



GSEU

GEOLOGICAL SERVICE | FOR EUROPE

INTRODUCTION



Funded by
the European Union

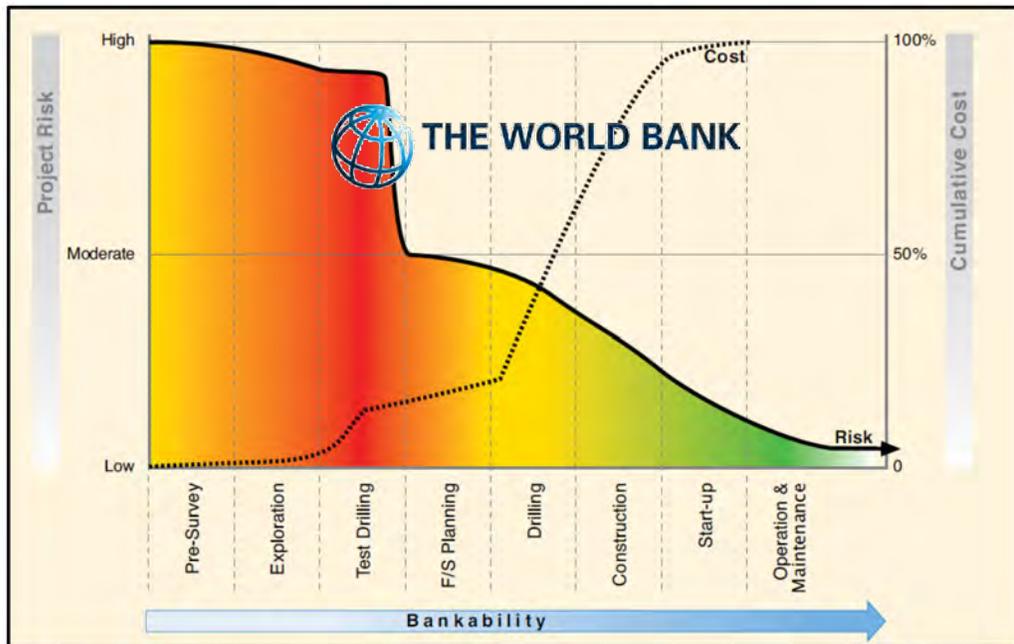


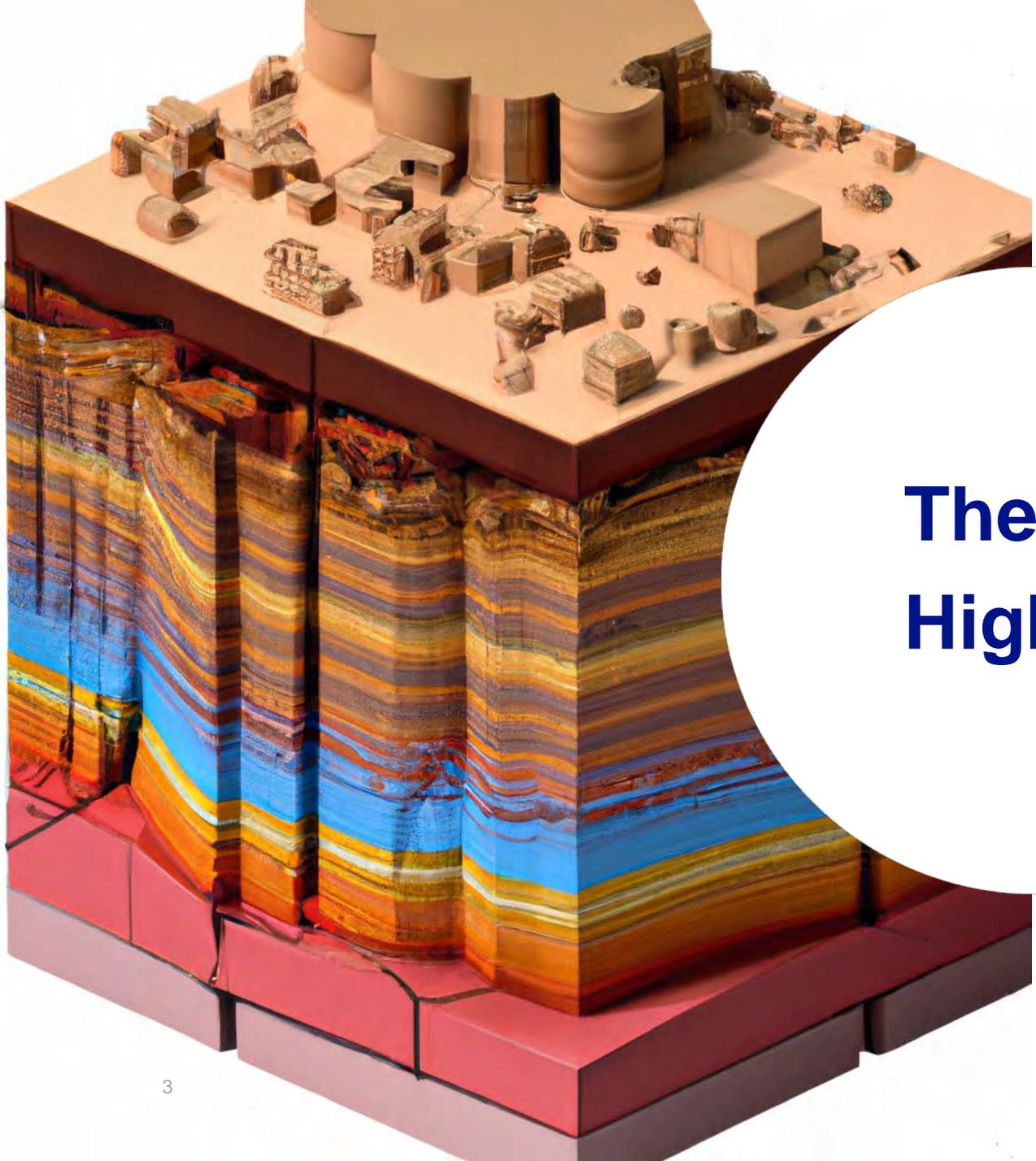


Why a Geological Service for Europe?

FINANCIAL TIMES
EU sounds alarm on critical raw materials shortages

Europe's groundwater – a key resource under pressure
Europe's groundwater — a key resource under pressure
 European Environment Agency 





**There is a Critical Need for
High-Quality Subsurface Data!**



Objective

The overall objective of the **GSEU** project is to establish a **Geological Service for Europe** as a permanent **collaborative network of European geological survey organisations**.



GSEU will structurally address specific challenges in the **sustainable management of the subsurface** at EU and national level.



From Geological Data to Policy Support

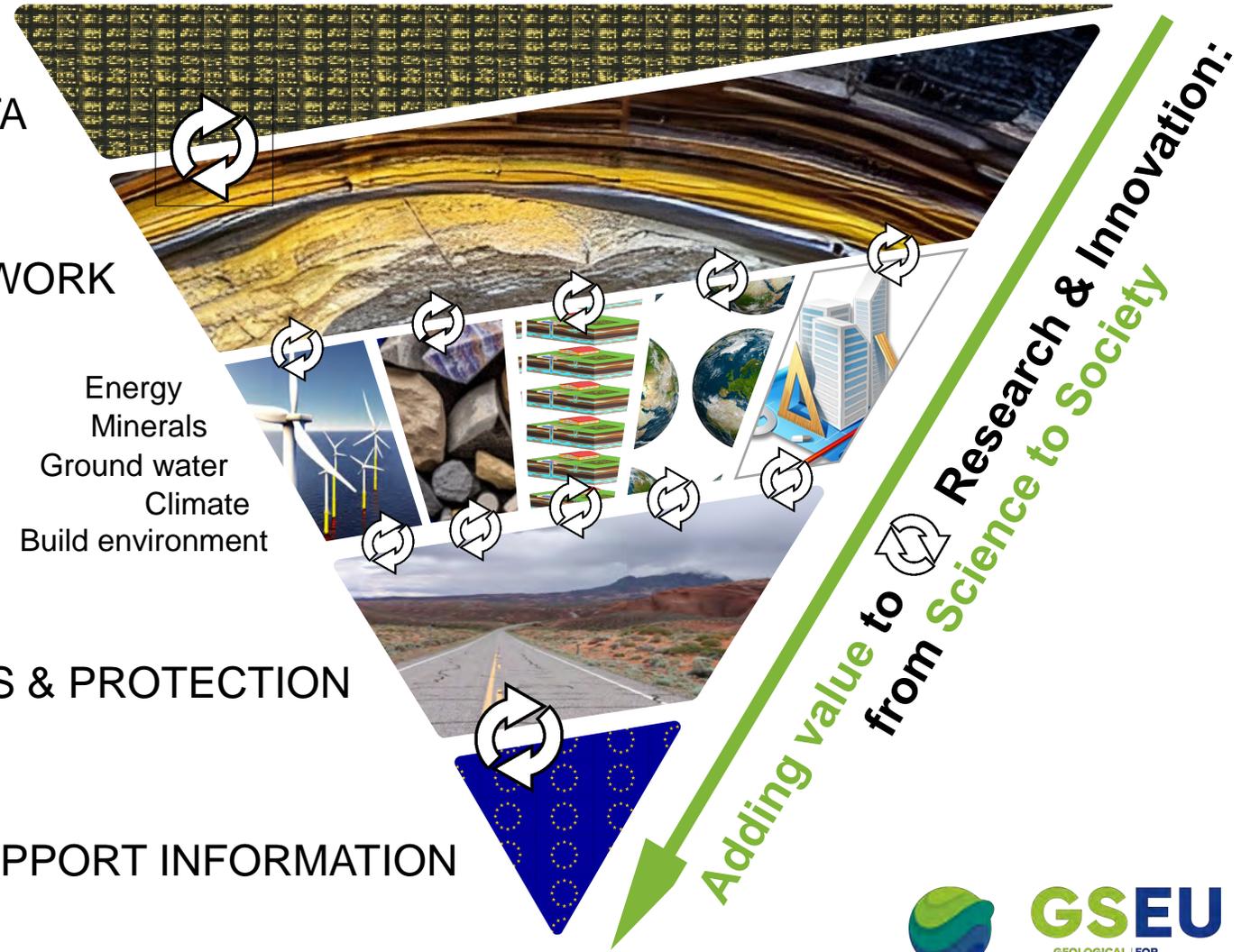
INTEROPERABLE GEOLOGICAL DATA

3D GEOLOGICAL FRAMEWORK

- Energy
- Minerals
- Ground water
- Climate
- Build environment

IMPACTS & PROTECTION

DECISION SUPPORT INFORMATION



*Adding value to Research & Innovation:
from Science to Society*



Past ... Present ... Future ...

2010



2014



2015



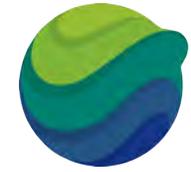
2021



2022



2027





Consortium



Consortium Members



National and Regional Geological Surveys are collaborating to build a **permanent network of organisations** focusing on the planet itself: the earth beneath our feet.

Find all partners at:

<https://www.geologicalservice.eu/about-us/project-partners>



Project Coordinator



The Geological Surveys of Europe



Research

Joint research with EU policy impact



Infrastructure

Harmonising pan-European geological data



Outreach

Sharing knowledge, capacity and research infrastructure

EuroGeoSurveys is a not-for-profit organisation representing the Geological Surveys of Europe.

Through the collaborative research and activities of Expert Groups and Task Forces, and the provision of open-access, harmonised geological data infrastructure, **EGS provides the European Institutions**, regulators, industry, and the public, **geoscientific data-based advice** to address key societal challenges.



Pan-European Challenges



Cross-border Solutions

In order to address **transnational** and **continental-scale subsurface problems** we need to be able to zoom out and go beyond national borders.

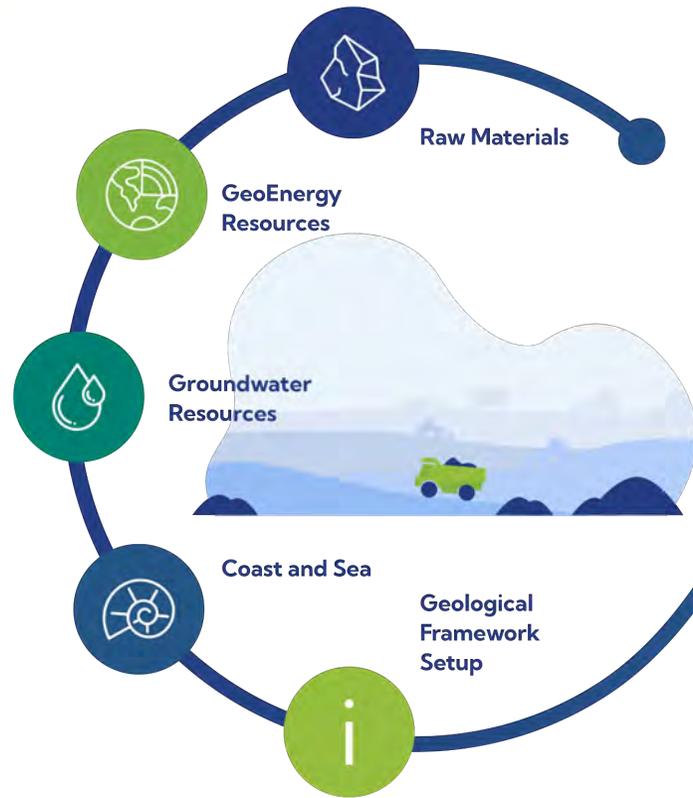




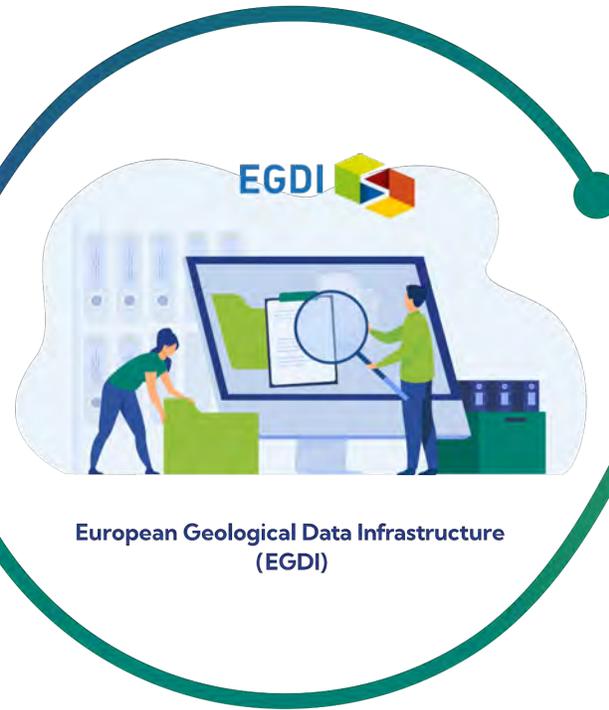
Project Structure



Project Structure



Developing Harmonised Data & Information Service



Developing Information Structure



Communication, Dissemination, Exploitation & Outreach

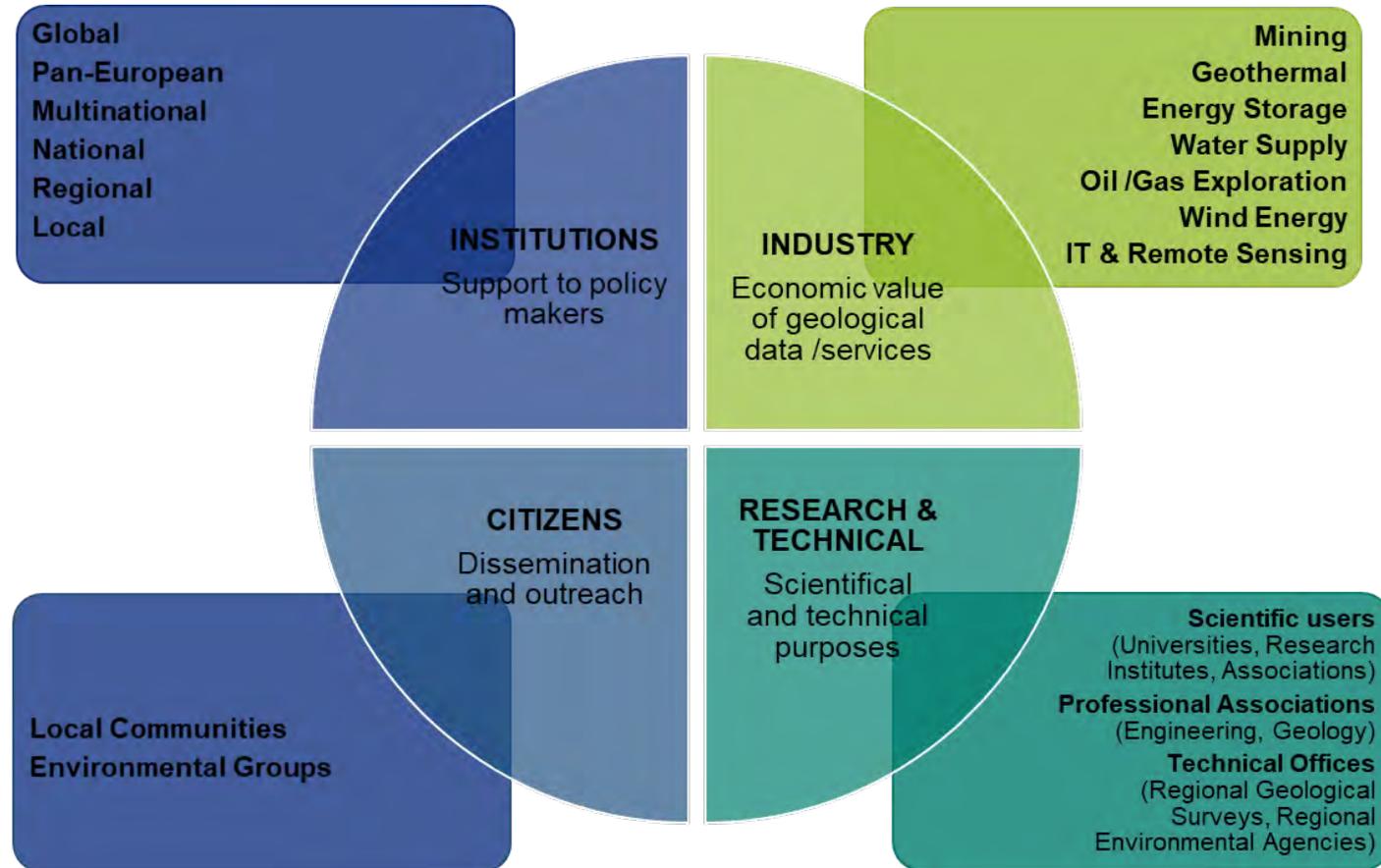
Maximise Social Impact





Stakeholder Engagement

We aim to inform and support a broad range of stakeholders through a programme of communication, dissemination and exploitation – to raise awareness of the critical value of the earth beneath our feet and its role in a sustainable future.





**Bringing the subsurface into the light -
drawing together the baseline data and
knowledge needed to manage Europe's
natural resources and reach Net Zero**



GSEU

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the European Union





Uncertainty Quantification and Sensitivity Analysis for Informed Decisions with Geological Models: Open Tools and Open Questions

GSEU Workshop

Florian Wellmann, Miguel de la Varga, Denise Degen, Zhouji Liang, Jan von Harten, Nils Chudalla, Christin Bobe, Kaifeng Gao, Jian Yang, David Nathan, Jan Niederau, Peter Ahtziger, Sophie Apts

Numerische Geowissenschaften, Geothermie und Reservoirgeophysik, RWTH Aachen

Abteilungsleiter Georessourcen, Fraunhofer IEG

Terranigma Solutions GmbH

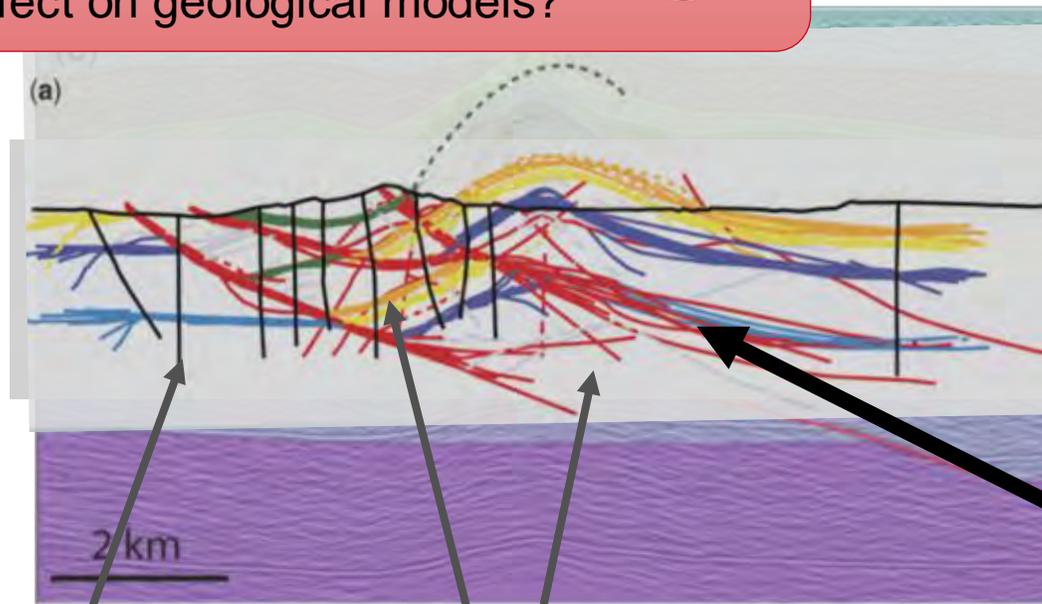


Computational
Geoscience and
Reservoir
Engineering



“What we talk about when we talk about Structural Uncertainties”

Where do these differences come from and what is the effect on geological models?



