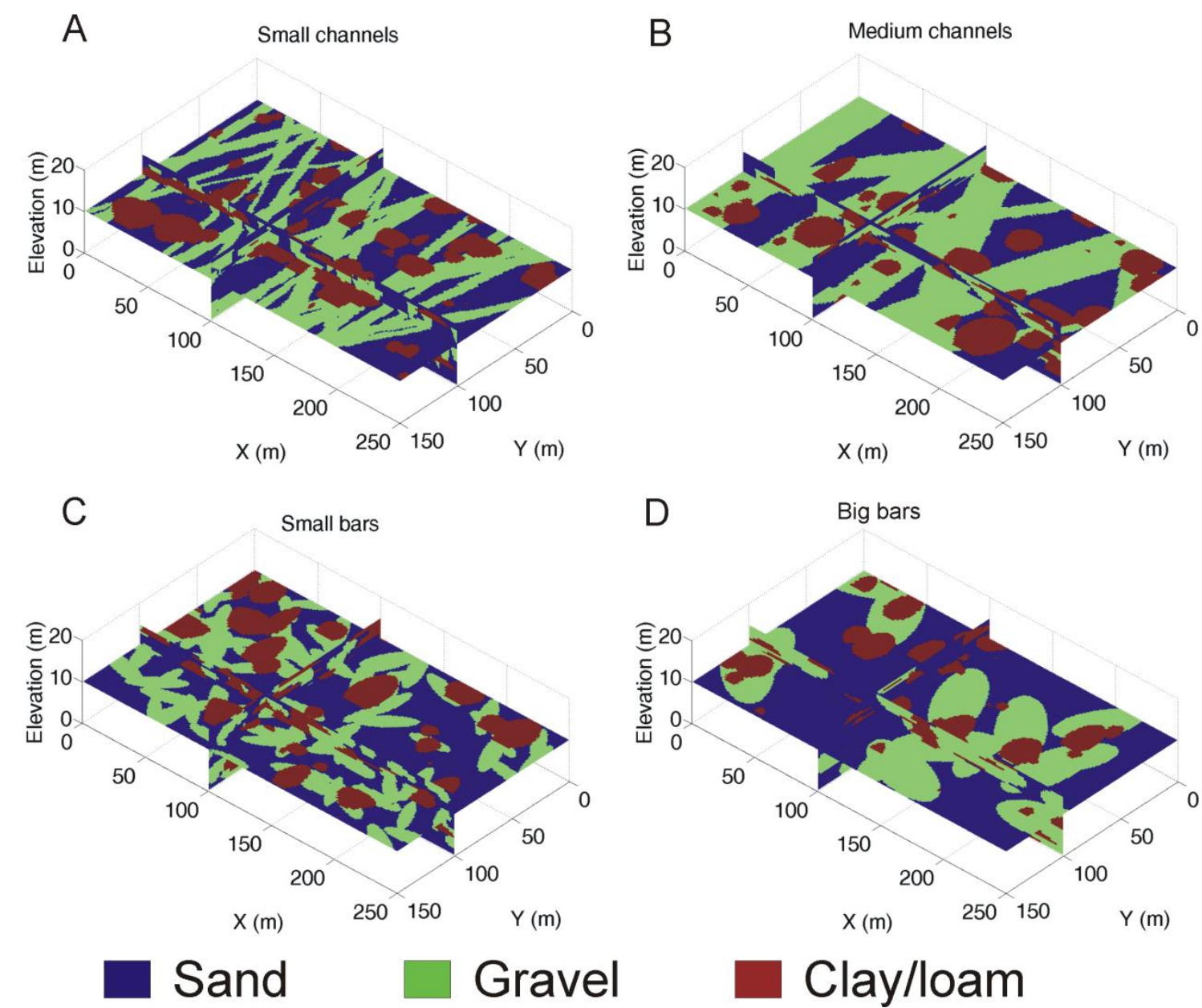


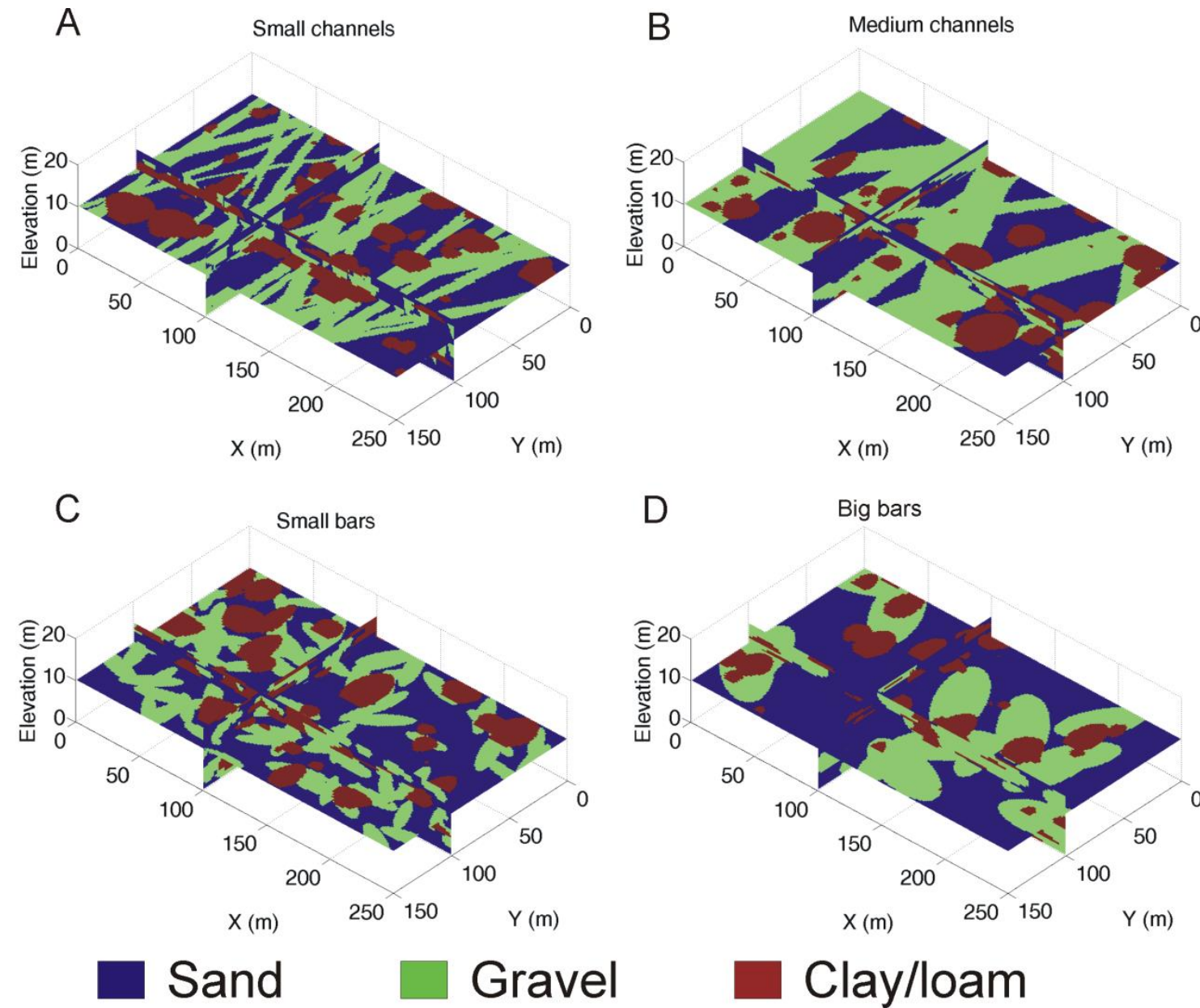
Table 4. Scenario and Updated Probability

Scenario	Gravel Geometry	$P(Sc_i)$	$P(Sc_i D_{ERT})$ —2-D	$P(Sc_i D_{ERT})$ —5-D
Sc ₁	Small channels	0.25	0.2	0.29
Sc ₂	Medium channels	0.25	0.18	0.14
Sc ₃	Small bars	0.25	0.27	0.27
Sc ₄	Big bars	0.25	0.35	0.30

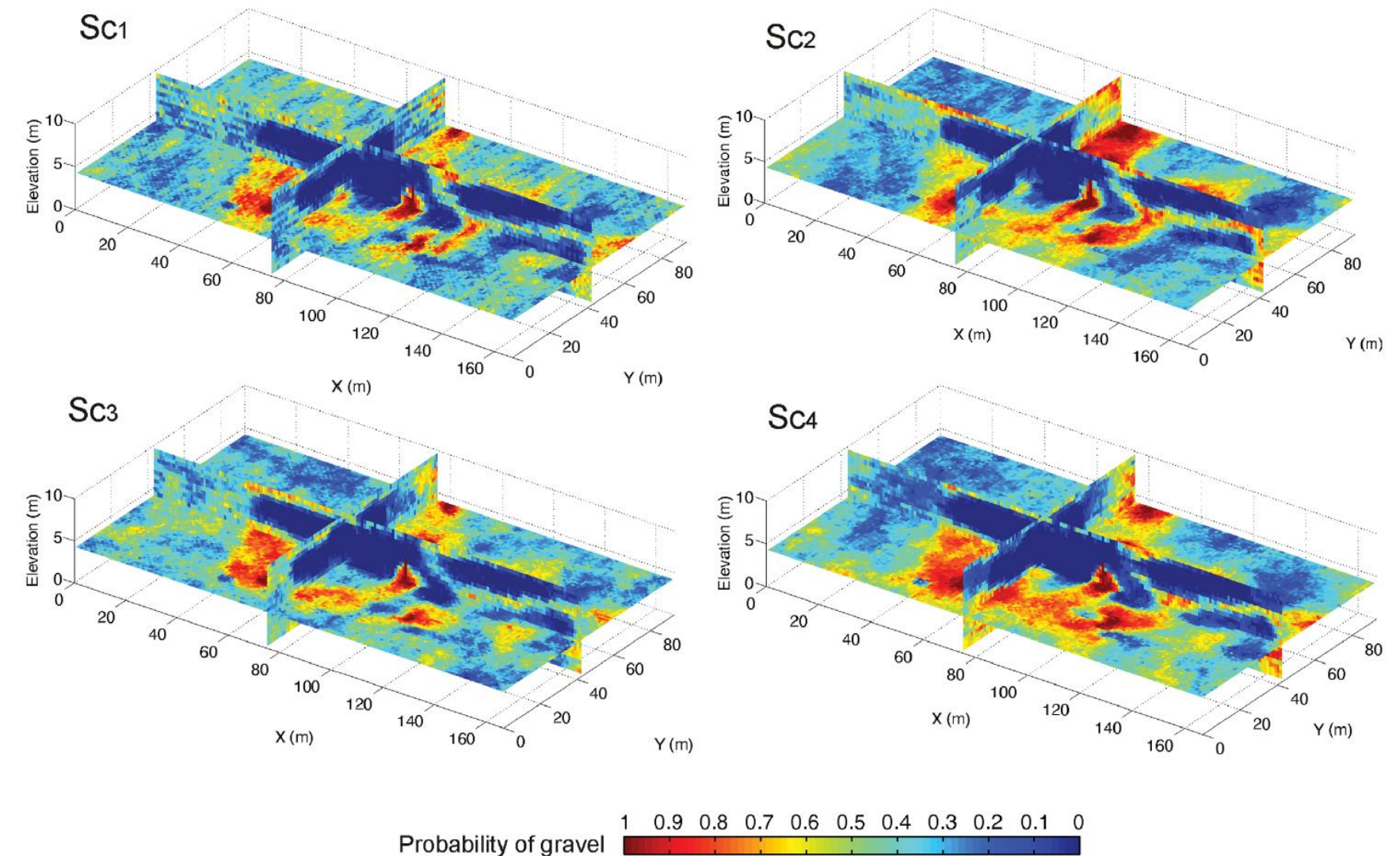
The choice of the TI has an influence on the posterior distribution, hence the importance to assess the probability and consistency with geophysical data