Boreholes

Relevant geological structures
(Boundary surfaces, faults)

(Bond e

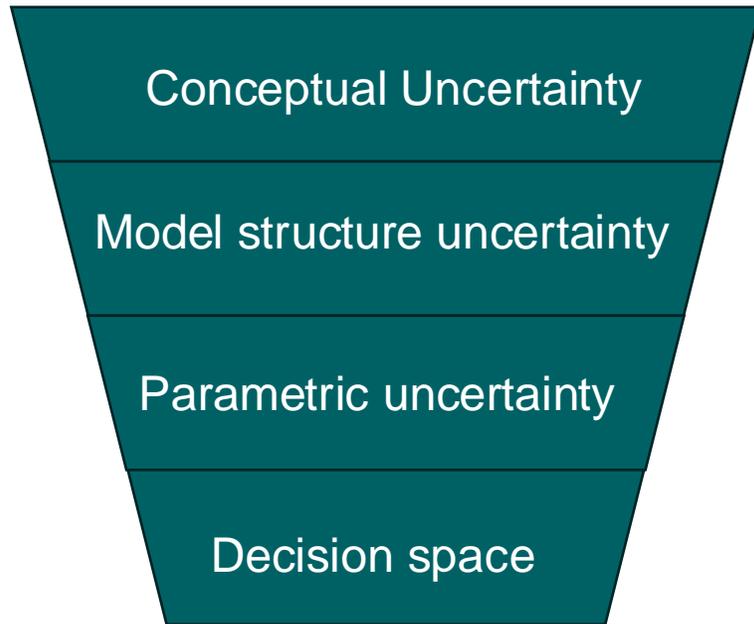
Different interpretations by 19 geologists (mostly > 10 years experience!)

=> Significant uncertainties!

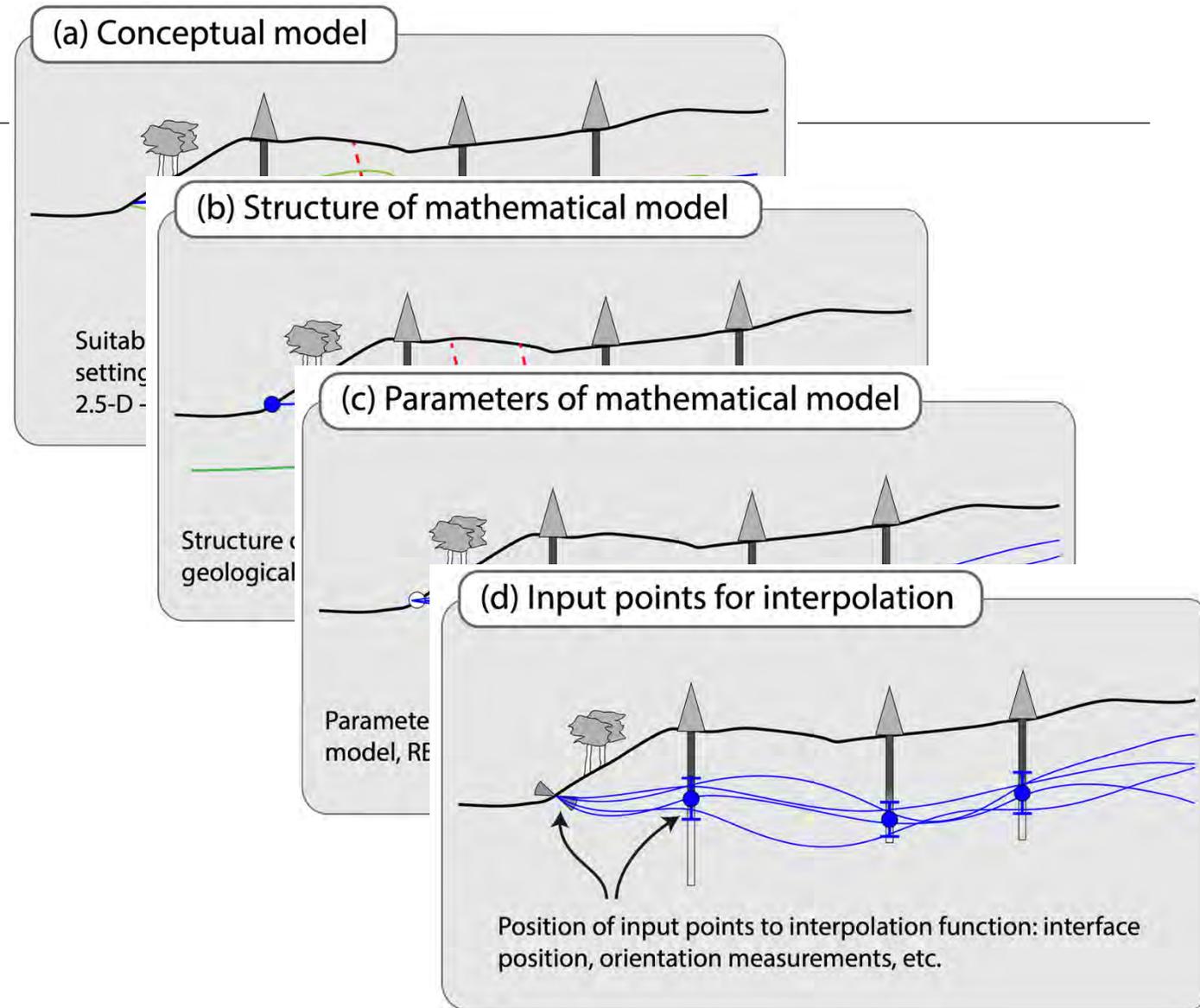
Consider furthermore:

- Often less data available
- Legacy data sets
- Higher complexity...

The “decision funnel”

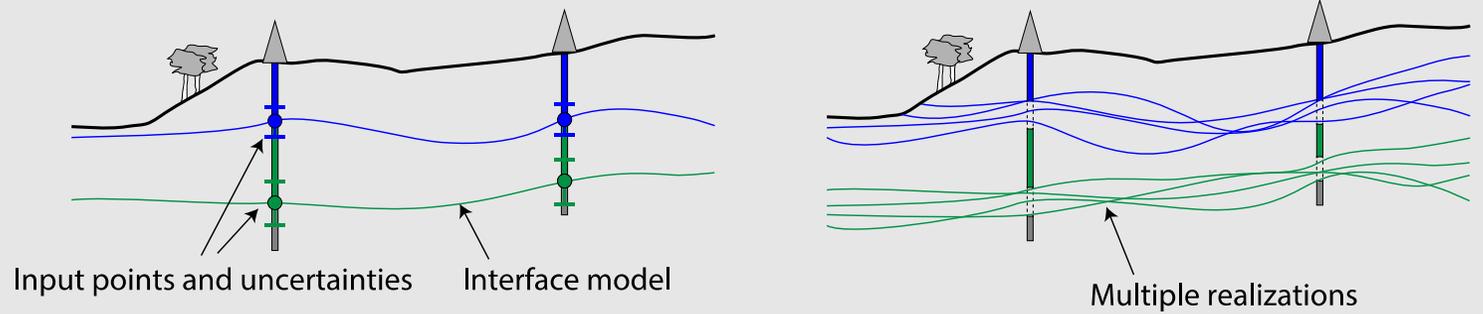


Relevant models

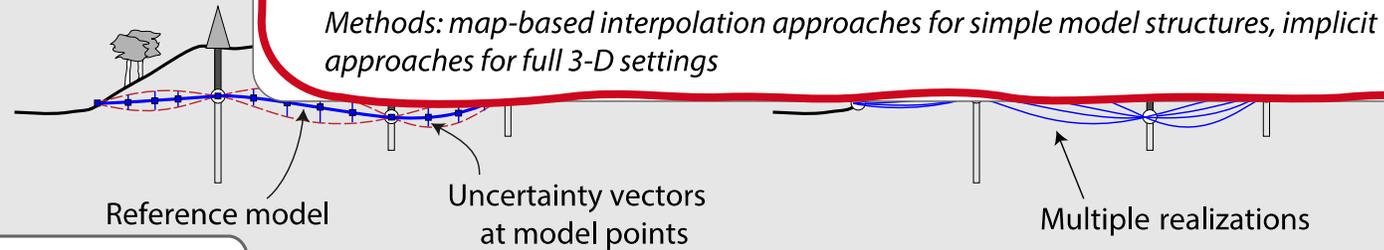


Which uncertainties?

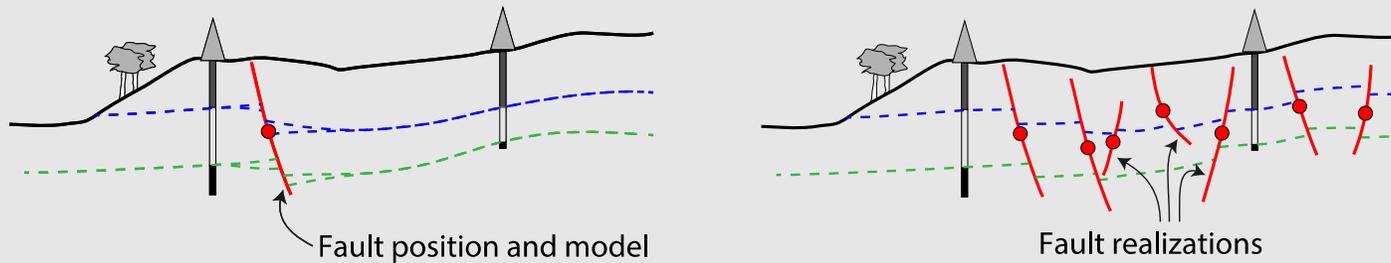
(a) Positions of data points



(b) Uncertainties

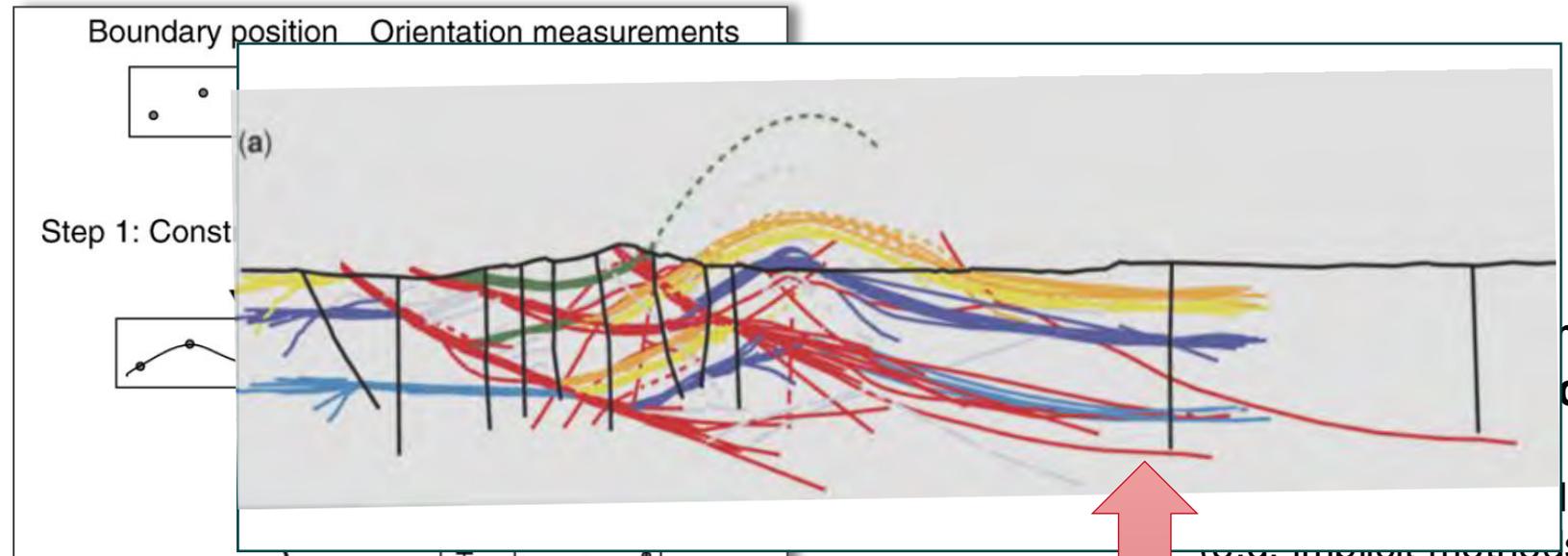


(c) Position and number of faults



Methods: stochastic fault modeling methods, combined workflows for integrated stochastic structural modeling

(Wellmann and Caumon, Adv. Geohys.. 2018)



manual interpretations
 ce

ing method for automation
 (e.g. implicit methods)

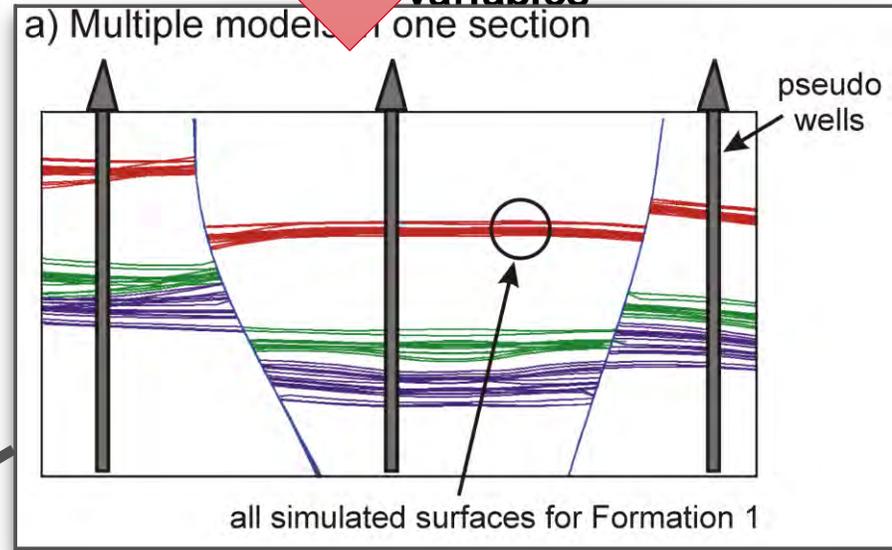
parameters (surface contact
 points, orientation measurements) as **random
 variables**

So, this is comparable....

...really?

Step 3: Create different input data sets

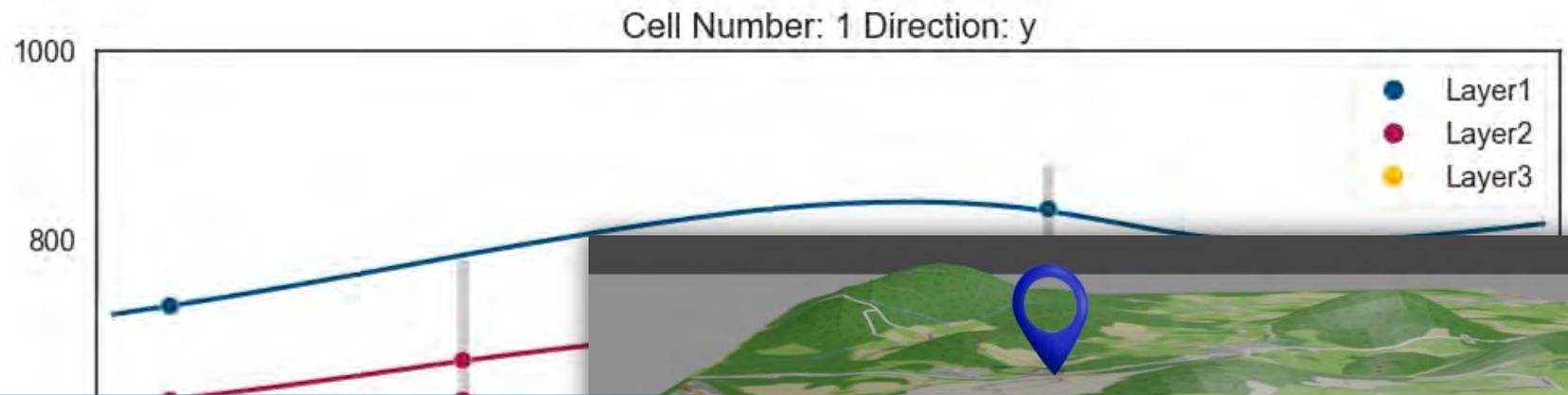
Side note:
 Additional work also on the definition
 of prior distributions, model
 parameterizations and comparisons
 with field studies (e.g.: Heim et al.,
 Brisson et al.)



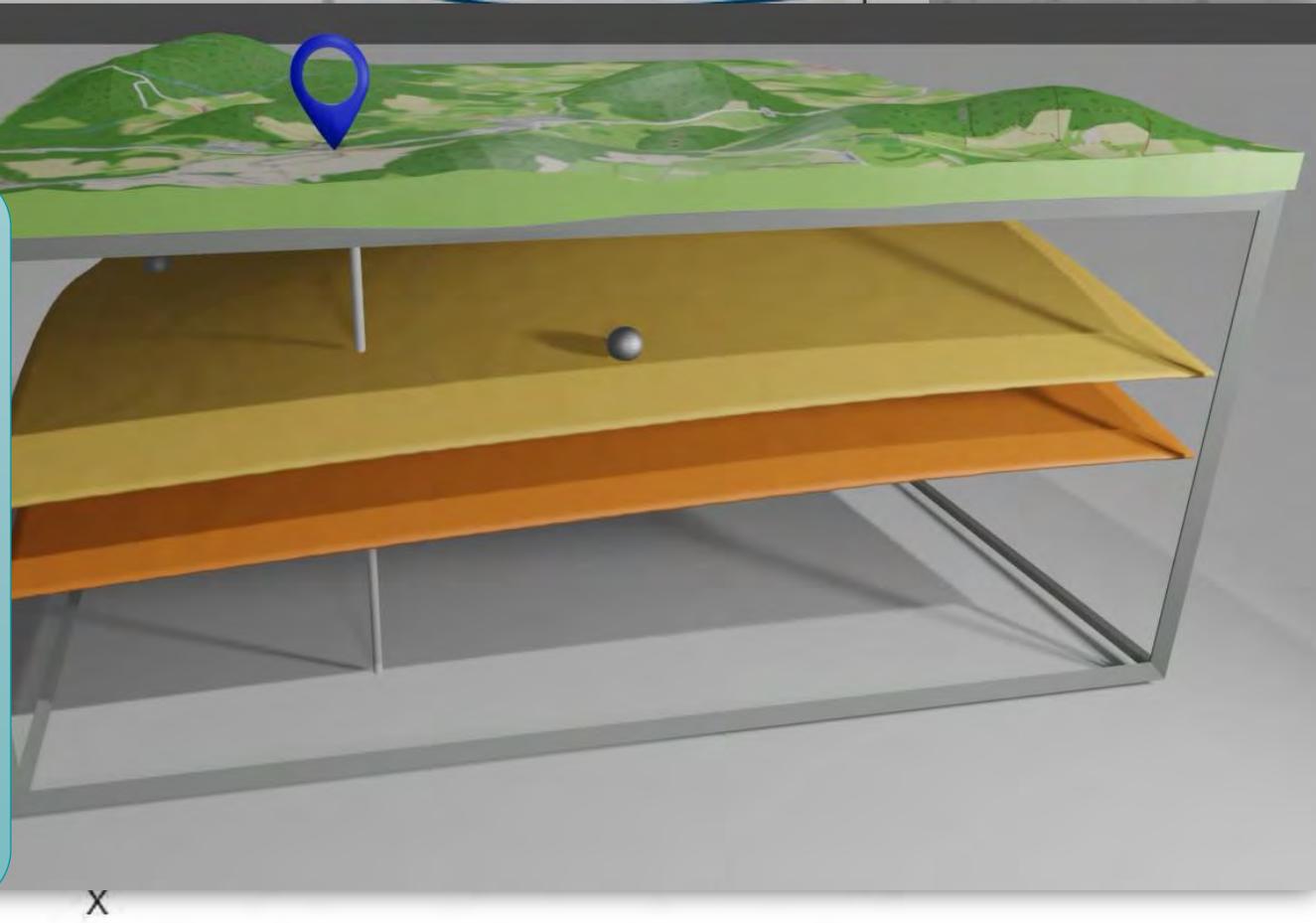
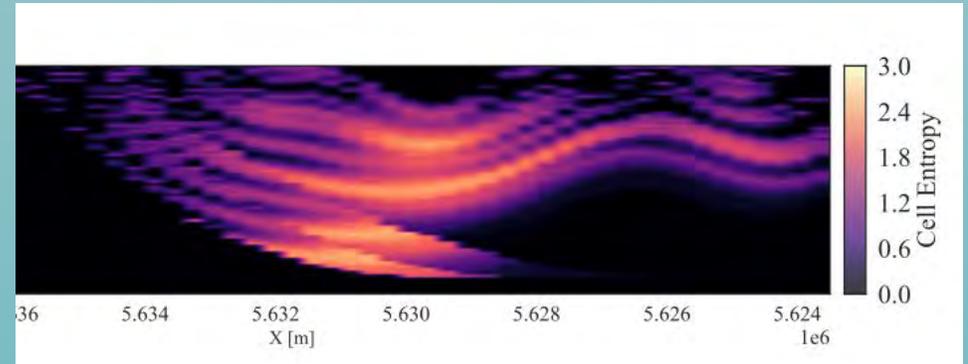
algorithm
 realisations

Step 5: Analyse and visualise uncertainties





Side note:
 Visualization of uncertainty in 3D?
 ⇒ **Information theory**
 (Appl. In Geo: Wellmann & Regenauer-Lieb, 2012)

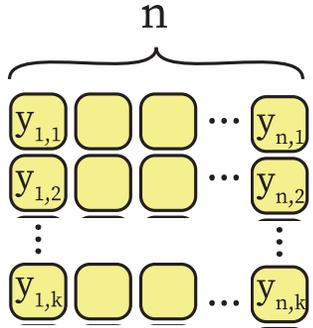
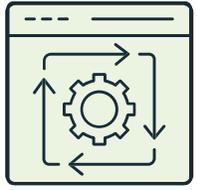
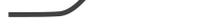
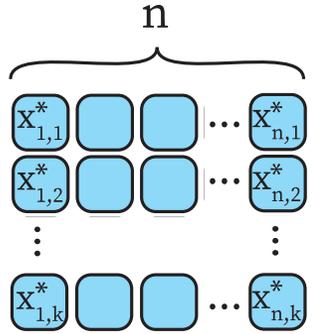
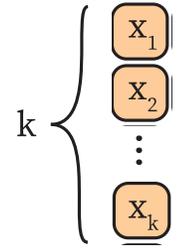


k Parameters

n Input sets x^*

n Model runs

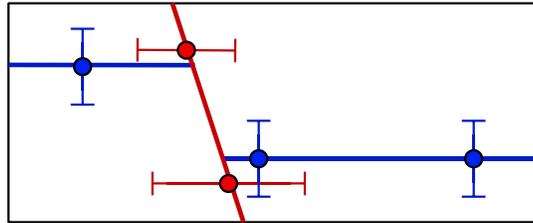
n Outputs



Problems with stochastic forward modeling

- What could possibly go wrong?

Initial model and input points and their uncertainties



Clearly: **not respecting correct parameter correlations**, final evaluation necessary!

(Automatic workflow missing geological knowledge, experience, ...)

(Wellmann et al., 2014)

Geological Modelling as a probabilistic inference problem

- Consider methods to discard models that are **geologically and/or geophysically impossible => characterize performance measures**
- Describe parameters as **random variables with distributions**
- Estimate **parameter distributions and correlations**
- **Quantify uncertainty** in predicted models



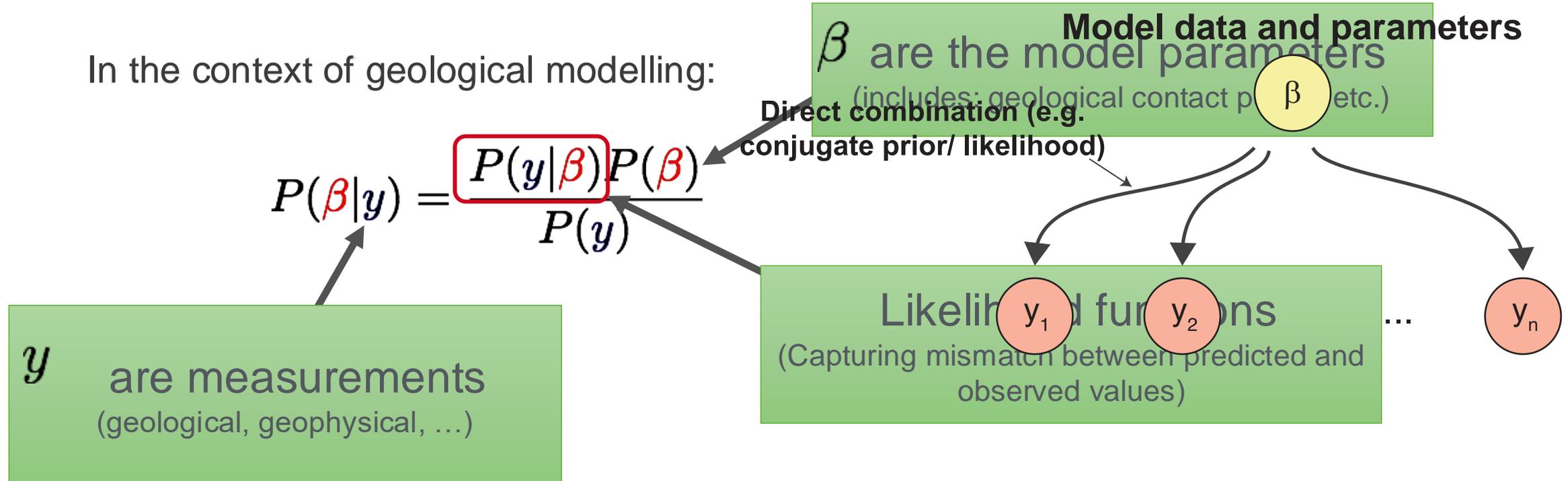
Thomas Bayes
(1701-1761)

=> Consider **geological modelling as a probabilistic inference problem!**



Here the theory:

In the context of geological modelling:

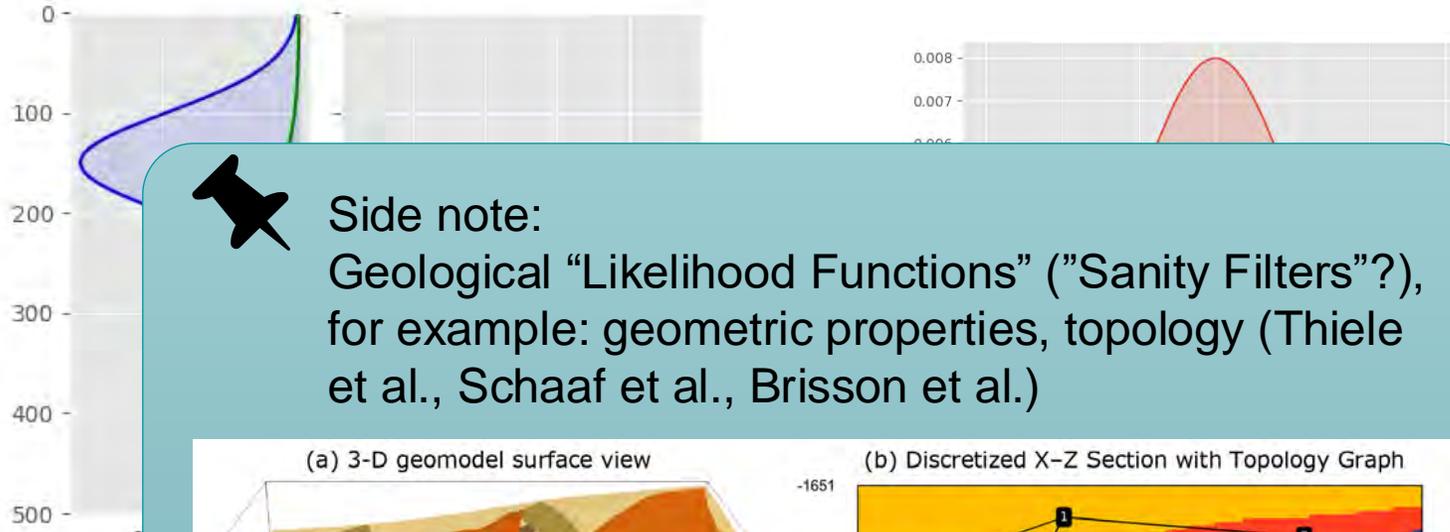


Extension to multiple parameters:

$$P(\beta_0, \beta_1, \sigma | \mathbf{y}) = \frac{\prod_{i=1}^n P(y_i | \beta_0, \beta_1, \sigma) P(\beta_0) P(\beta_1) P(\sigma)}{\int \int \int \prod_{i=1}^n P(y_i | \beta_0, \beta_1, \sigma) P(\beta_0) P(\beta_1) P(\sigma) d\beta_0 d\beta_1 d\sigma}$$

Uncertainty reduction with additional information: a schematic example (PhD de la Varga)

Prior predictive models

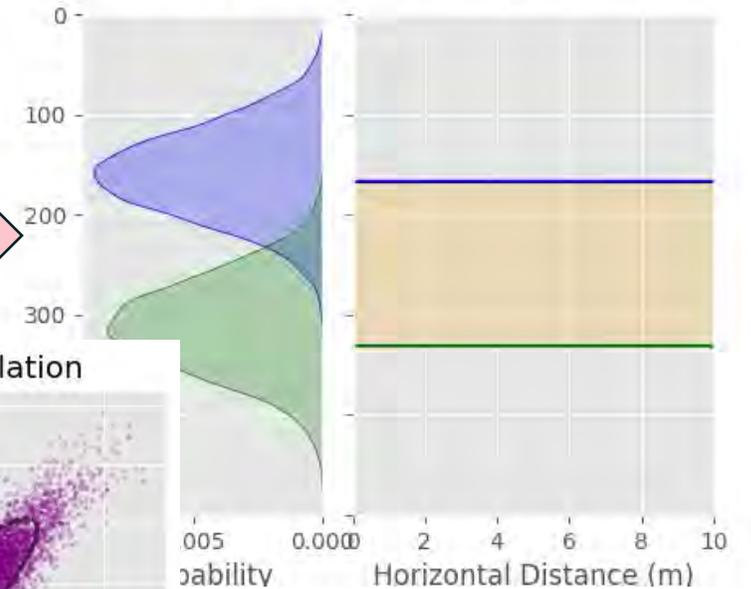


Side note:
 Geological “Likelihood Functions” (“Sanity Filters”),
 for example: geometric properties, topology (Thiele
 et al., Schaaf et al., Brisson et al.)

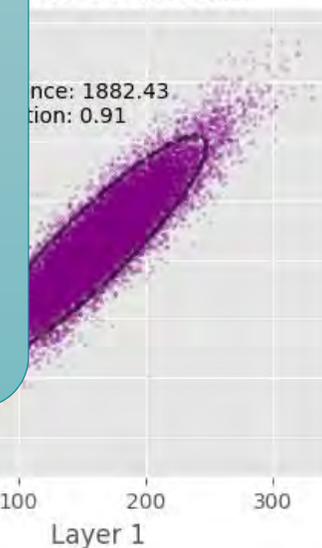
(a) 3-D geomodel surface view

(b) Discretized X-Z Section with Topology Graph

Geological Model with Posterior Distributions



Prior correlation



red layer thickness

(de la Varga & Wellmann, 2016)

- Two horizontal interf.
- Uncertain position

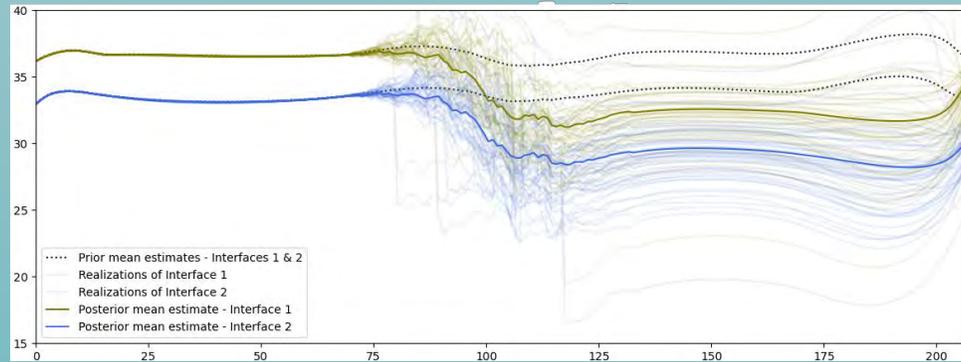
Linking geometric interpolations and geophysics

Model-based geophysical inversion:

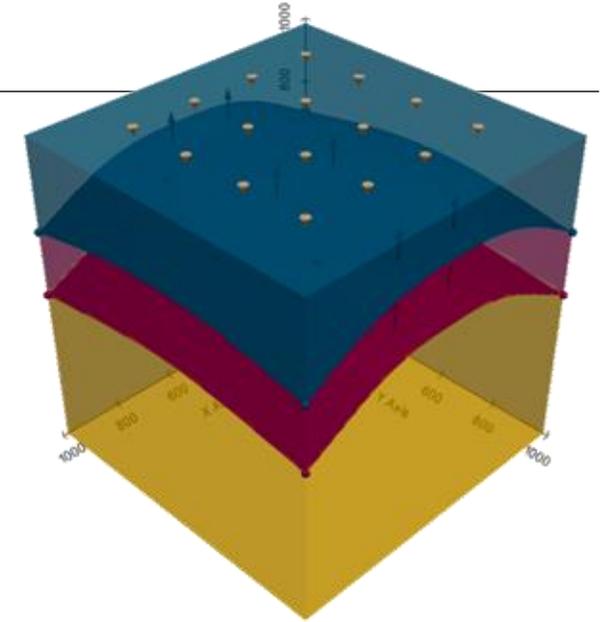
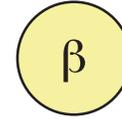
- Start with **initial geological model** (low parameterisation)
- **Assign uncertainties** to input



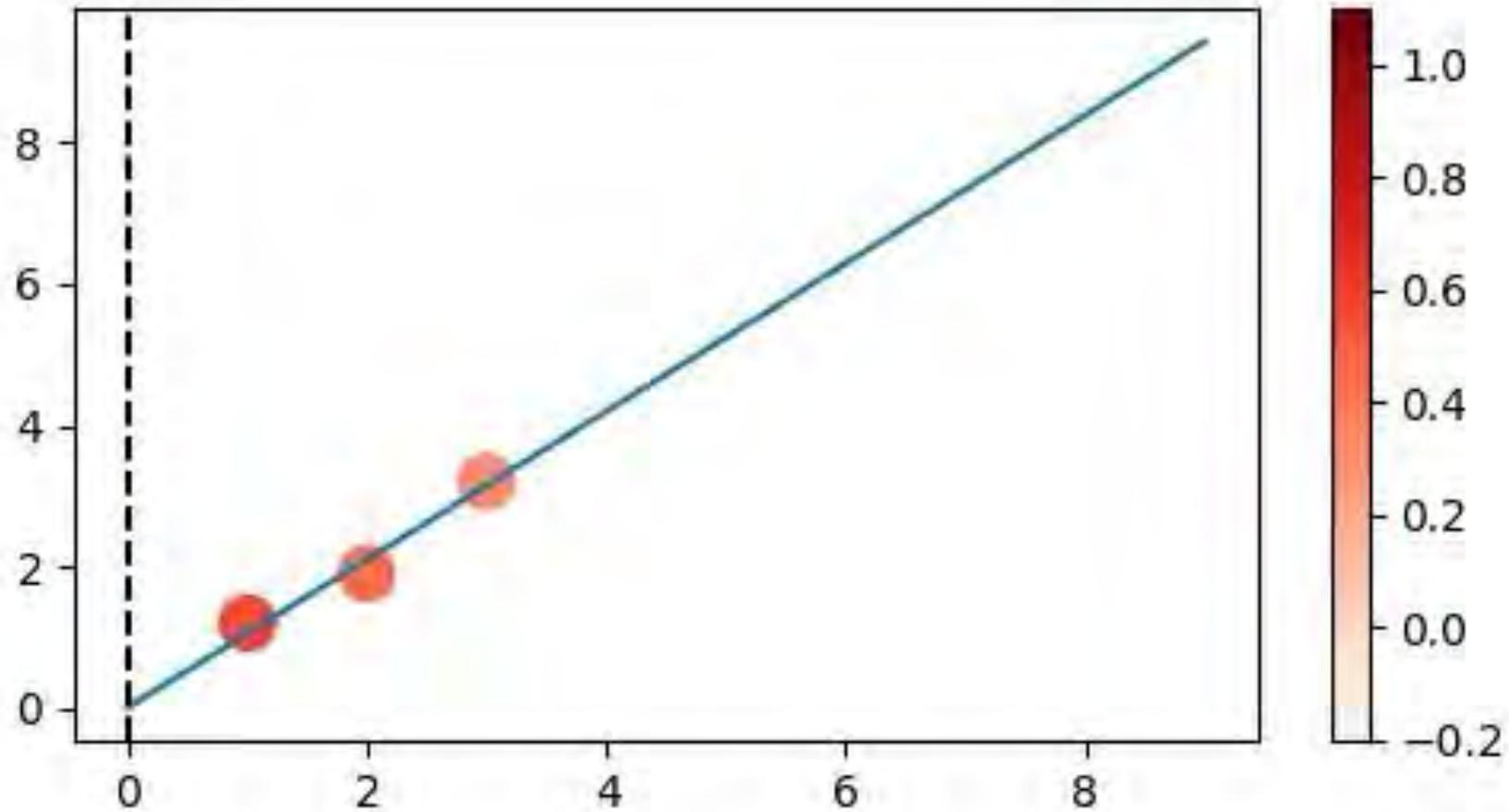
See Bobe et al., (GeoHEAT project),
Liang et al., Balza-Morales et al., ...



Model data and parameters

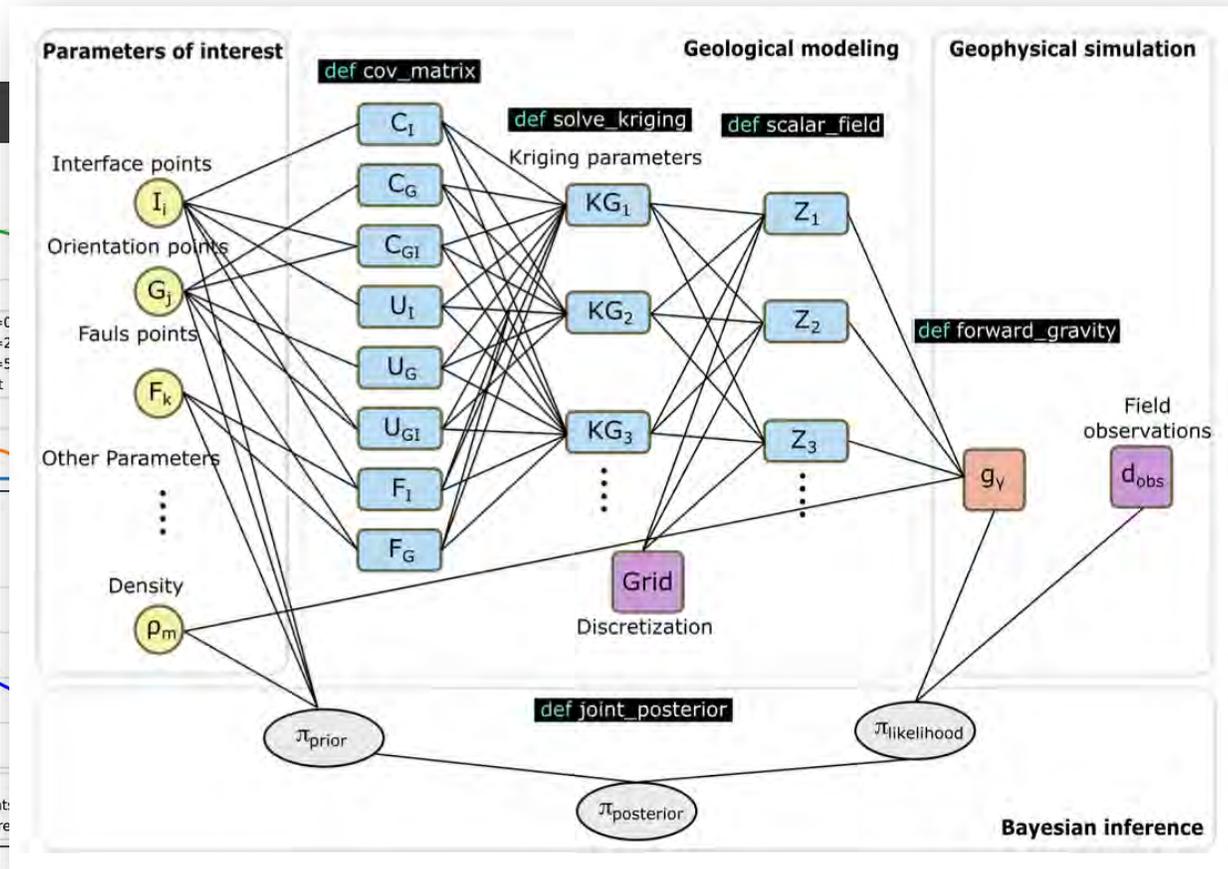
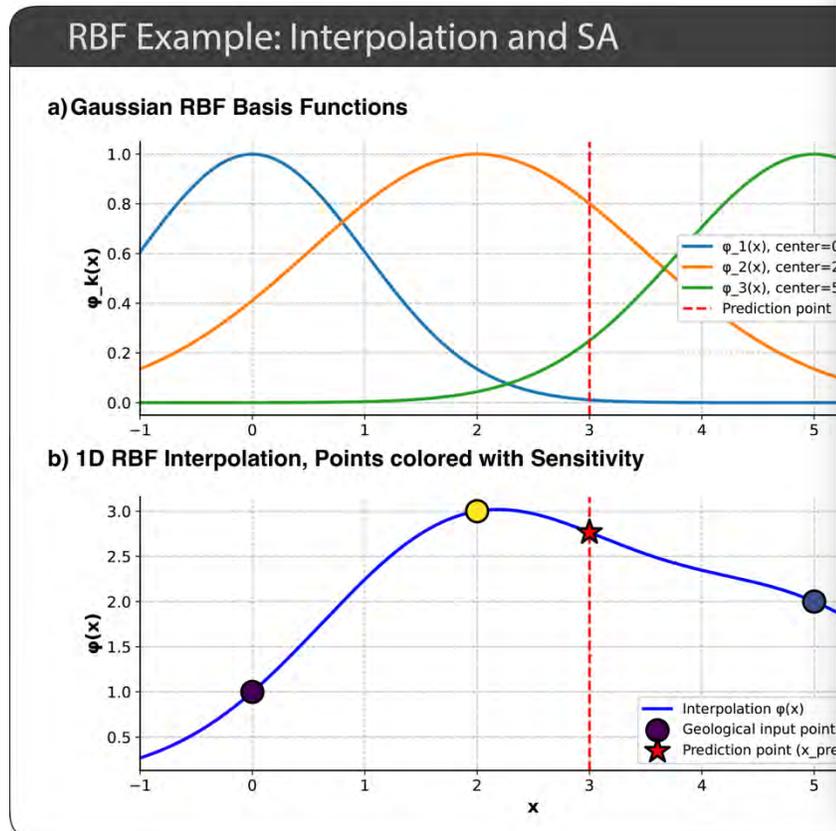


Related question: which *parameters* actually matter?