None of the TI is falsified → the process is repeated for each TI

PROBABILISTIC APPROACH



(Hermans et al., 2015, WRR)

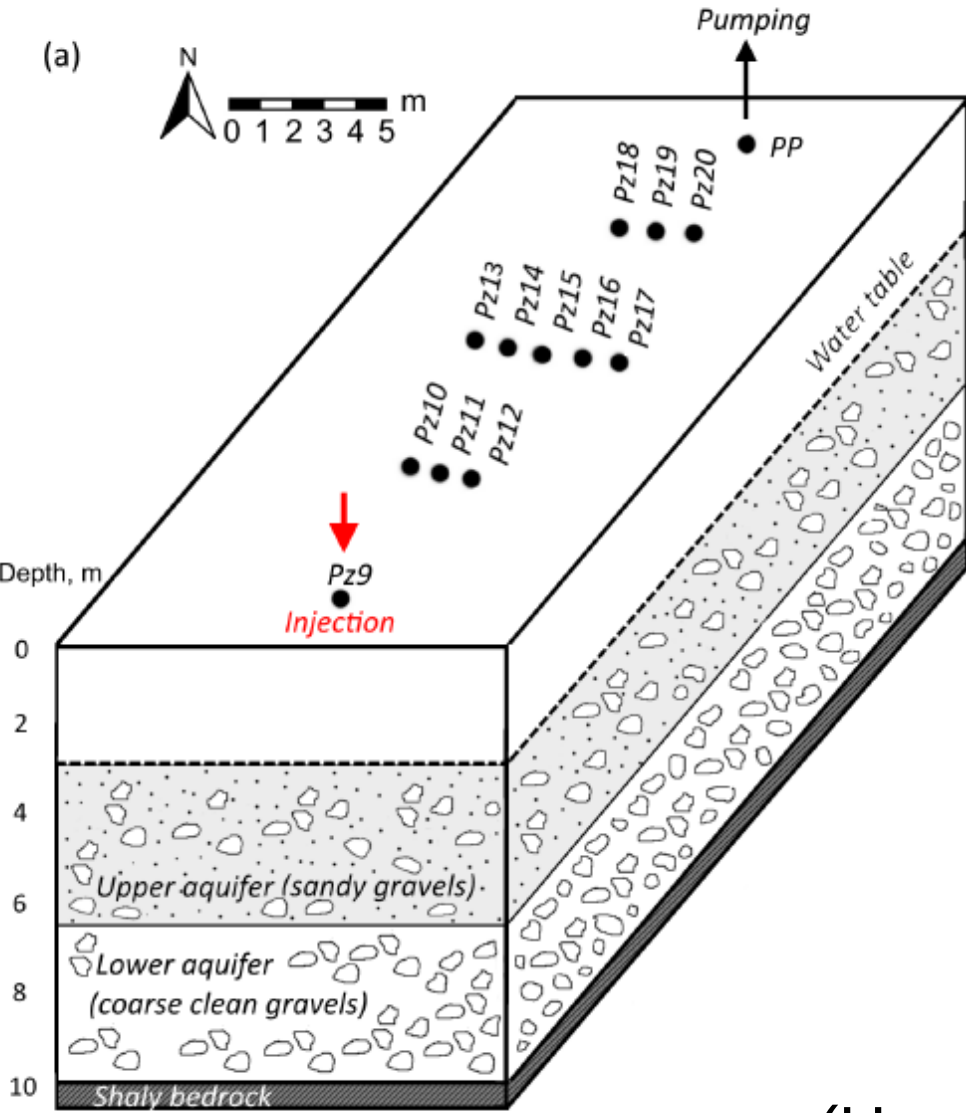


The posterior distribution varies → The assembled posterior accounts for the probability of each scenario

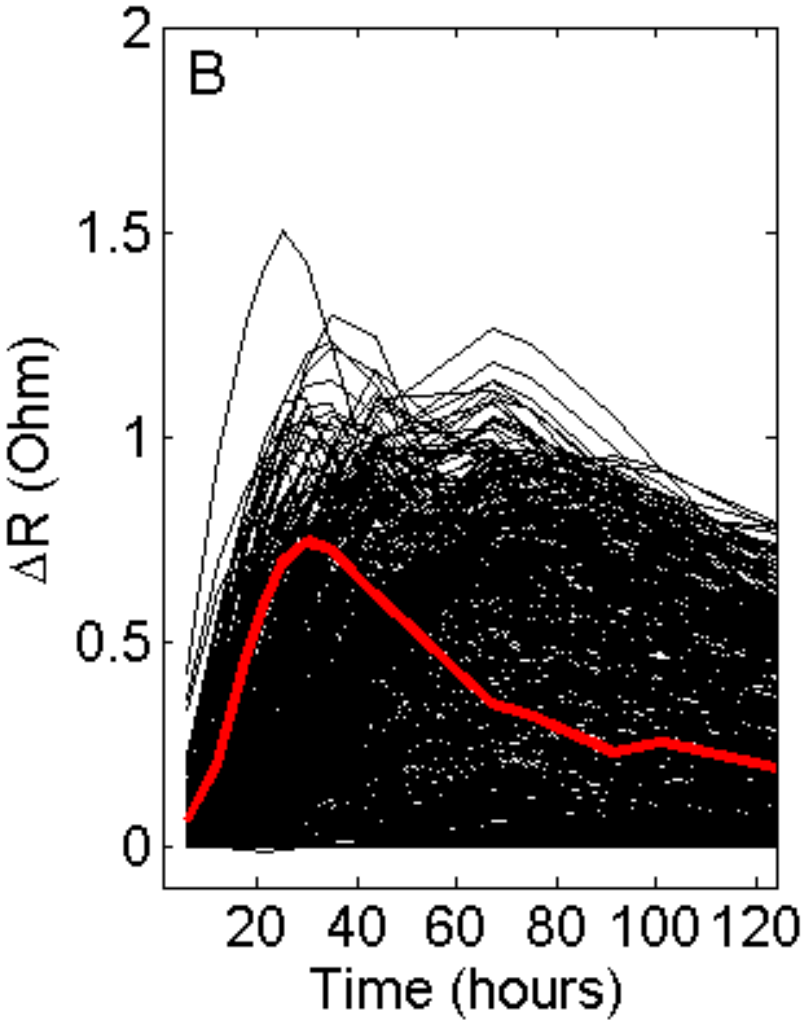
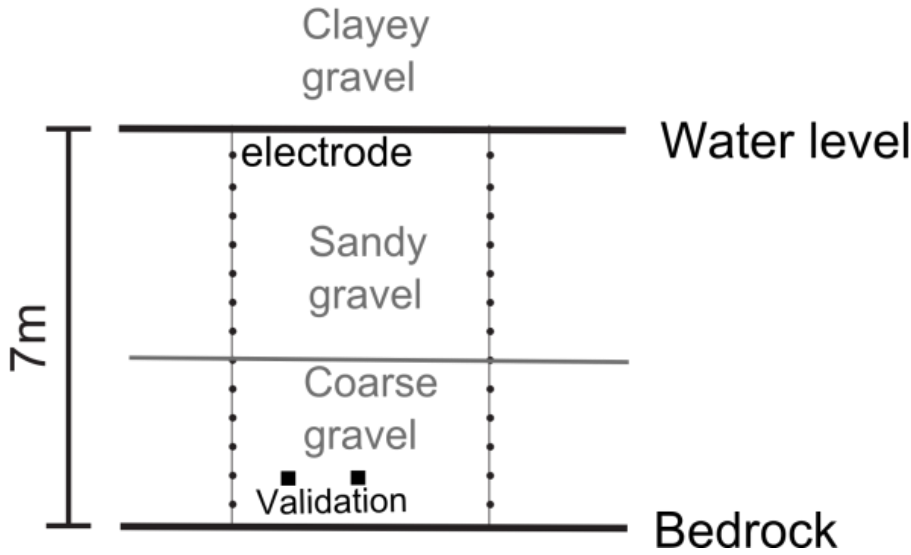
BAYESIAN EVIDENTIAL LEARNING

Data

A heat tracing experiment monitored with ERT
Identification of transport processes and heterogeneity