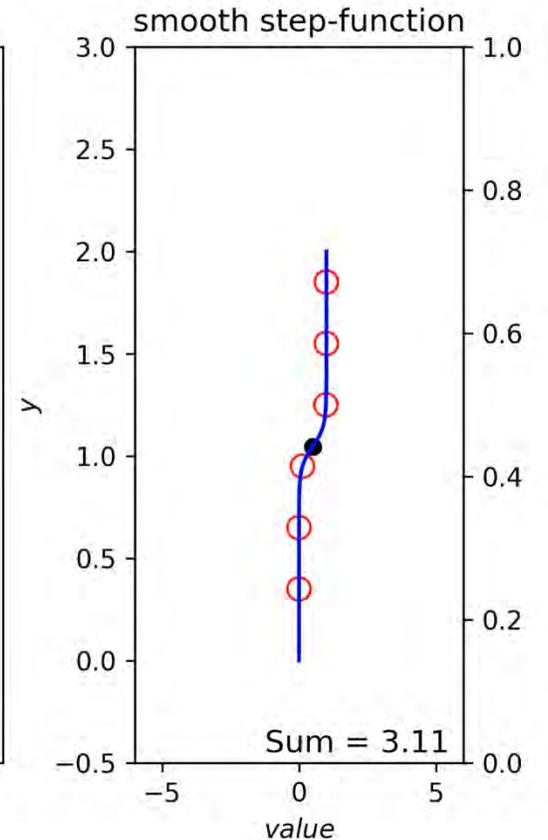
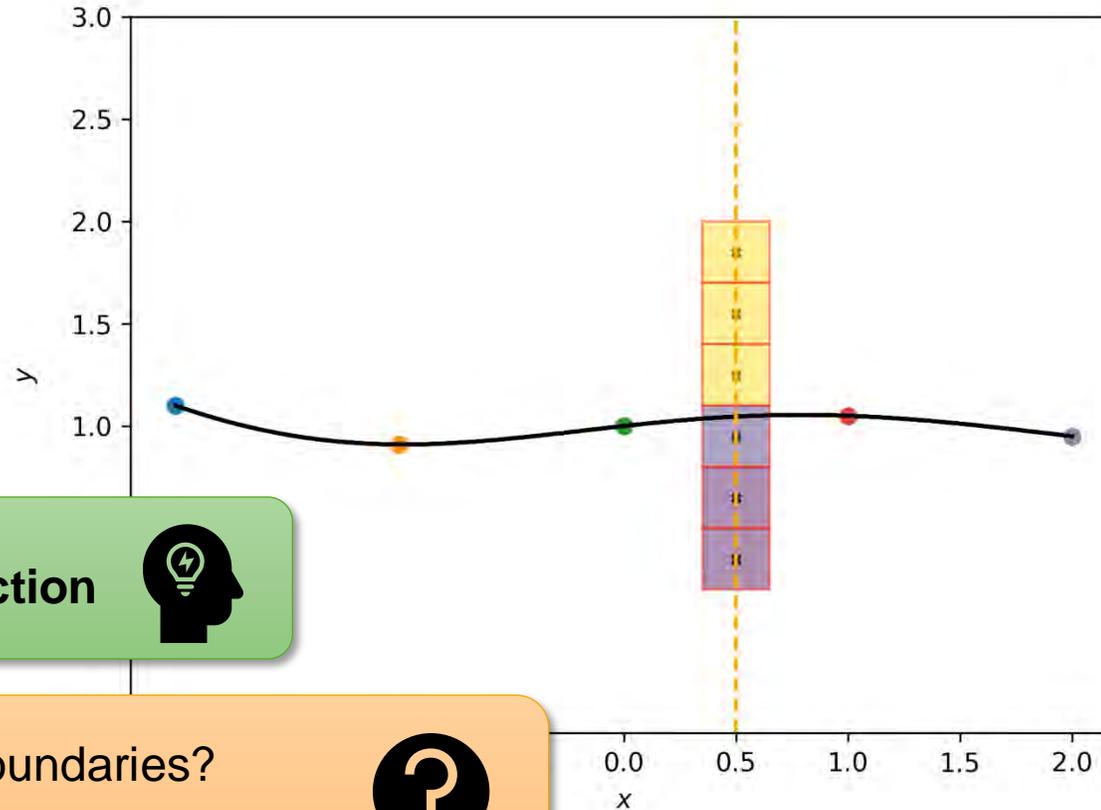
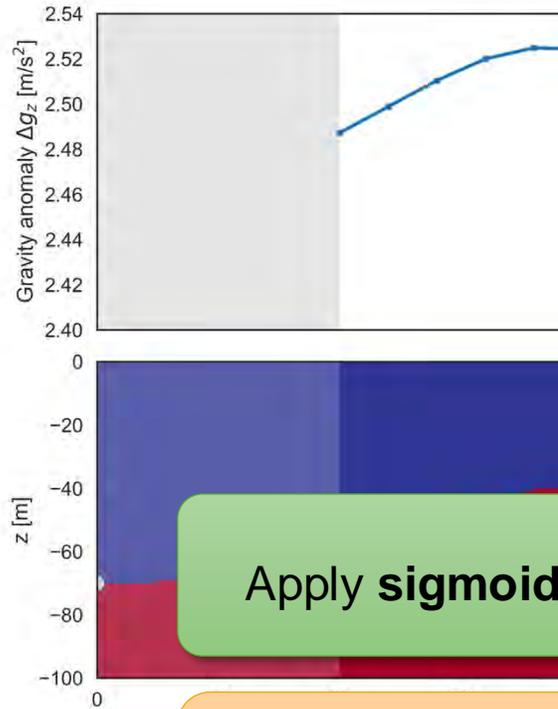


Sensitivity Analysis: using ML developments in Geomodeling (PhD Liang)

- Concept: use modern ML frameworks (PyTorch, JAX, TensorFlow) to enable Automatic Differentiation in Geomodeling (and subsequent tasks):



One important challenge: discontinuities at layer boundaries!

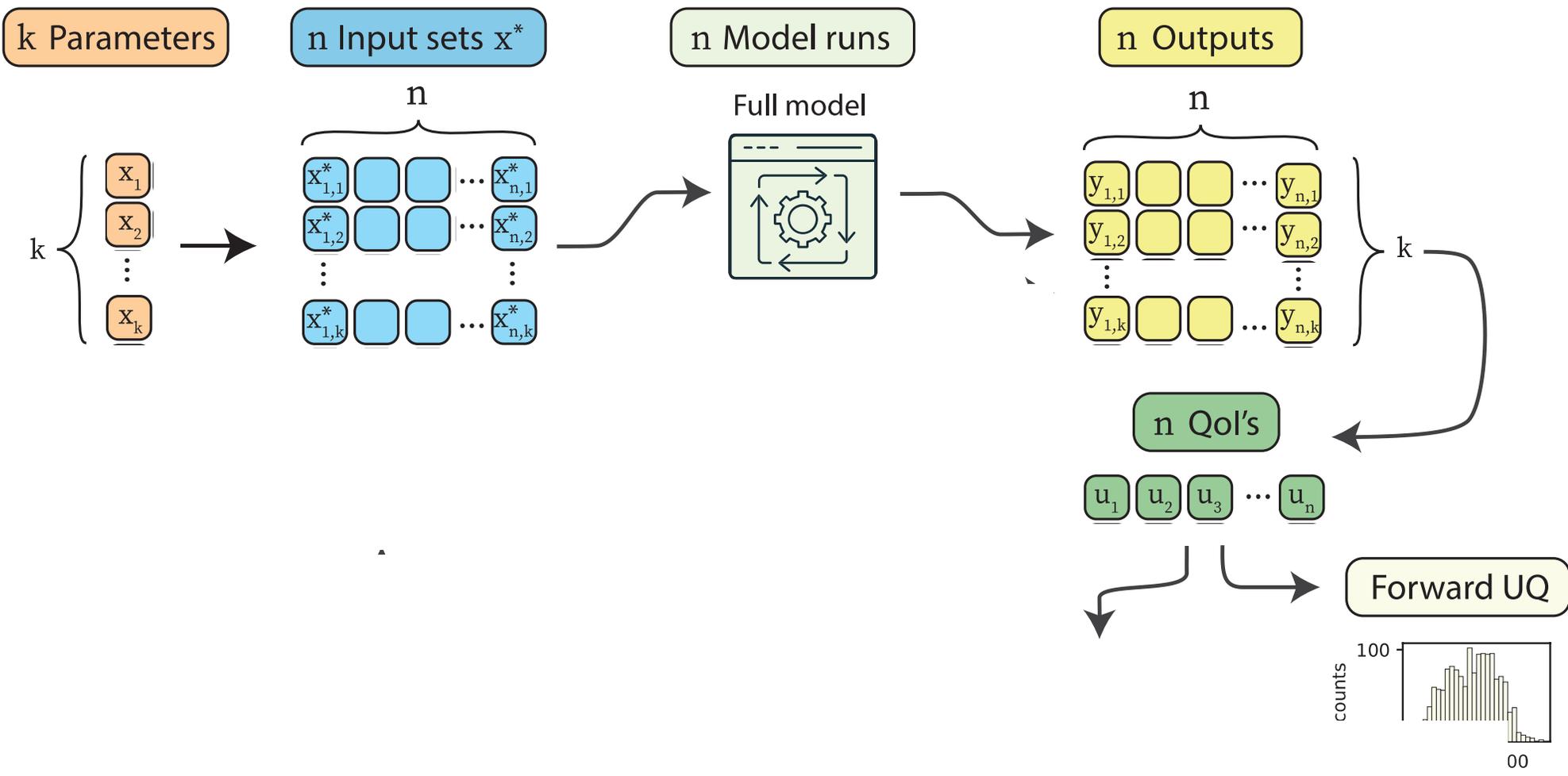


Apply **sigmoid function**

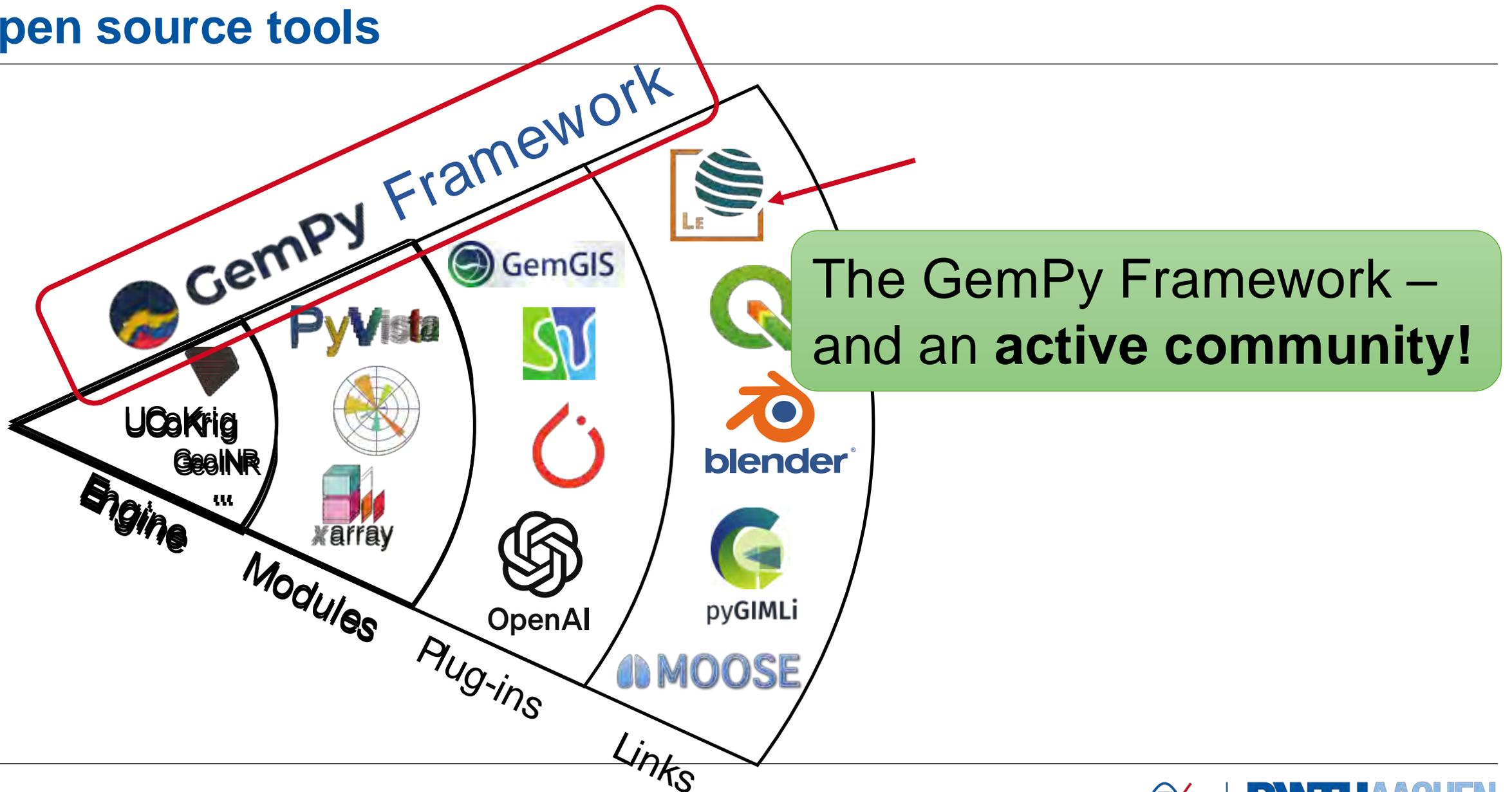


What to do at layer boundaries?
Note: no gradient!





Open source tools



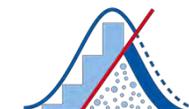
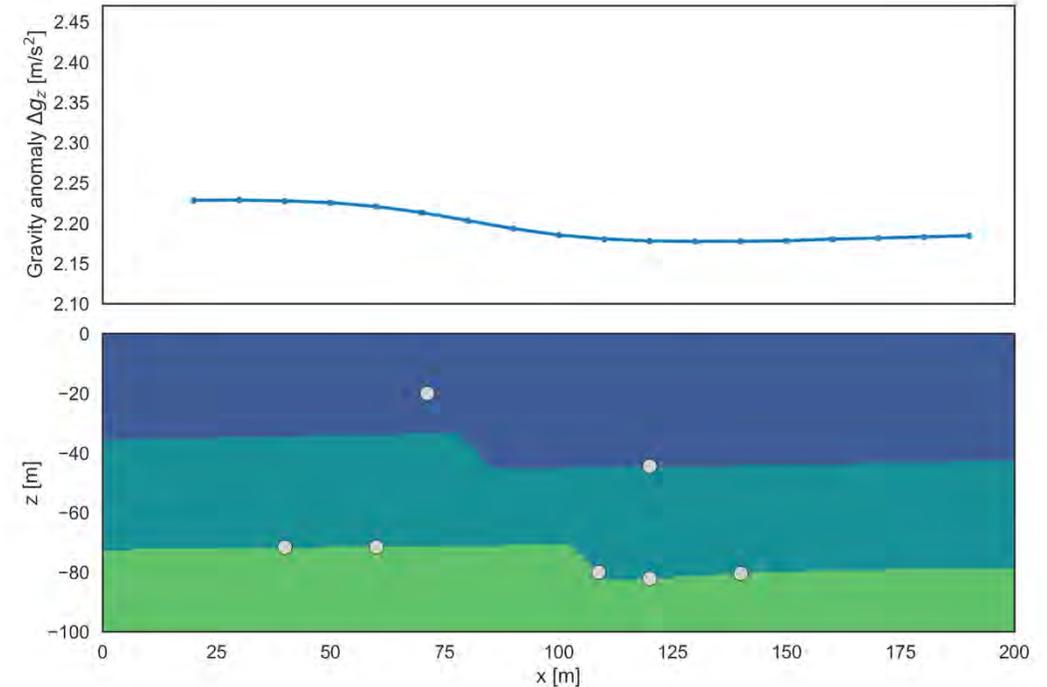
Links to Machine Learning frameworks



TensorFlow

PyTorch

- **Probabilistic geomodeling** at the core of GemPy development, originally in Theano and pymc3, but deprecated
 - **Intermediate work: implementation in TensorFlow Probabilistic (Liang et al.**
 - now in **PyTorch**, one of the most famous Machine Learning frameworks
- => Link to ML frameworks **enables geomodel-based inversion**

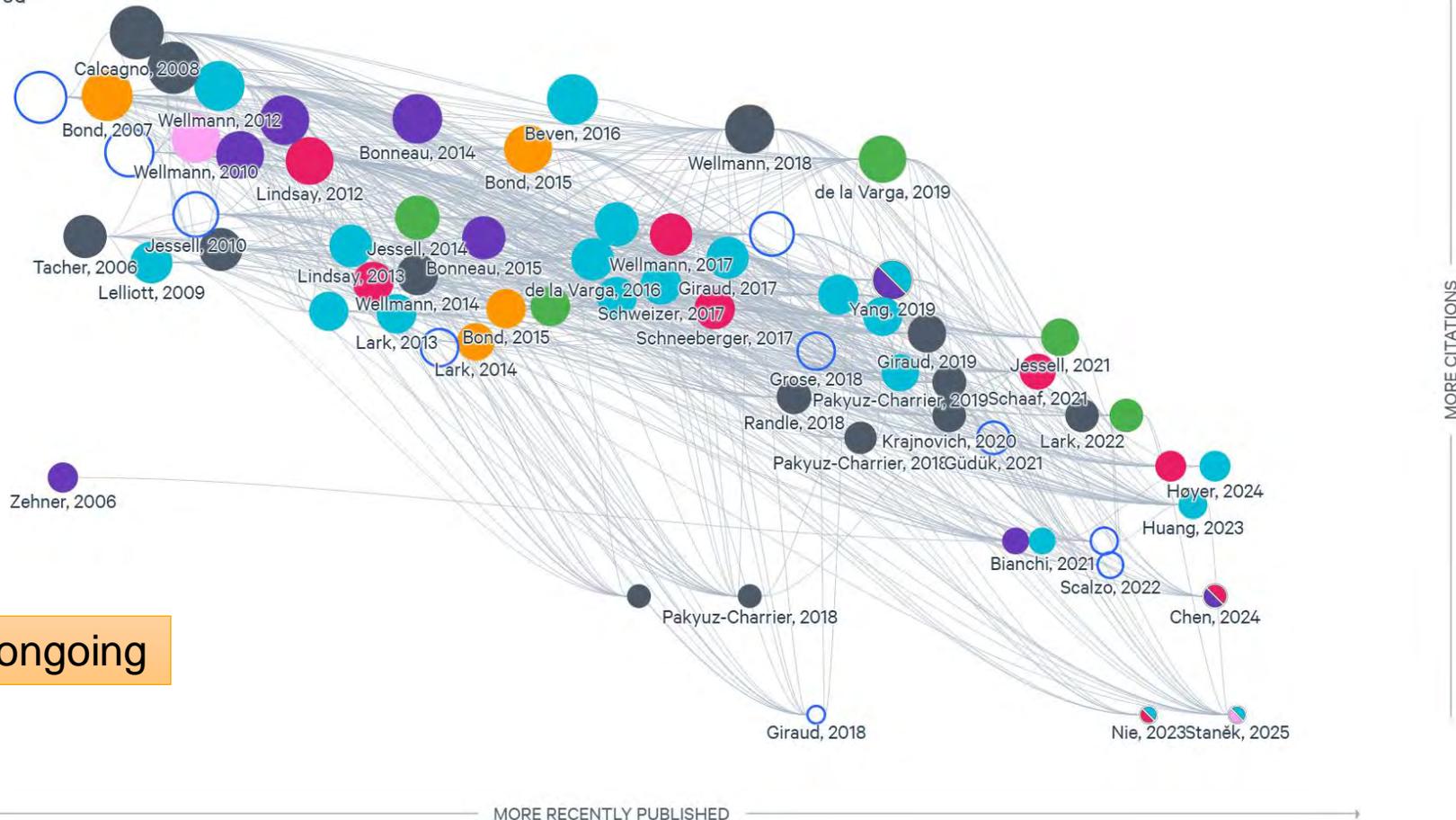


A lot of work on uncertainties in geological models...