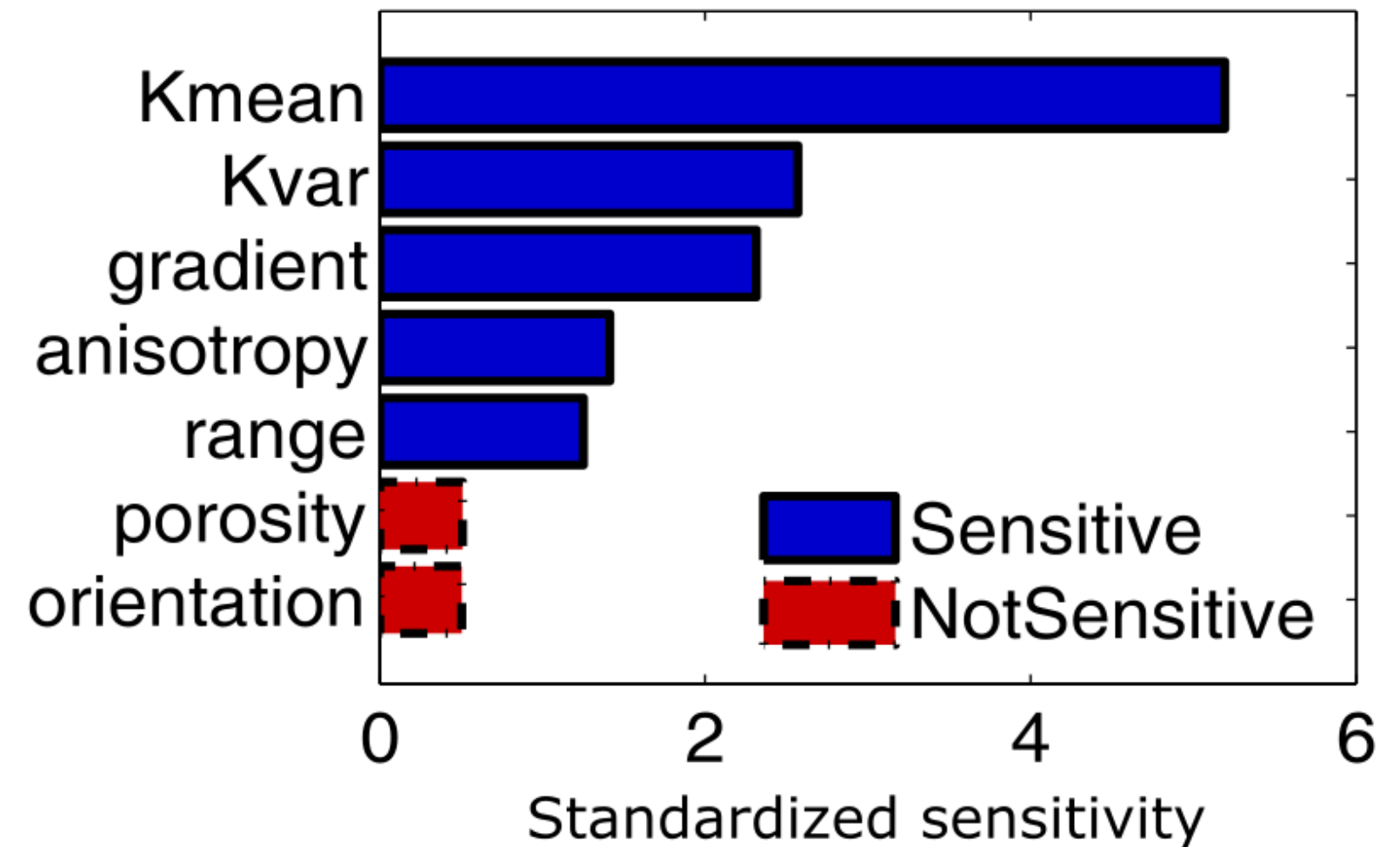
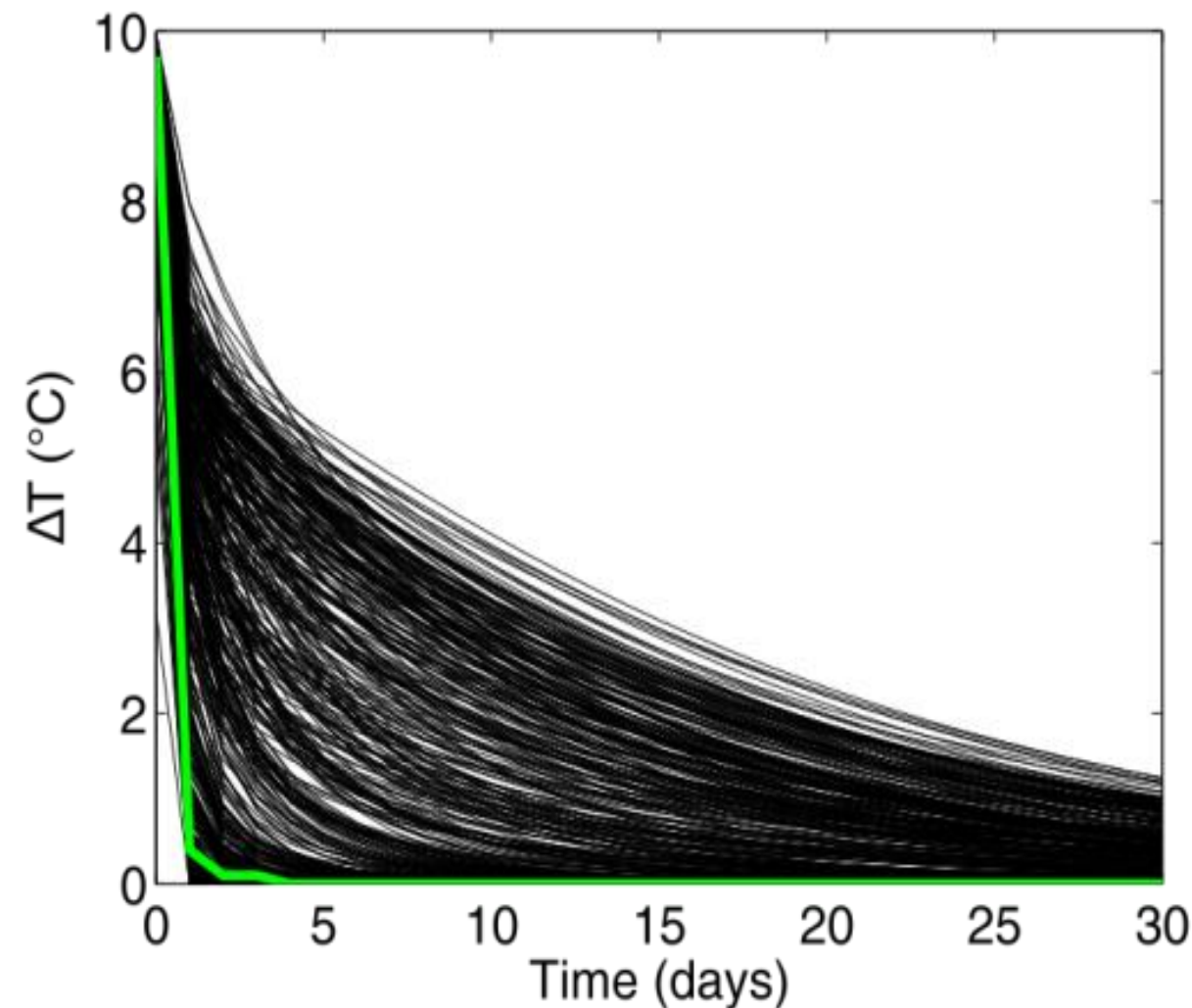
Cross-section of the ERT panel



(Hermans et al., WRR, 2018)

BAYESIAN EVIDENTIAL LEARNING

Prediction = heat storage capacity of the aquifer

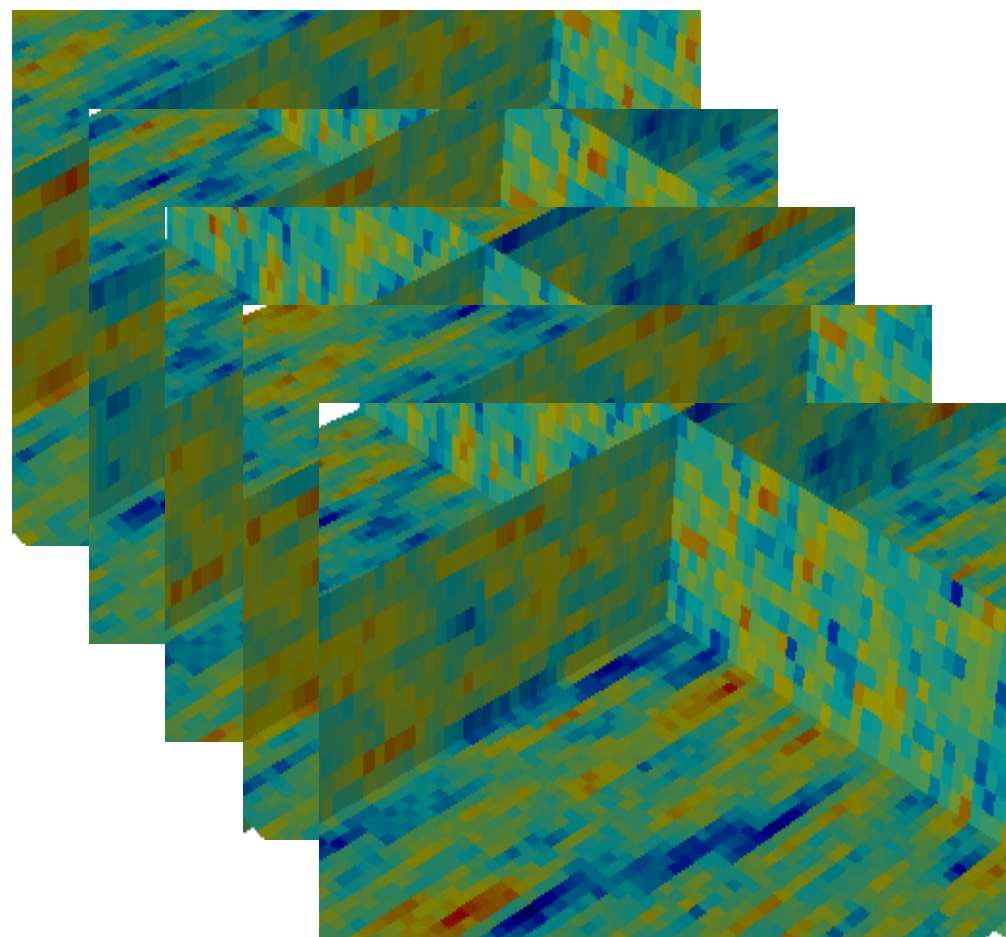


Identification of the most sensitive parameters

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Models

What do we know, what do we ignore about this aquifer ?



500 realizations =
surrogate models

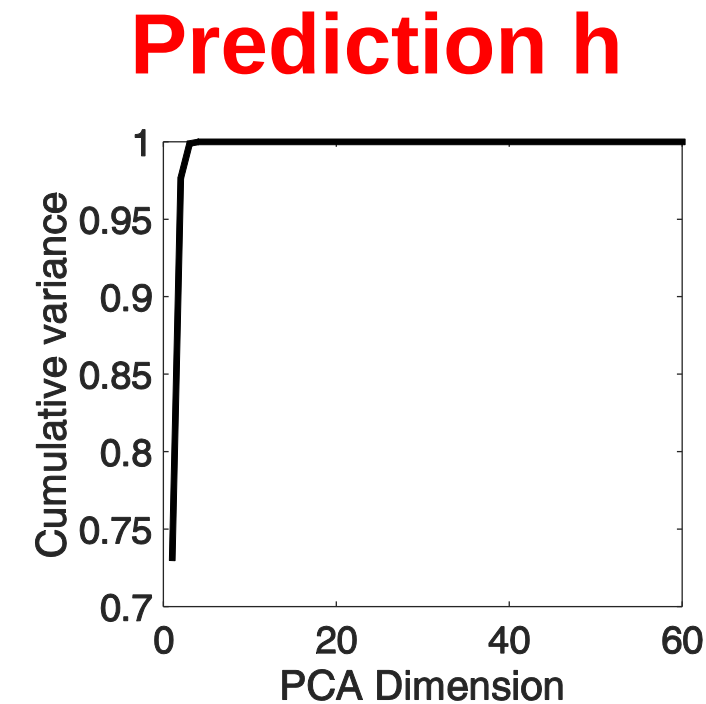
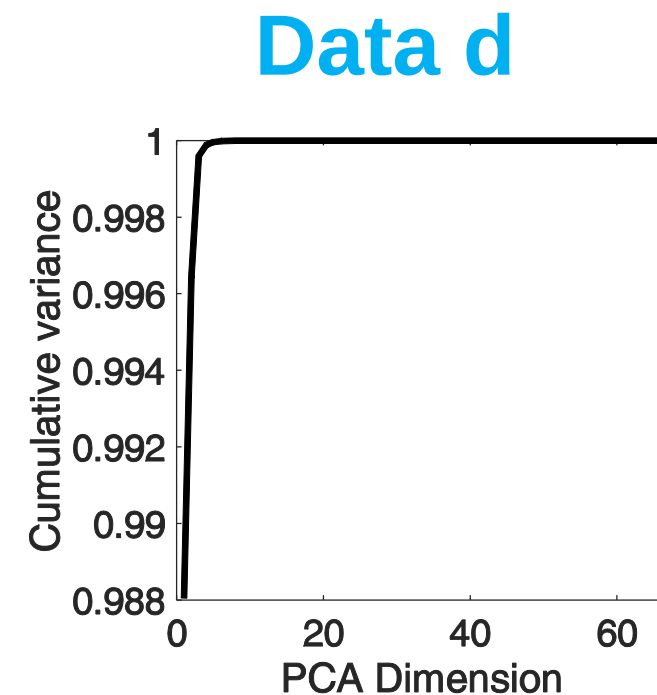
Parameters	Status	Value
Mean of $\log_{10} K$ (m/s)	Variable	U[-4 -1]
Variance $\log_{10} K$ (m/s)	Variable	U[0.05 1.5]
Range (m)	Variable	U[1 10]
Anisotropy ratio	Variable	U[0.5 10]
Orientation	Variable	U[- $\pi/4$ - $\pi/4$]
Porosity	Variable	U[0.05 0.40]
Gradient (%)	Variable	U[0 0.167]
Other parameters	Fixed	