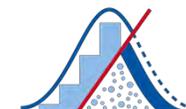
...but still a lot to be done!

Litmaps

- Data uncertainty
- Visualization
- Application
- Algorithm / Method for UQ
- Modeling Software
- Interpretation



Project Eva3D – ongoing



Summary - 🧭 Navigating Geological Uncertainty

1. Geological uncertainty is hierarchical.

- Conceptual assumptions constrain structural models.

- Structural

2. Uncertainty

- sufficient

- **Uncertainty**

3. Sensitivity

- Only un

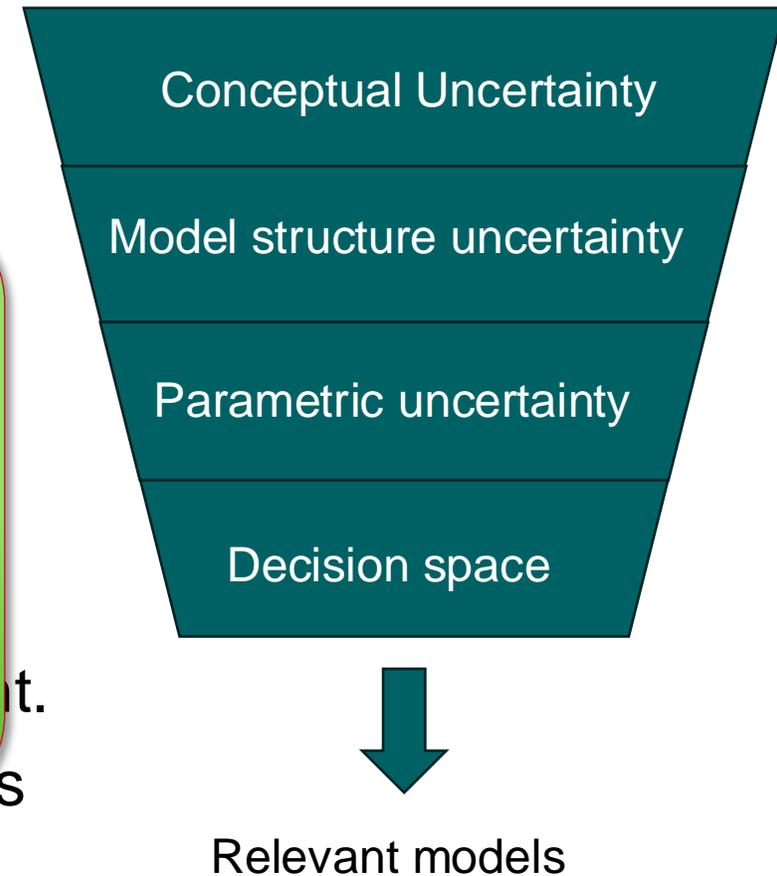
4. Open to

- remain.

- Conceptual uncertainty and decision-relevance are still underdeveloped.

Exciting times to work on open-source geological modeling (and inversion)...

Thank you to GSEU and the workshop organisers – and to you for your attention!



Uncertainty quantification and the importance of model verifiability

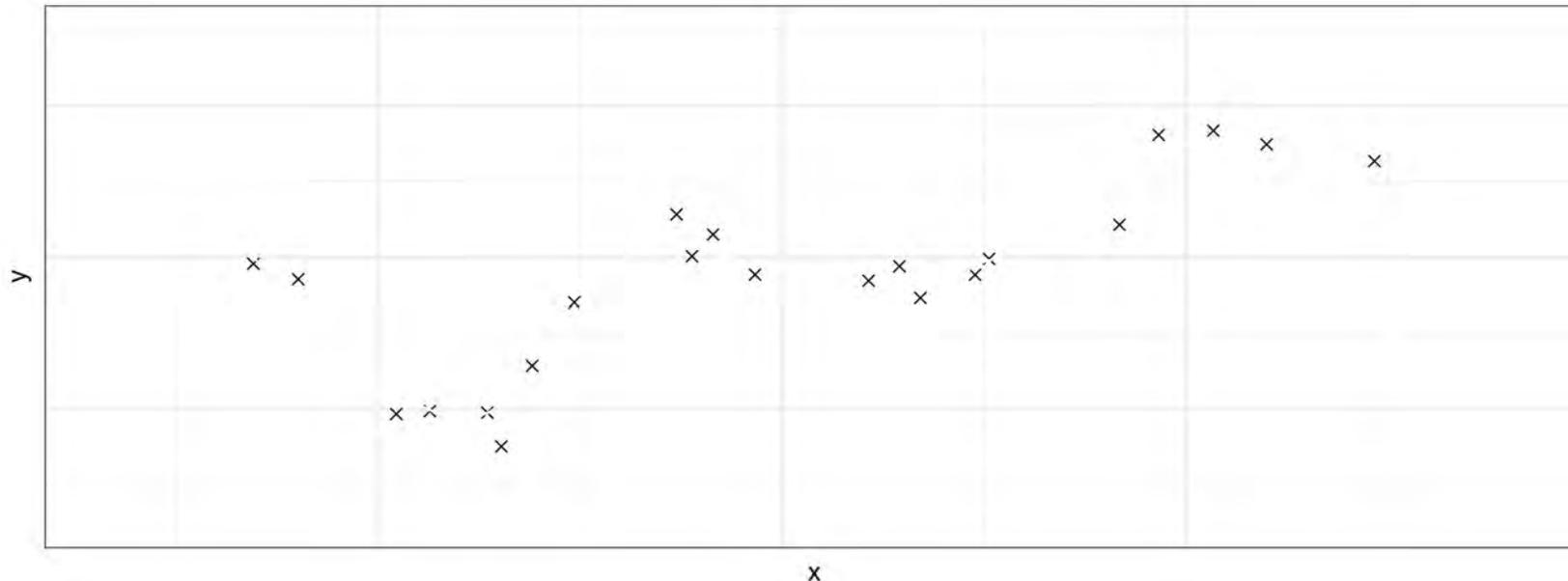
Charlie Kirkwood, University of Exeter
c.kirkwood@exeter.ac.uk

GSEU workshop:
Exploring, Quantifying and Communicating Uncertainties in Geological Models

2nd-3rd March 2026

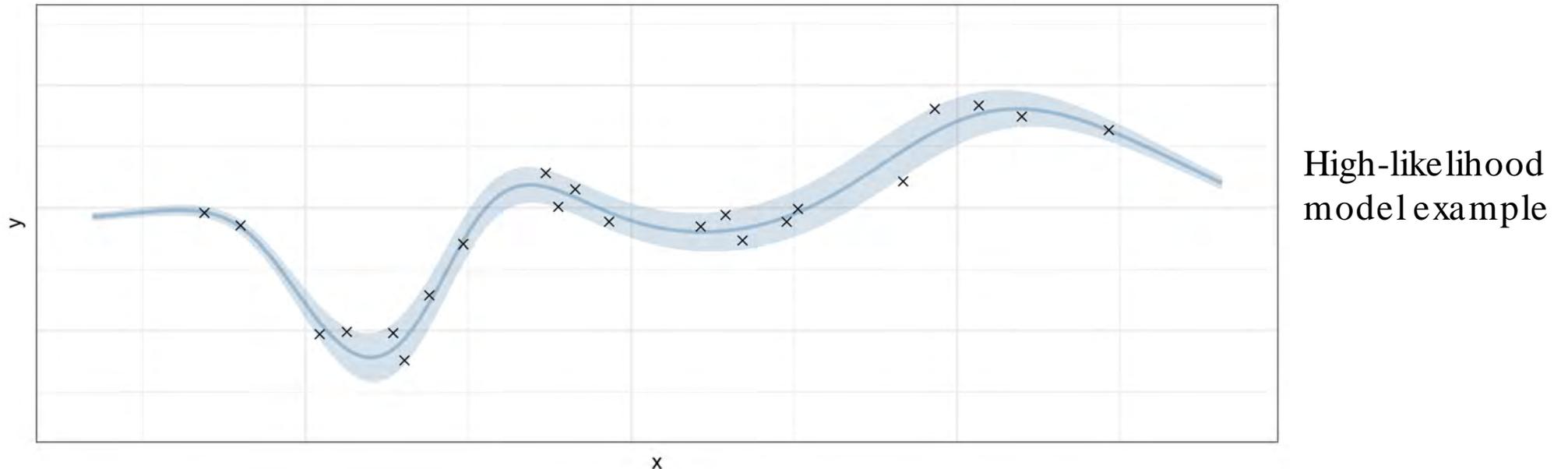
Frequentist vs Bayesian modelling

- In Frequentist statistics maximum likelihood estimation (MLE) would typically be used to fit a model, m , that maximises the likelihood, $P(\text{data}|\text{model})$.



Frequentist vs Bayesian modelling

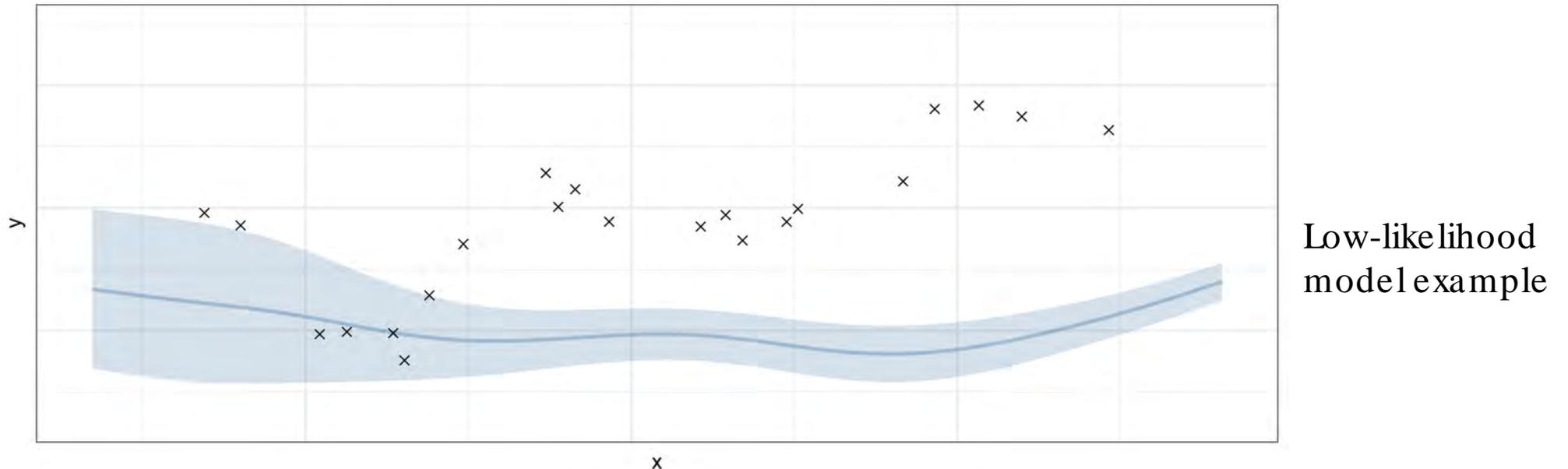
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$$\text{Likelihood} = L(\text{model}) = P(\text{data}|\text{model}) = \prod p(\text{datapoint}_i|\text{model})$$

Frequentist vs Bayesian modelling

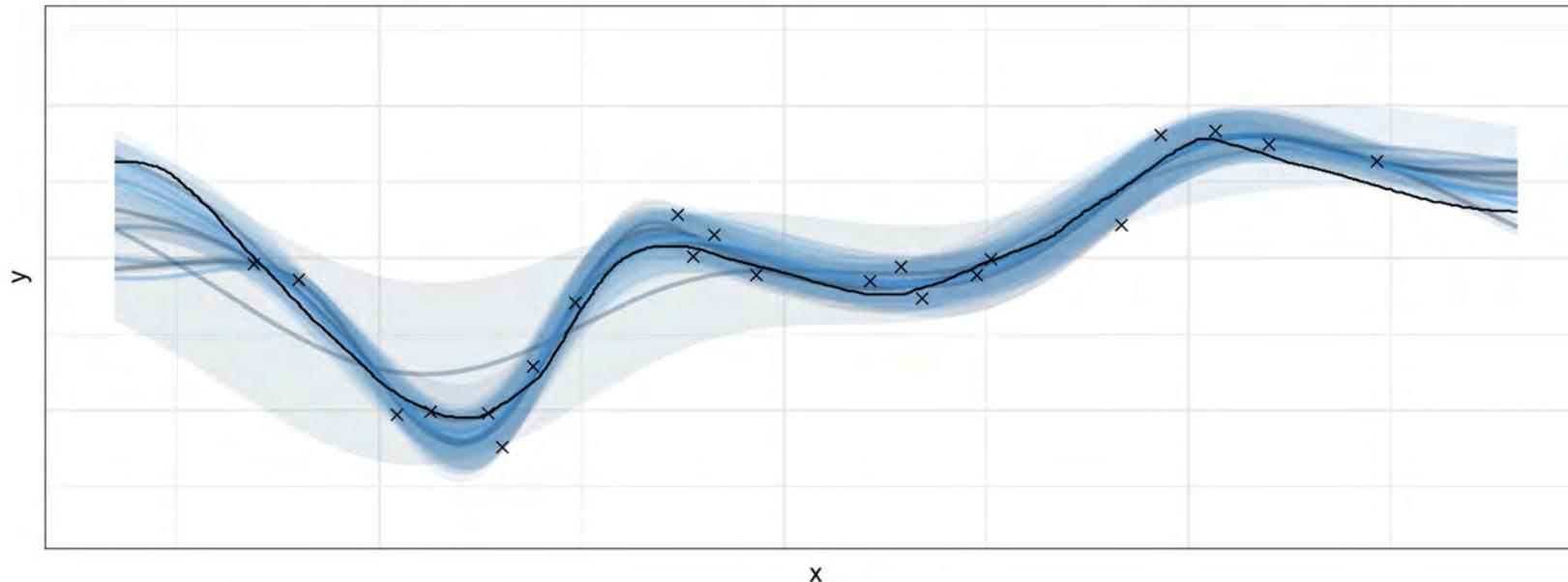
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$$\text{Likelihood} = L(\text{model}) = P(\text{data}|\text{model}) = \prod p(\text{datapoint}_i|\text{model})$$

Frequentist vs Bayesian modelling

- It is inevitable that with a finite number of observations many different model fits could have similarly high likelihood – so how should we quantify our belief in them?

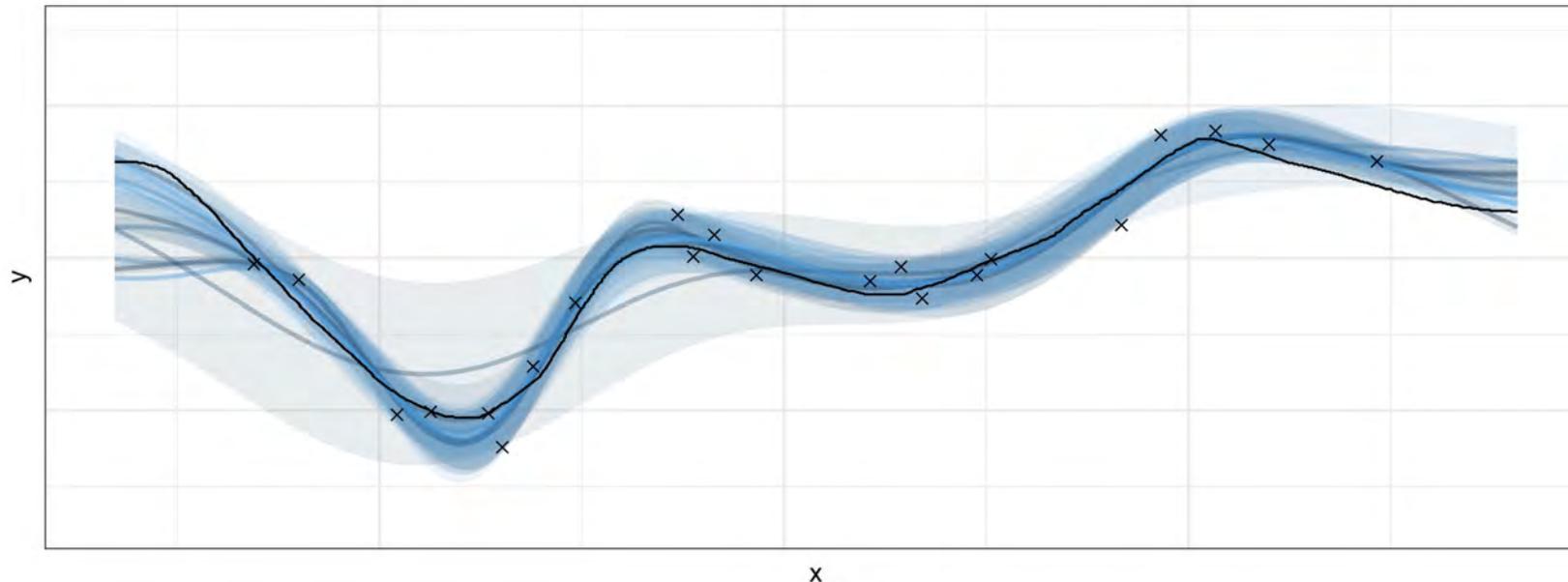


Multiple different
high-likelihood
model examples

- Bayesian inference provides a framework for quantifying uncertainty by enabling the modelling of a distribution over models, $p(\text{model}|\text{data})$

Frequentist vs Bayesian modelling

- It is inevitable that with a finite number of observations many different model fits could have similarly high likelihood – so how should we quantify our belief in them?



Multiple different high-likelihood model examples

In Bayesian inference these could be samples from the posterior distribution $p(\text{model}|\text{data})$

- Bayesian inference provides a framework for quantifying uncertainty by enabling the modelling of a distribution over models, $p(\text{model}|\text{data})$

Bayes' Rule: the essence of Bayesian UQ

$$P(\text{model}|\text{data}) = \frac{P(\text{data}|\text{model})P(\text{model})}{P(\text{data})}$$

Bayes' rule says that the **posterior probability of a model** is proportional to its **likelihood** multiplied by **our prior belief in that model**.

The incorporation of **prior belief** enables models that we believe to be sensible to be favoured over models we believe to be nonsensical.

Bayes' Rule: the essence of Bayesian UQ

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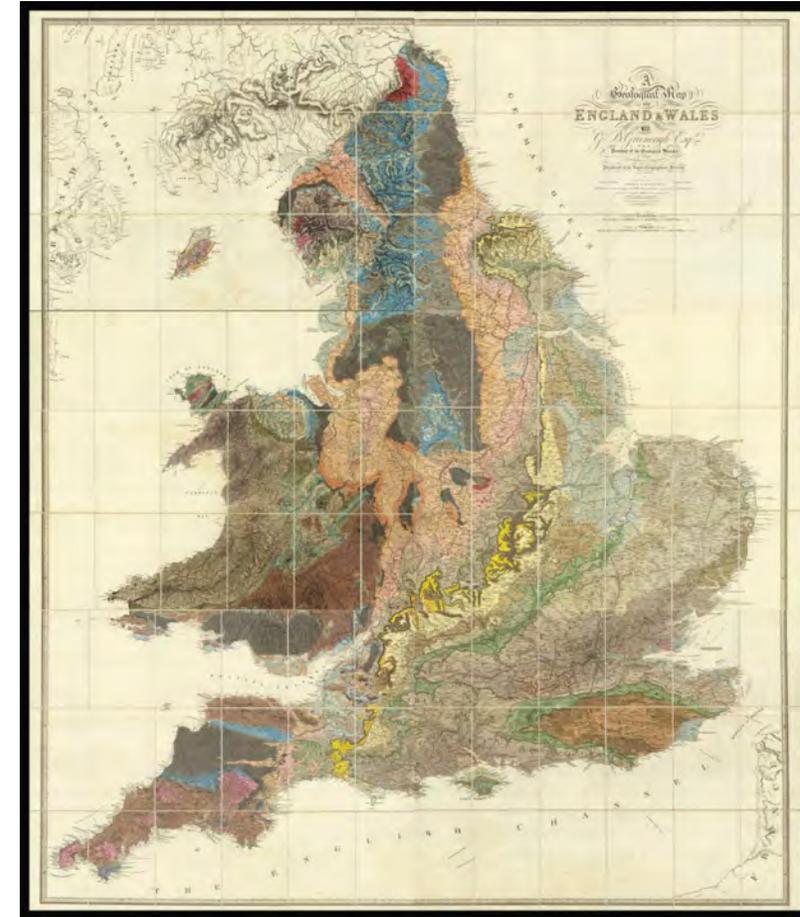
The incorporation of **prior belief** enables models that we believe to be sensible to be favoured over models we believe to be nonsensical.

>>> Likelihood is key to both frequentist modelling and Bayesian modelling for uncertainty quantification. <<<

The concept of likelihood in geological modelling

$$p(\text{data}|\text{model})$$

“What’s the probability that we would see the geological observations that we see if the geological scenario depicted by the model were true?”

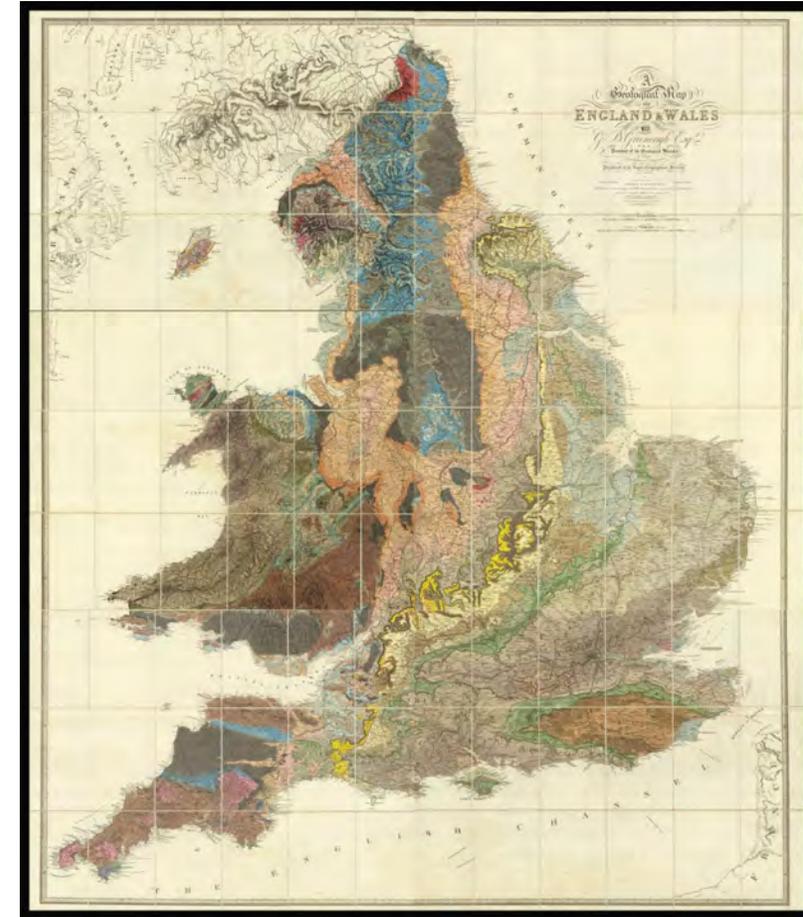


The concept of likelihood in geological modelling

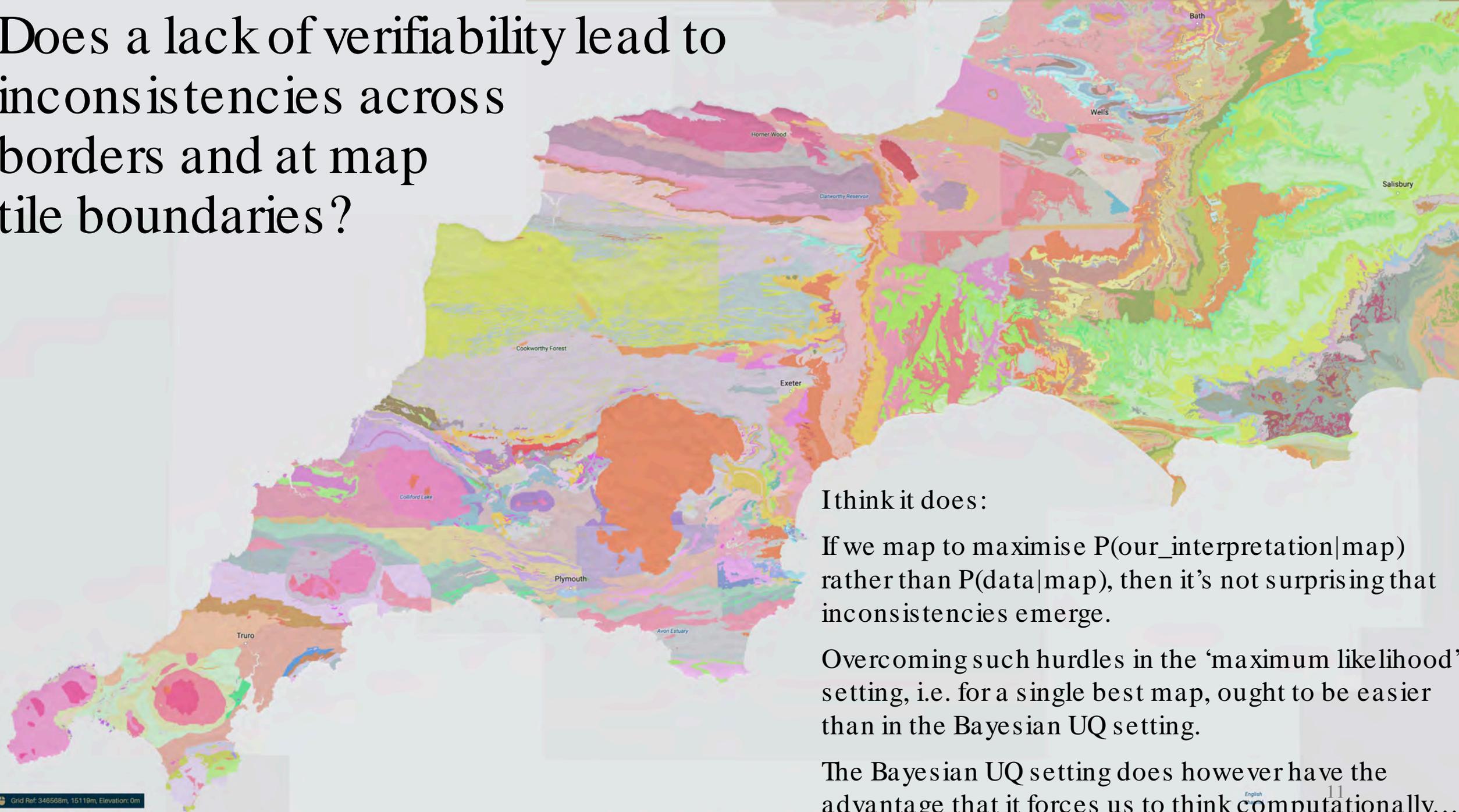
$$p(\text{data}|\text{model})$$

“What’s the probability that we would see the geological observations that we see if the geological scenario depicted by the model were true?”

- A geological model or map traditionally outputs a collection of discrete classes representing different rock types.
- Such a model is difficult (or even impossible?) to objectively verify against reality, because the classes are decided by subjective interpretation, and cannot be objectively measured or checked by any instrument.
- This lack of verifiability brings a problem for uncertainty quantification, because it is not clear how the likelihood can be calculated. The model outputs classes but the observational data do not come in classes, the observational data are measurements of properties.
- When dealing with interpretive classes the likelihood would become something like $p(\text{interpretation}|\text{model})$, but that would be flawed, because the model itself is already an interpretation. We shouldn’t be interpreting to maximise the probability of our interpretation given our interpretation!



Does a lack of verifiability lead to inconsistencies across borders and at map tile boundaries?



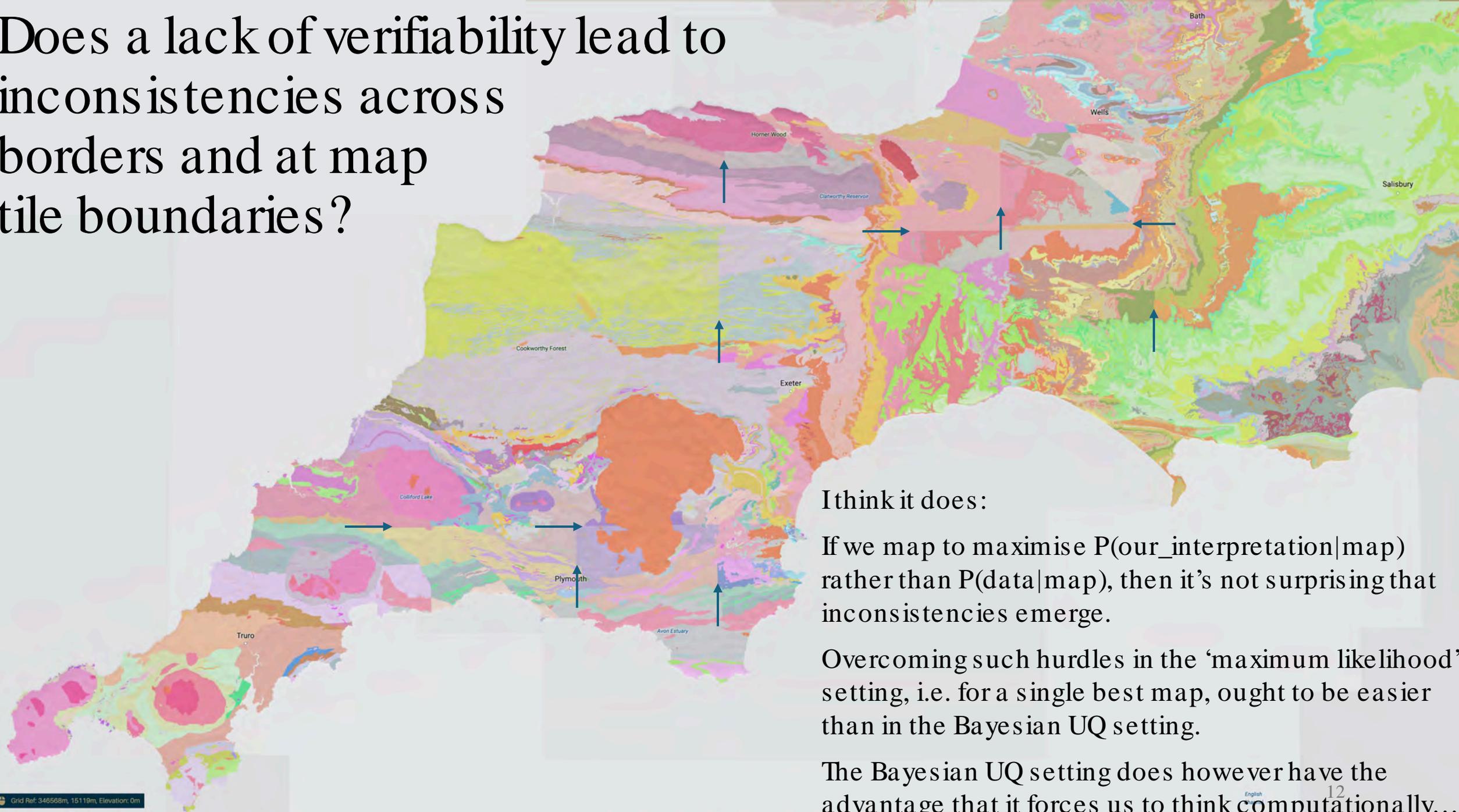
I think it does:

If we map to maximise $P(\text{our_interpretation}|\text{map})$ rather than $P(\text{data}|\text{map})$, then it's not surprising that inconsistencies emerge.

Overcoming such hurdles in the 'maximum likelihood' setting, i.e. for a single best map, ought to be easier than in the Bayesian UQ setting.

The Bayesian UQ setting does however have the advantage that it forces us to think computationally...

Does a lack of verifiability lead to inconsistencies across borders and at map tile boundaries?



I think it does:

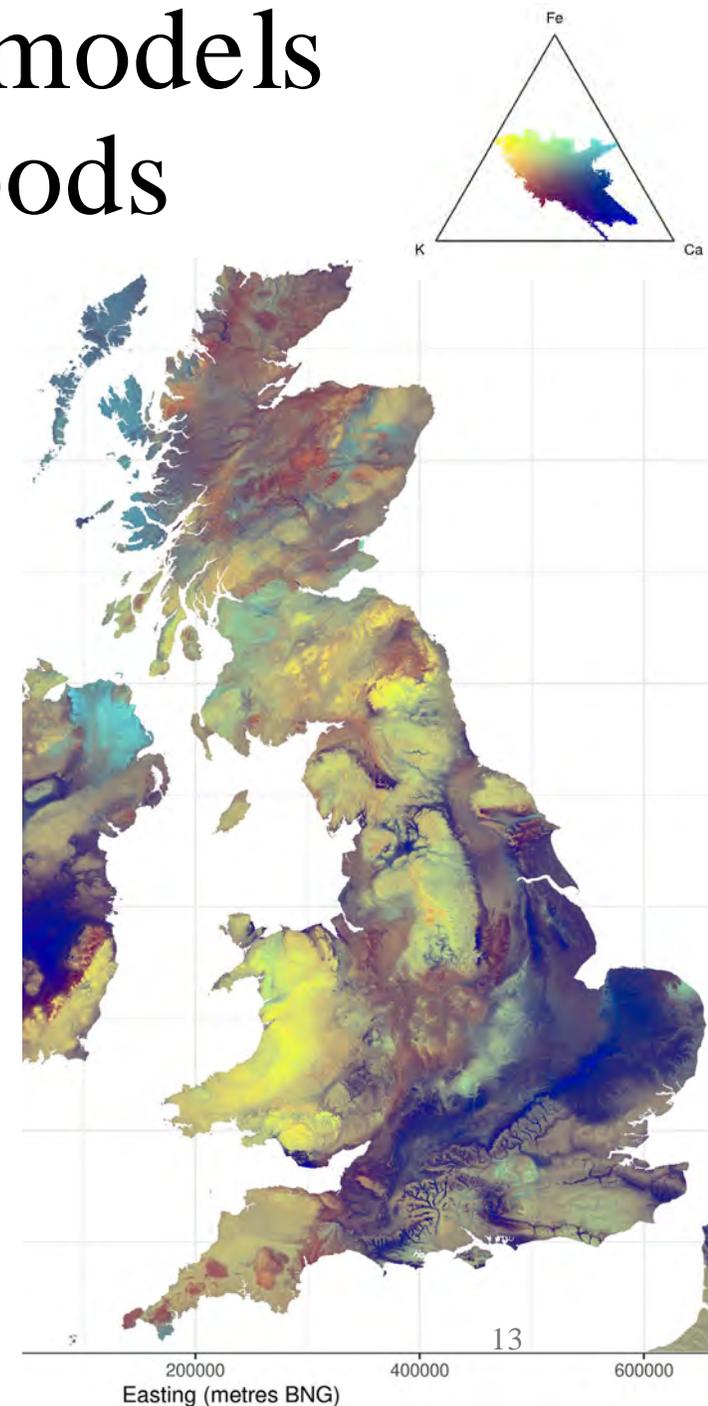
If we map to maximise $P(\text{our_interpretation}|\text{map})$ rather than $P(\text{data}|\text{map})$, then it's not surprising that inconsistencies emerge.

Overcoming such hurdles in the 'maximum likelihood' setting, i.e. for a single best map, ought to be easier than in the Bayesian UQ setting.

The Bayesian UQ setting does however have the advantage that it forces us to think computationally...

Achieving verifiable geological models with cleanly defined likelihoods

- Classification-based geological models are difficult to verify, or calculate a likelihood for, because the classes are subjectively interpreted and not objectively measurable.
- The classes are however based on objectively measurable geological properties such as age, composition, texture and more.
- Designing our geological models to output predictions of objectively measurable geological properties, rather than subjectively interpreted geological classes, makes the models objectively verifiable, and enables model likelihoods to be calculated.
- This opens the door to uncertainty quantification by Bayesian inference, and makes it possible to develop probabilistic geological models that are well-calibrated with respect to reality, potentially greatly improving utility.



To summarise...

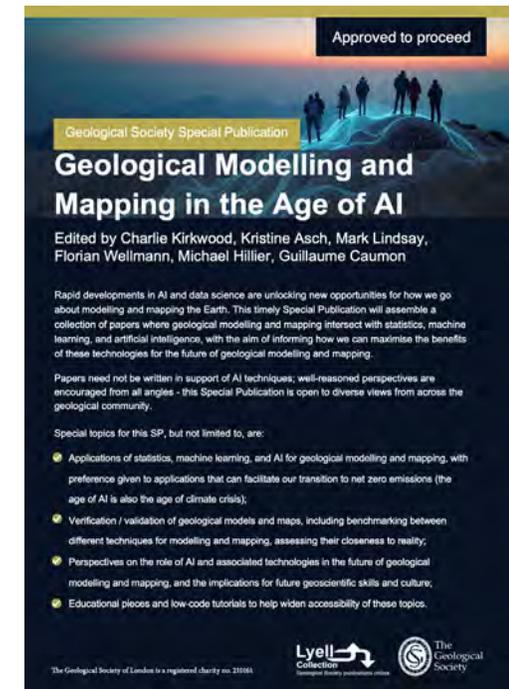
- The likelihood, $P(\text{data}|\text{model})$, is key to Bayesian modelling (and Frequentist modelling).
- Bayesian modelling is the backbone of uncertainty quantification.
- Traditional classification-based geological models and maps make it difficult to calculate likelihood, because they output subjective classes but there is no way to objectively measure such classes on the ground.
- If we design our geological models and maps to directly predict objectively measurable geological properties such as age, composition, texture, mechanical properties etc, then likelihoods can easily be calculated, opening the door to uncertainty quantification by Bayesian inference and the delivery of geological models that are well-calibrated with respect to reality.

Thanks for listening

And a quick pitch for the upcoming 2nd AI for Geological Modelling and Mapping Conference taking place in Utrecht on 2nd-3rd of June 2026. Abstract submission deadline is 31st March!

Organisation led by Suzanne Atkins at TNO

And a second quick pitch for the upcoming GSL Special Publication on Geological Modelling and Mapping in the Age of AI, a big community effort being co-edited by myself, Florian Wellmann, Kristine Asch, Mark Lindsay, Michael Hillier, Guillaume Caumon. There's still time to submit your works if you have something in the pipeline you would like to have included.