(Hermans et al., WRR, 2018)

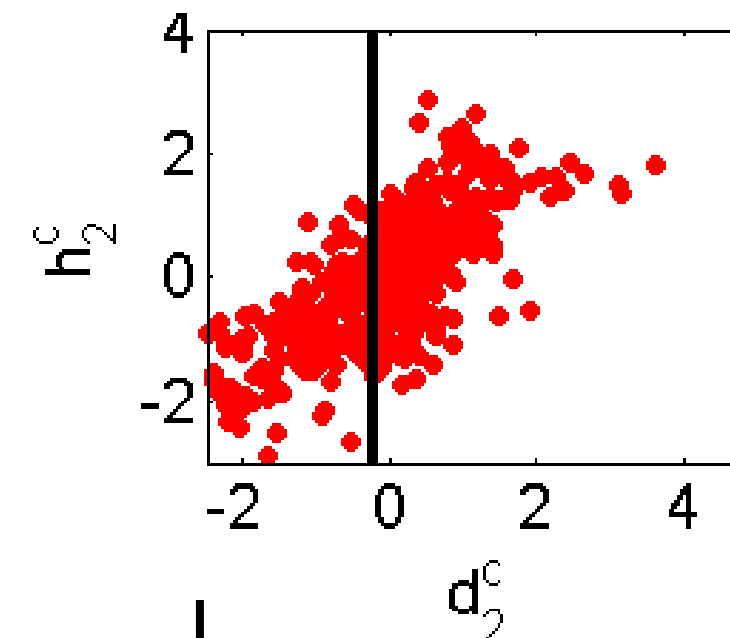
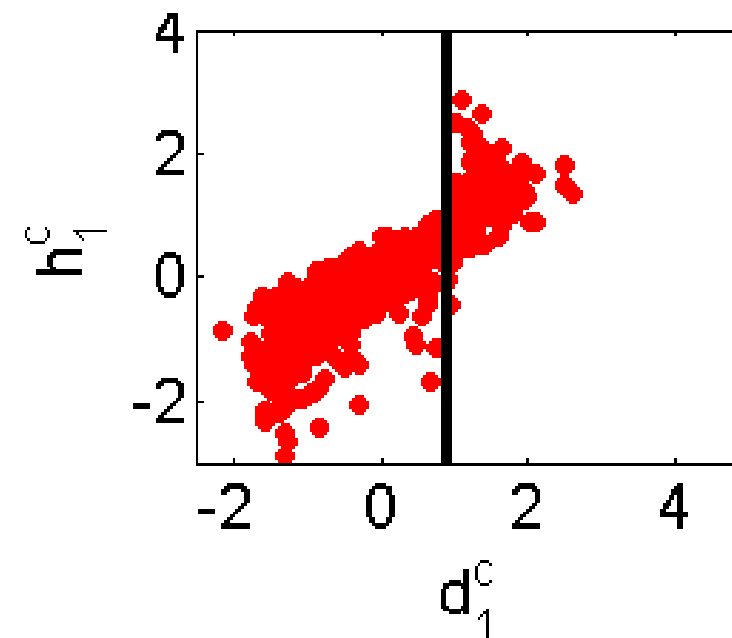
BAYESIAN EVIDENTIAL LEARNING