UNCERTAINTIES IN JOINT ANALYSIS OF GEOLOGICAL AND MULTI-SOURCE GEOPHYSICAL DATA

Lessons from a blind interpretation exercise

Jeremy Rohmer*, Cecile Allanic, Adnand Bitri, Frederic Dubois, Sandrine Grataloup, Thomas Jacob, Alexandre Stopin, Renaud Coueffe, Agathe Faure, Aurelie Peyrefitte, Angelie Portal, Anne Raingeard, Pierre Wawrzyniak, Romain Chassagne, Nicolas Coppo, Mathieu Darnet, and Philippe Calcagno

02/03/2026

Motivation

Geological reasoning: **Geology as an interpretive** and historical science

Robert Frodeman *Department of Geological Sciences and Department of Philosophy, University of Colorado,
Boulder, Colorado 80301*

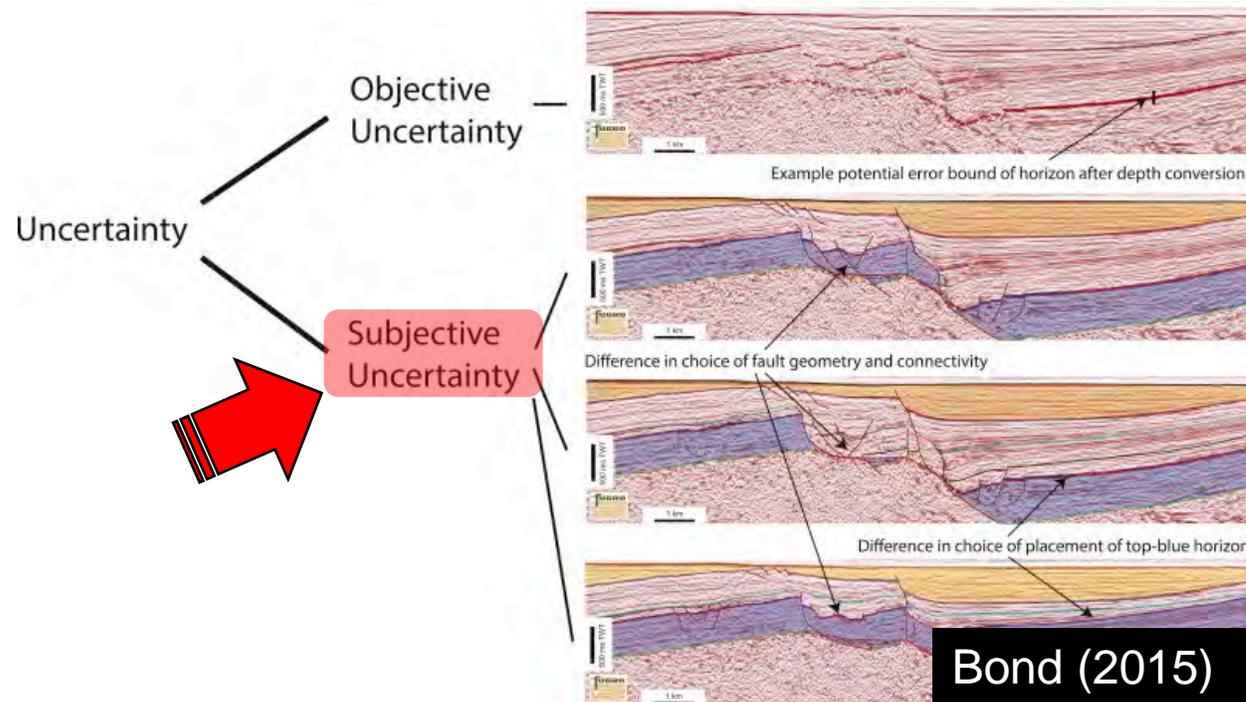


Adapted from <https://colamaga.com/> ©

Motivation

Geological reasoning: Geology as an interpretive and historical science

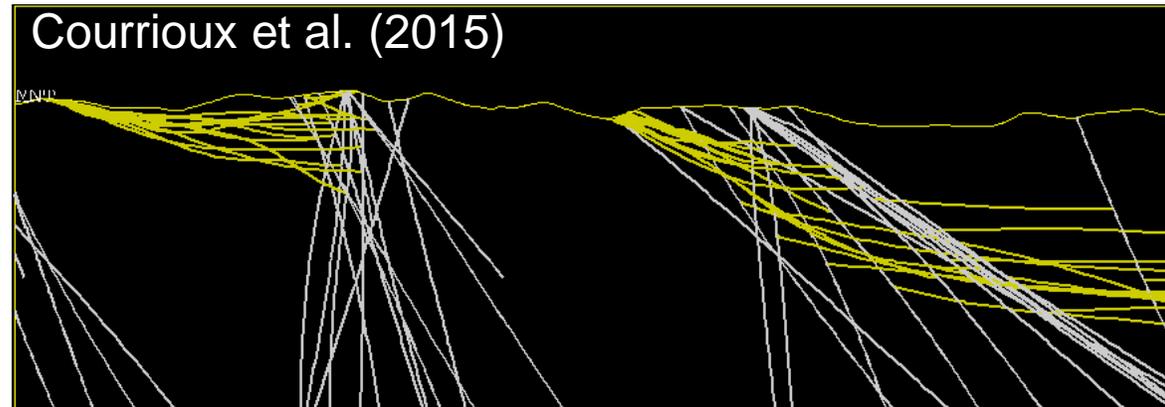
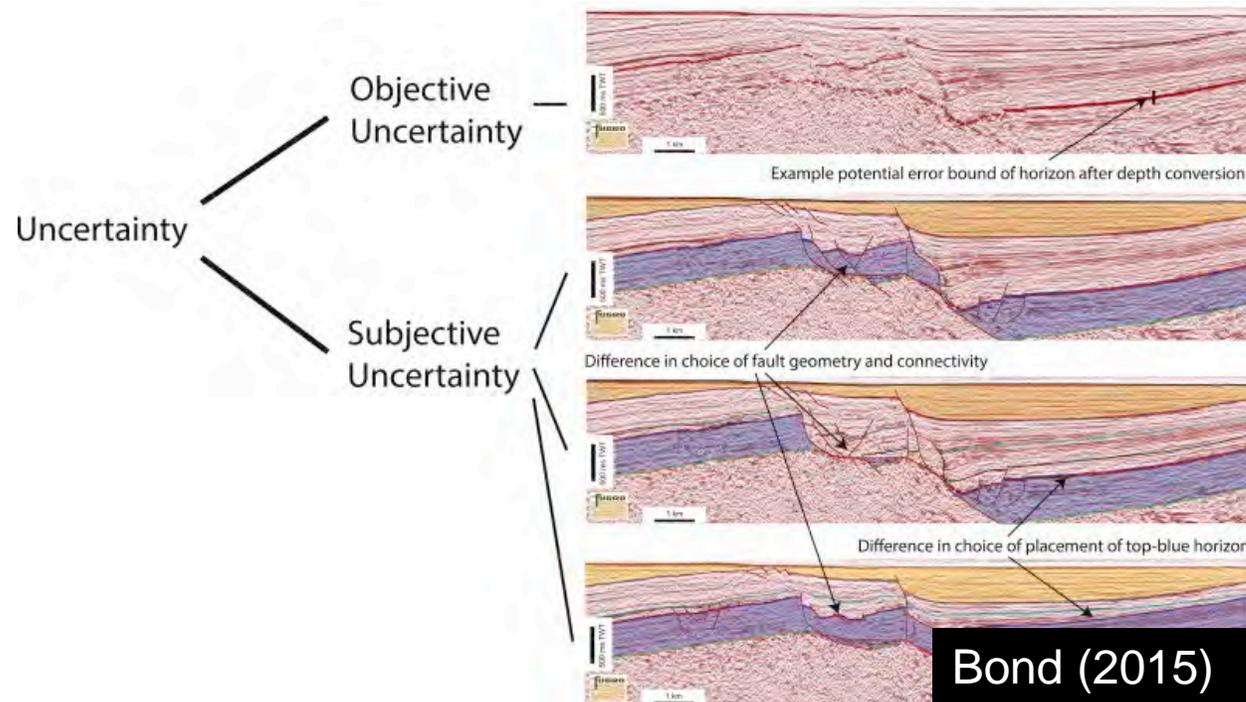
Robert Frodeman *Department of Geological Sciences and Department of Philosophy, University of Colorado, Boulder, Colorado 80301*



Motivation

Geological reasoning: Geology as an interpretive and historical science

Robert Frodeman *Department of Geological Sciences and Department of Philosophy, University of Colorado, Boulder, Colorado 80301*

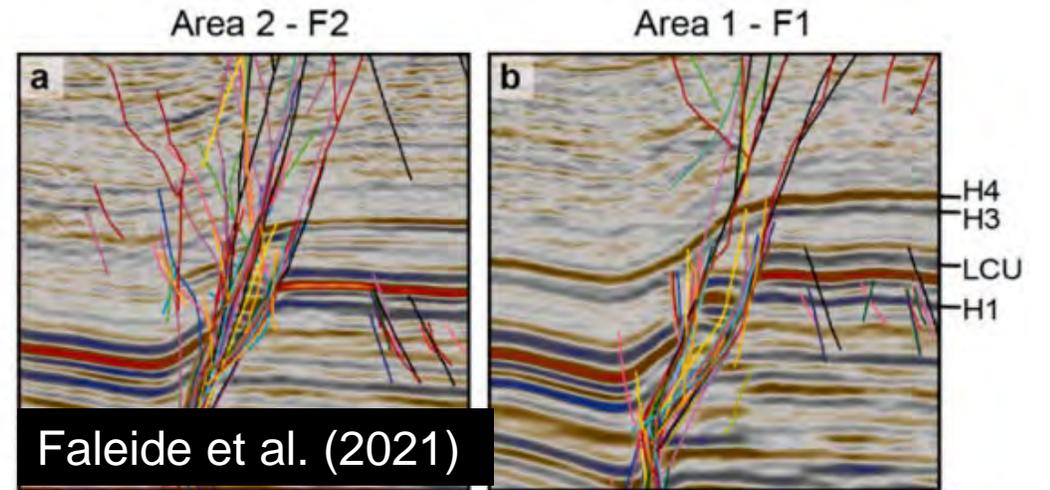
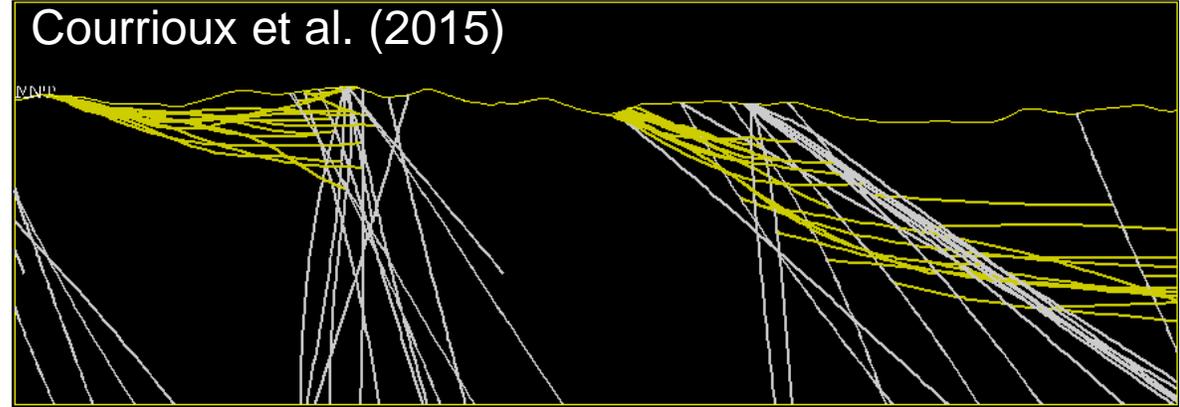
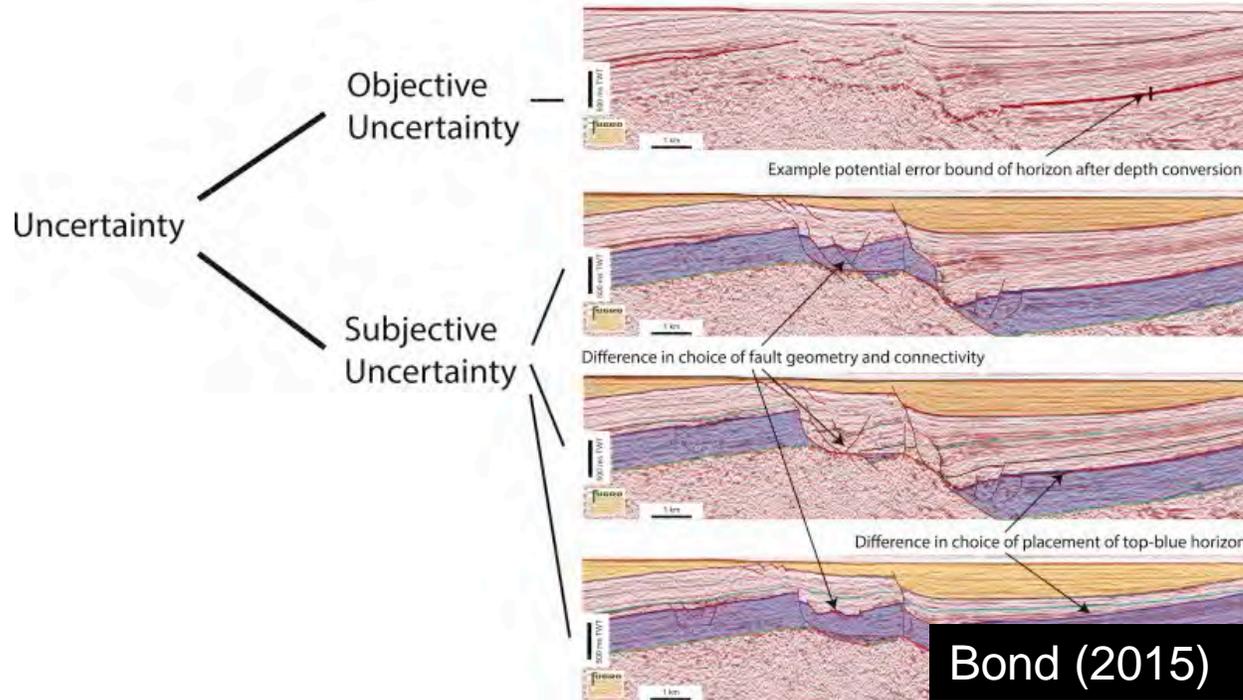


Geomodels for all training sessions at Ales (France)

Motivation

Geological reasoning: Geology as an interpretive and historical science

Robert Frodeman *Department of Geological Sciences and Department of Philosophy, University of Colorado, Boulder, Colorado 80301*



When jointly analyzing **geological** and **multi-source geophysical** datasets (seismic, gravimetric, electric/magneto-telluric):

Do the **errors** associated with each of the different datasets **influence / bias** the geological interpretation?

If so, **how?**

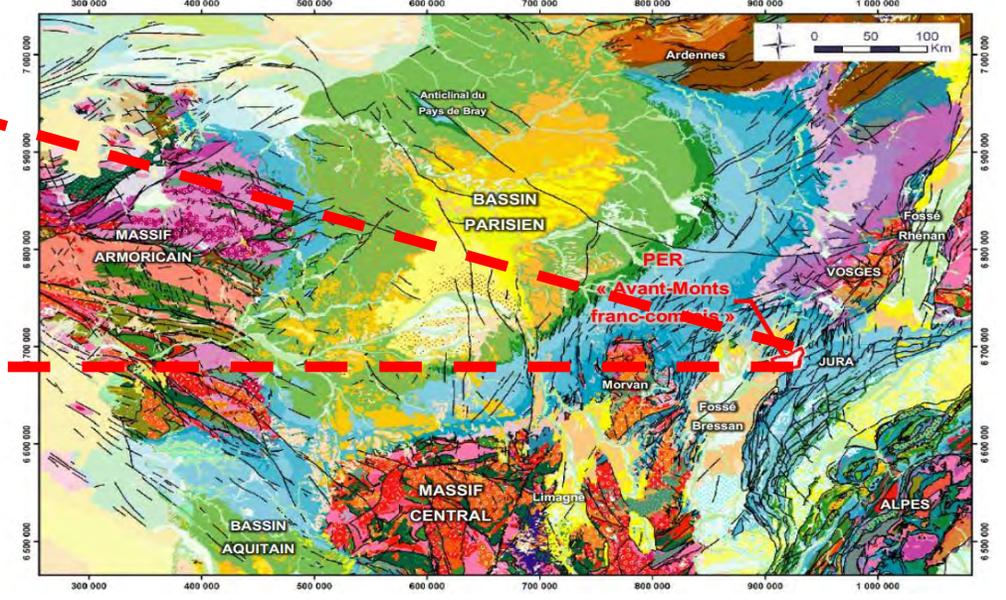
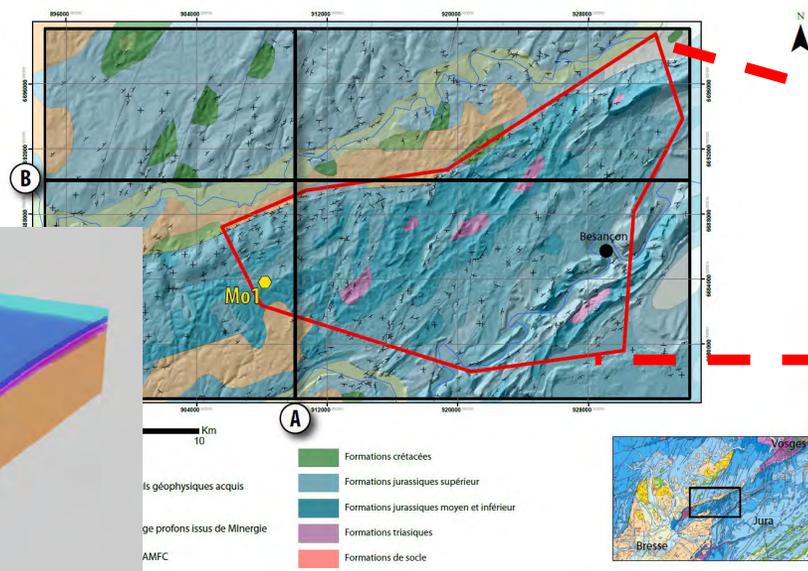
Or do the errors **cancel each other out?**

>> Blind interpretation exercise <<



Bond (2015)

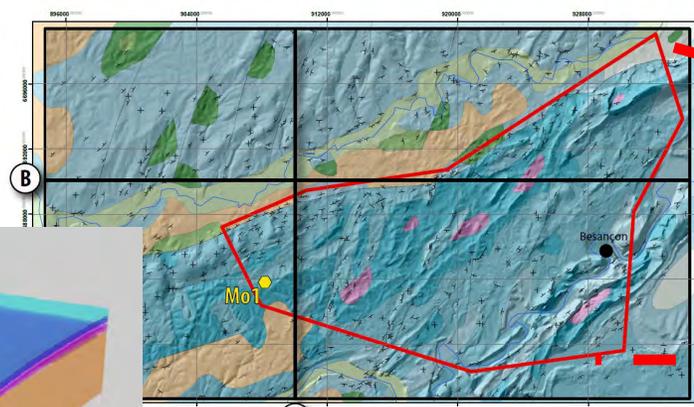
Geological 'truth'



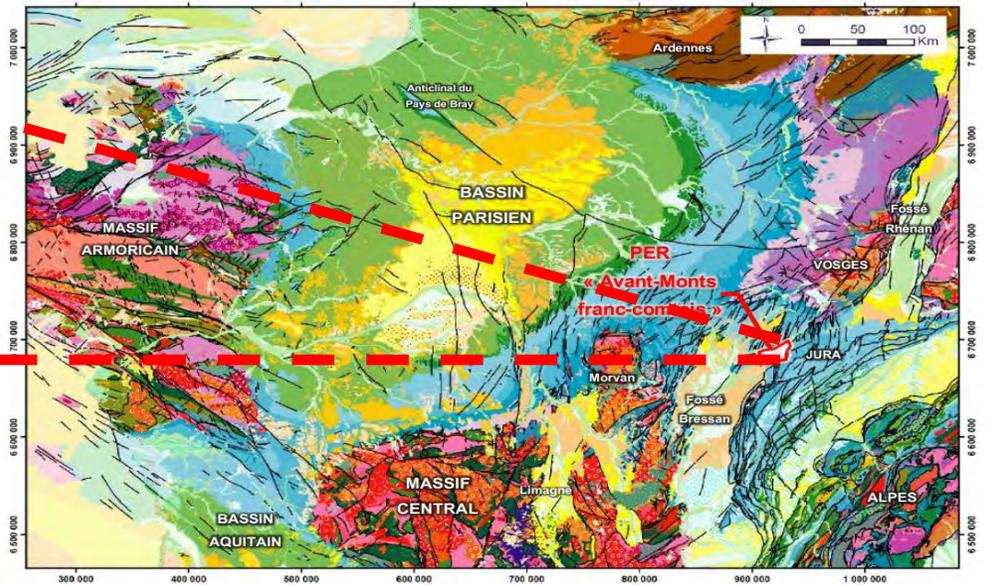
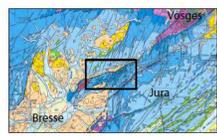
Extraction of **2 cross-sections** from a realistic 3D geological model ($\approx 20\text{km} \times 30\text{ km}$)

Adapted from a real exploration project dedicated to the characterization of helium reservoirs in a deep Permian sedimentary basin

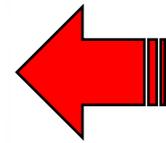
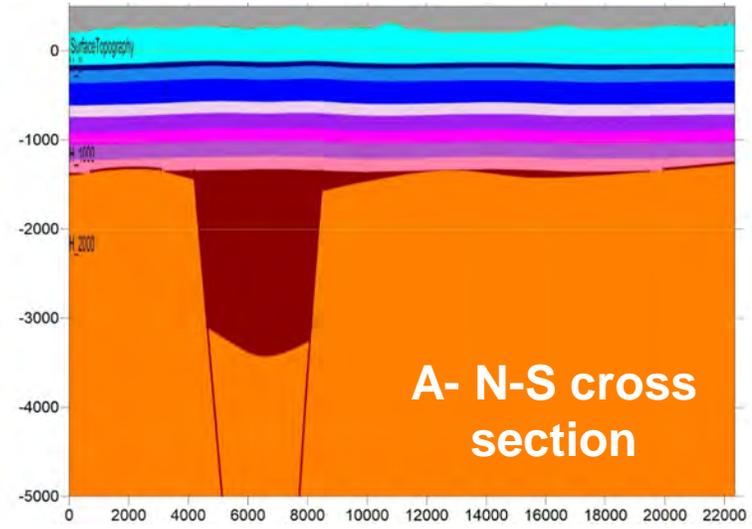
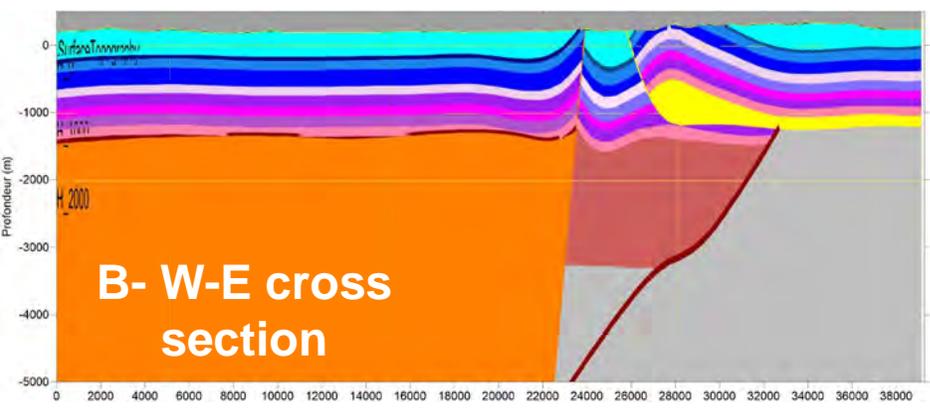
Geological 'truth'



- Formations crétacées
 - Formations jurassiques supérieur
 - Formations jurassiques moyen et inférieur
 - Formations triasiques
 - Formations de socle
- Is géophysiques acquis
ge profonds issus de Minergie
AMFC