Finding a direct relationship between data and prediction

1. Dimension reduction (PCA)



2. Linearization (CCA)



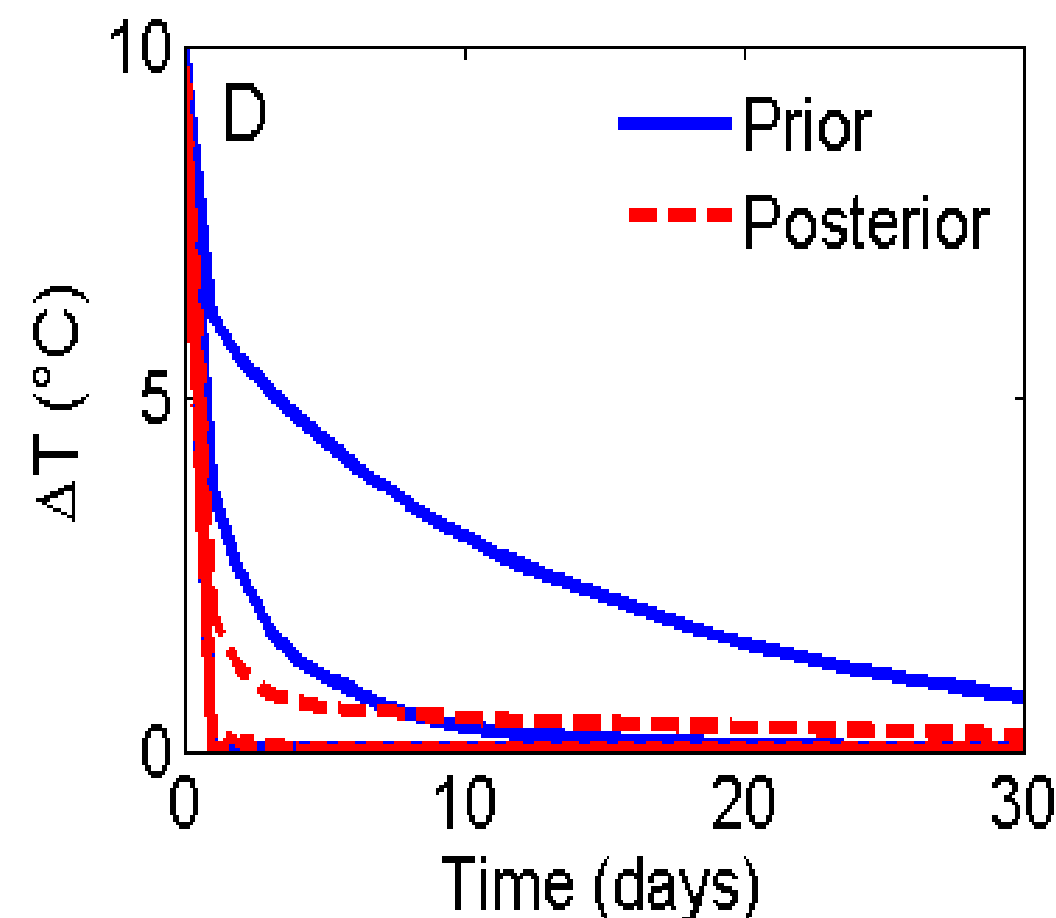
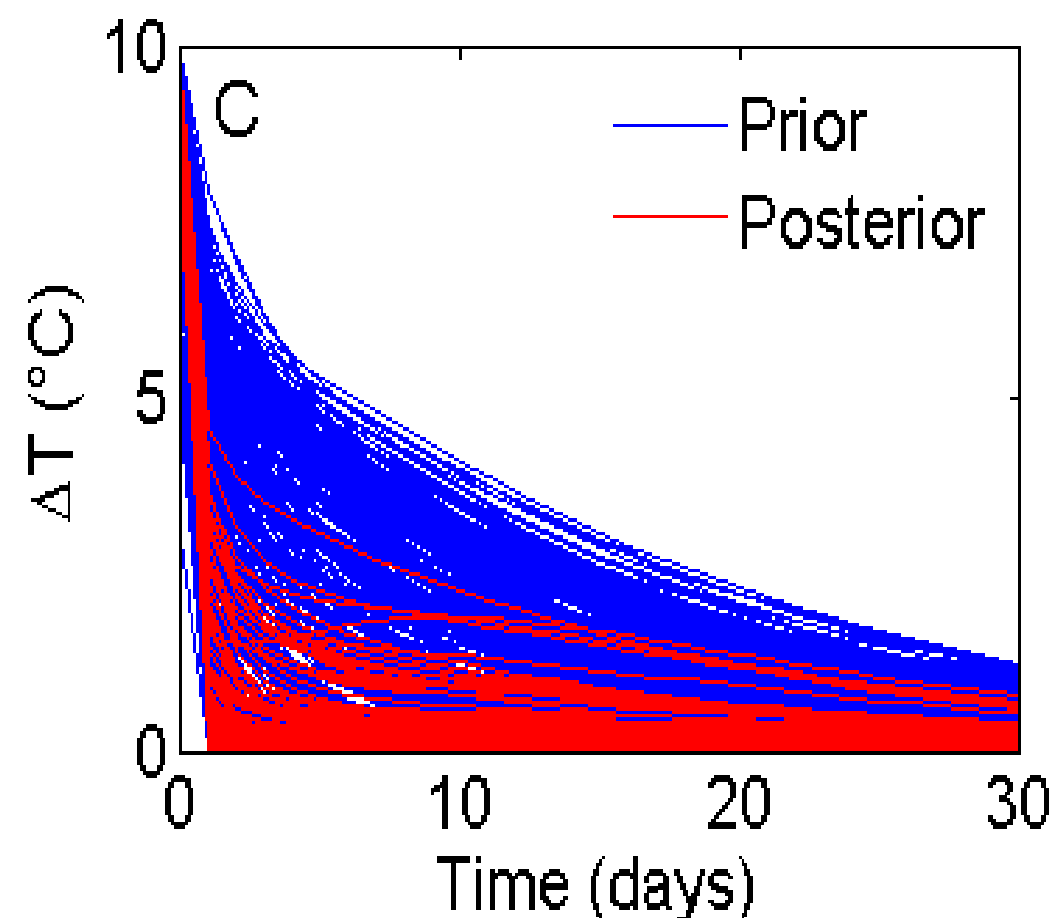
● models from the prior | field observations

(Hermans et al., WRR, 2018)

BAYESIAN EVIDENTIAL LEARNING

- 1) It is « easy » to solve the linear relationship in reduced dimension and generate samples
 - 2) We back-transform the samples in the original space
- The heat storage capacity of the aquifer is low
 - No distinction between geophysical and hydrological data
 - Everything is contained in the prior and forward model

(Hermans et al., WRR, 2018)



CONCLUSION

- Geophysics is an amazing tool to reveal spatial heterogeneity, but...
 - Resolution is limited
 - Discriminating facies comes with uncertainty
 - Using adapted inversion strategies is needed
- Geophysics can be used to identify subsurface scenarios
 - No need for inversion
 - Reduces prior uncertainty
- Geophysical data can be integrated in hydrological models using different approaches
 - Coupled vs uncoupled (effect of inversion and hidden parameters such as petrophysics)
 - Limitation of inversion also applies to hydrology (smoothing, deterministic approach)
 - Stochastic approaches adapted for uncertainty analysis
 - BEL offers a straightforward framework to include geophysical data

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