Extraction of **2 cross-sections** from a realistic 3D geological model ($\approx 20\text{km} \times 30\text{ km}$)



=Target (not provided to the interpreters)

Objective of the blind exercise

3 teams of interpreters

A geologist + A geophysicist
(senior / mid career)

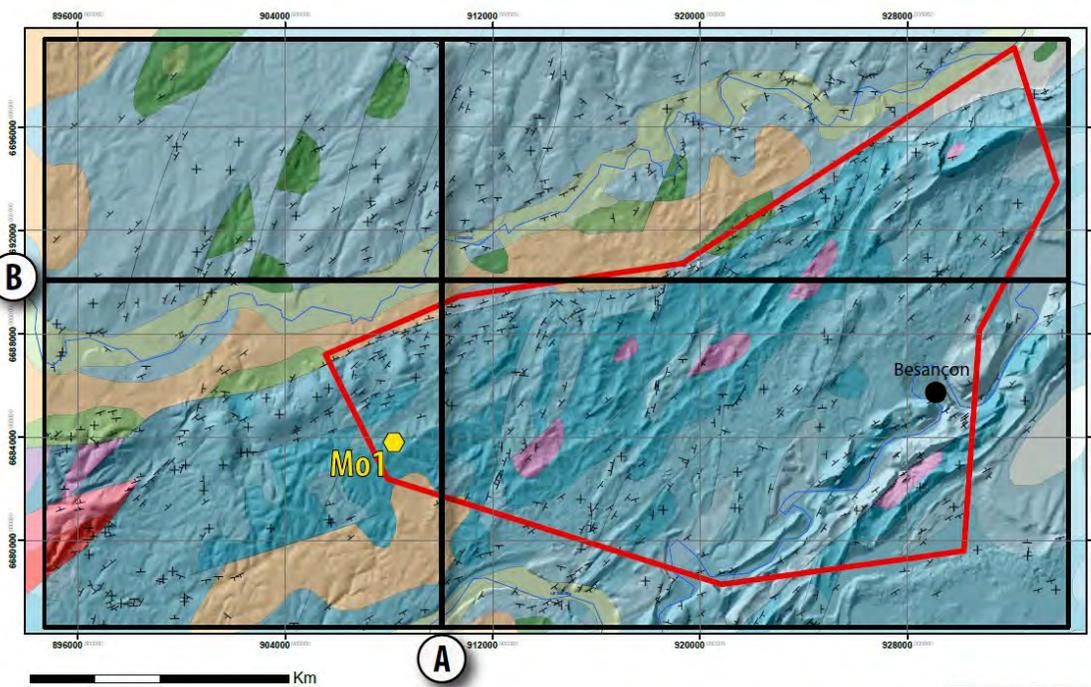
Identify **structural traps** + geometry, identify the **potential migration pathways** on the **two cross-sections**
From a series of documents

Objective of the blind exercise

3 teams of interpreters
 A geologist + A geophysicist
 (senior / mid career)

Identify **structural traps** + geometry, identify the **potential migration pathways** on the **two cross-sections**
From a series of documents

- 1:1,000,000 scale **geological map** + **borehole** (with stratigraphy)

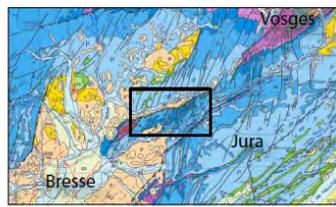


A B — Profils géophysiques acquis

Mo1 — Forage profonds issus de Mnergie

— PER AMFC

- Formations crétacées
- Formations jurassiques supérieur
- Formations jurassiques moyen et inférieur
- Formations triasiques
- Formations de socle



Borehole Mo1

05018X0002

DÉPARTEMENT : DOUBS Fiche 1
Feuille I

COMMUNE : JALLERANGE Indice de classement : 501 8 2

DÉSIGNATION : No 1 Cote du sol (z) = ±. 259,16m

Coupe établie par : SAI 26P
 Interprétation de : M. SAPREP

PROFONDEURS m	NATURE DES TERRAINS	INTERPRÉTATION	COTE
0 m à 402 m	Calcaires blancs massifs	Malm	
402 m à 479 m	Marnes noires	Oxfordien	
479 m à 567 m	Calcaires jaunes et ocre à entroques quelques passages oolithiques, Interca- lations de marnes grises.	Bajocien	
567 m à 618 m	Calcaires marneux ferrugineux.	Aalésien	
618 m à 682 m	Argilles et marnes grises à pill de quartz, Pyrite, Marnes et minces interca- lations de calcaires.	Lias marneux	+254,6m
682 m à 723 m	Calcaires bruns à passages marneux.	Sinemurien	
723 m à 867 m	Grès à ciment calcaire	Hettangien	
867 m à 997 m	Marnes gris, noires plus ou moins schisteuses et grès blancs siliceux.	Rhétien	
997 m à 1170 m	Argiles bariolées et puttes, bancs de calcaires dolomitiques, beige, Gyss et anhydrite abondants, marnes passées dolomitiques.	Keuper supérieur	+22,1m
1170 m à 1304 m	"Dolomie de ISM", Argiles bariolées.	Keuper	
1304 m à 1481 m	Grès à rougeaux à la base Marnes grise et fines passées gréseuses	Moyen Muschelkalk	

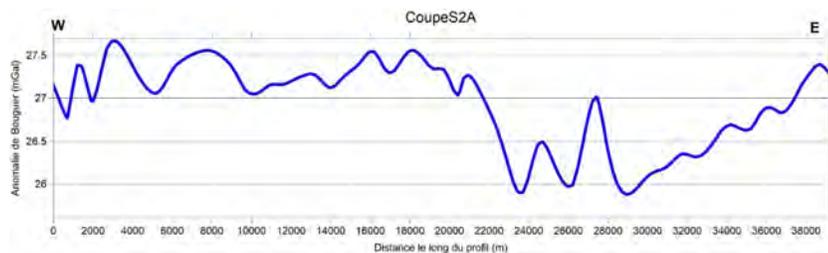
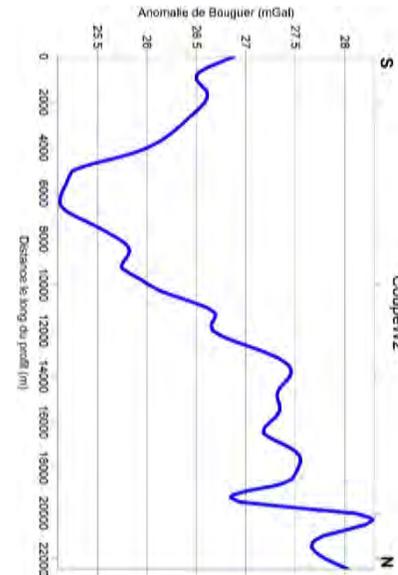
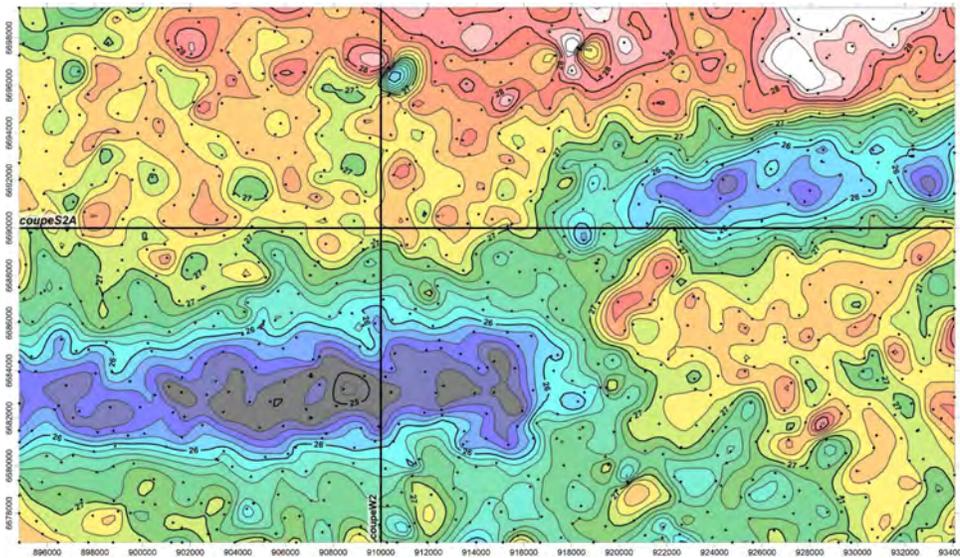
Objective of the blind exercise

3 teams of interpreters

A geologist + A geophysicist
(senior / mid career)

Identify **structural traps** + geometry, identify the **potential migration pathways** on the **two cross-sections**
From a series of documents

- 1:1,000,000 scale geological map + borehole (with stratigraphy)
- Map of **Bouguer anomaly (gravimetry)** + profiles along the cross sections



Based on forward geophysical modelling with 'realistic' measurement or processing error

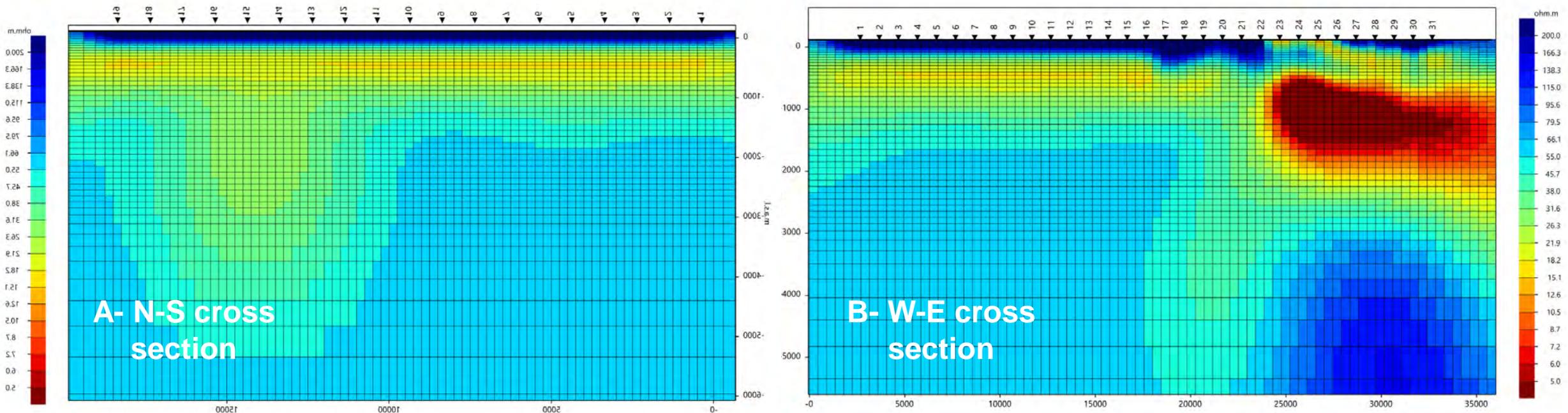
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- Map of Bouguer anomaly + profiles along the cross sections
- Cross sections of **electrical resistivity** from processing of magneto-telluric (**MT**) surveys



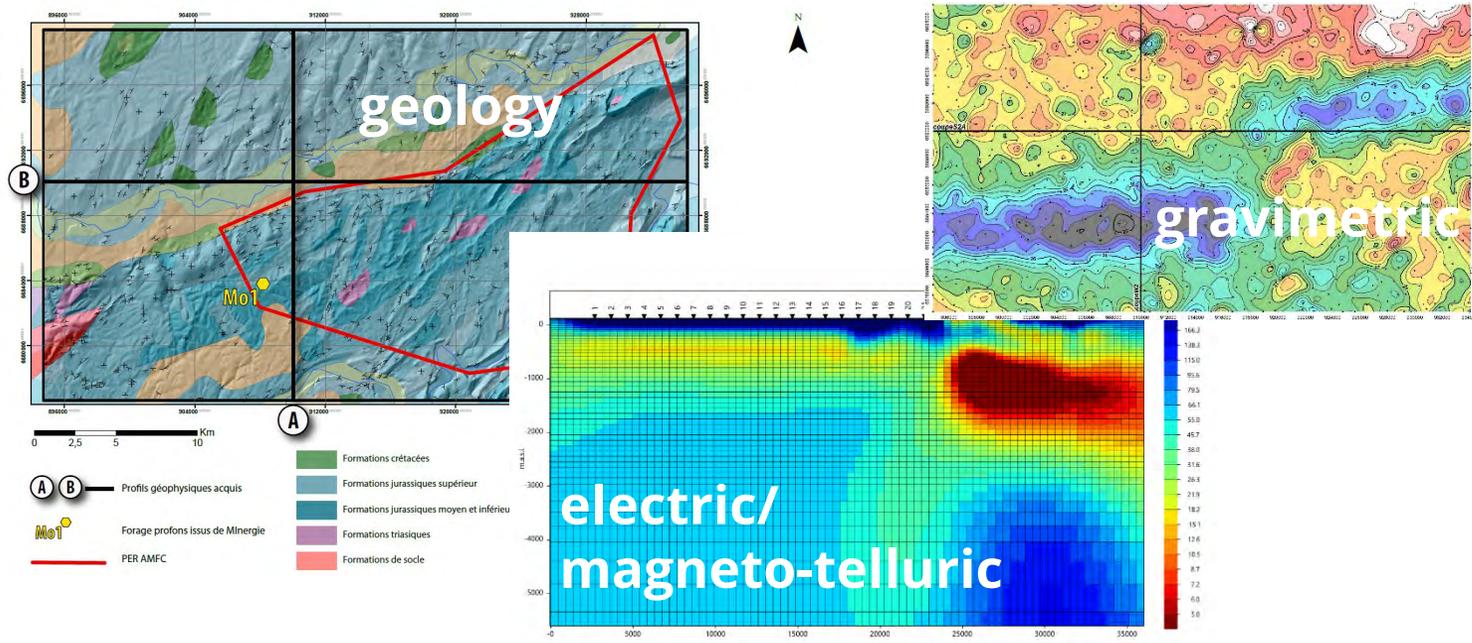
Objective of the blind exercise

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Exercice – phase1

2.5 hours

With Geology, MT,
Gravimetry

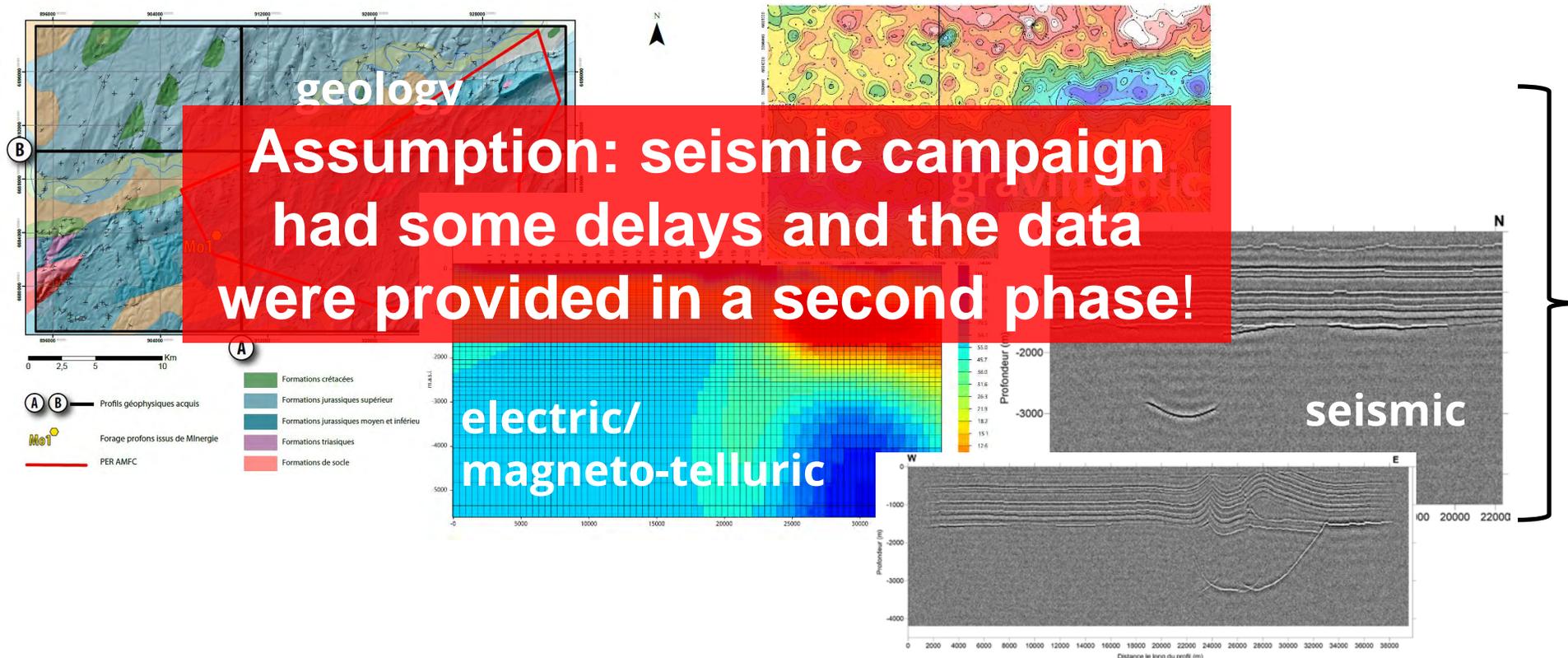
Work in pairs

Objective of the blind exercise

3 teams of interpreters
A geologist + A geophysicist
(senior / mid career)

Identify **structural traps** + geometry, identify the **potential migration pathways** on the two cross-sections
From a series of documents

- 1:1,000,000 scale geological map + borehole (with stratigraphy)
- Map of Bouguer anomaly + profiles along the cross sections
- Cross sections of electrical resistivity from processing of magneto-telluric (MT) surveys
- **HR seismic**: on the two cross sections



Exercice – phase2

2.5 hours

With Geology, MT,
Gravimetry
+Seismic

Work in pairs

A series of difficulties

1. Inherent to the imperfections in the **geophysical / geological data**
 - Effect of **noise** in the data
 - Effect of **mis-specifications** (model uncertainty) in the processing
 - **Resolution** of the data

A series of difficulties

1. Inherent to the imperfections in the **geophysical / geological data**

- Effect of **noise** in the data
- Effect of **mis-specifications** (model uncertainty) in the processing
- **Resolution** of the data

2. Inherent to the **exercice**

- **Time constraint:** <6 hours
- **3D effect:** two cross sections not necessarily orthogonal to main structures
- Choice of **representation format** incl. colorscale

A series of difficulties

1. Inherent to the imperfections in the **geophysical / geological data**
 - Effect of **noise** in the data
 - Effect of **mis-specifications** (model uncertainty) in the processing
 - **Resolution** of the data
2. Inherent to the **exercise**
 - **Time constraint**: <6 hours
 - **3D effect**: two cross sections not necessarily orthogonal to main structures
 - Choice of **representation format** incl. colorscale
3. Inherent to the '**human nature**' of the interpreters
 - Different **past experiences** (senior and mid career)
 - Different **working practices** incl. tools
 - Different **perceptions / understanding / biases**

A series of difficulties

Today
presentation

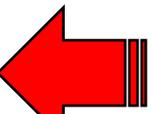
1. Inherent to the imperfections in the **geophysical / geological data**

- **Effect of noise in the data** 
- Effect of **mis-specifications** (model uncertainty) in the processing
- **Resolution of the data** 

2. Inherent to the **exercice**

- **Time constraint**: <6 hours
- **3D effect**: two cross sections not necessarily orthogonal to main structures
- **Choice of representation format incl. colorscale** 

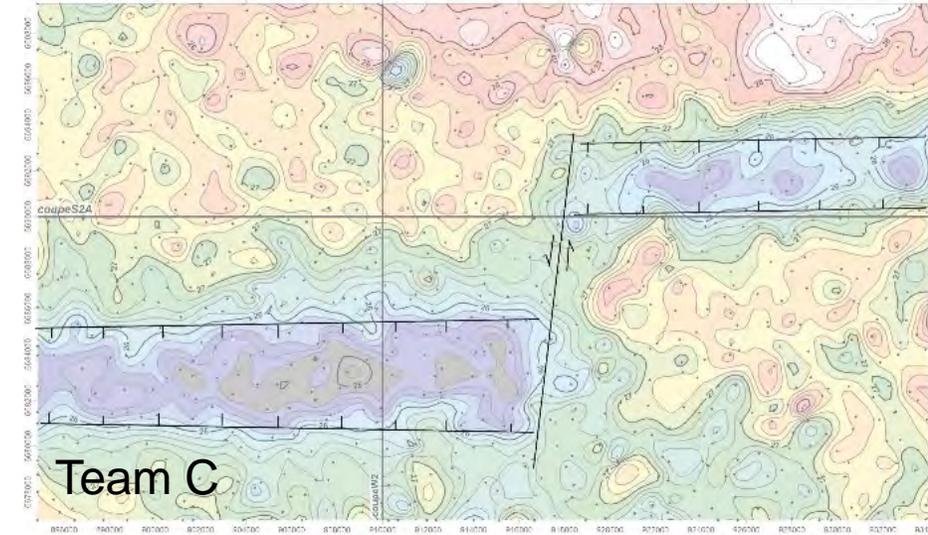
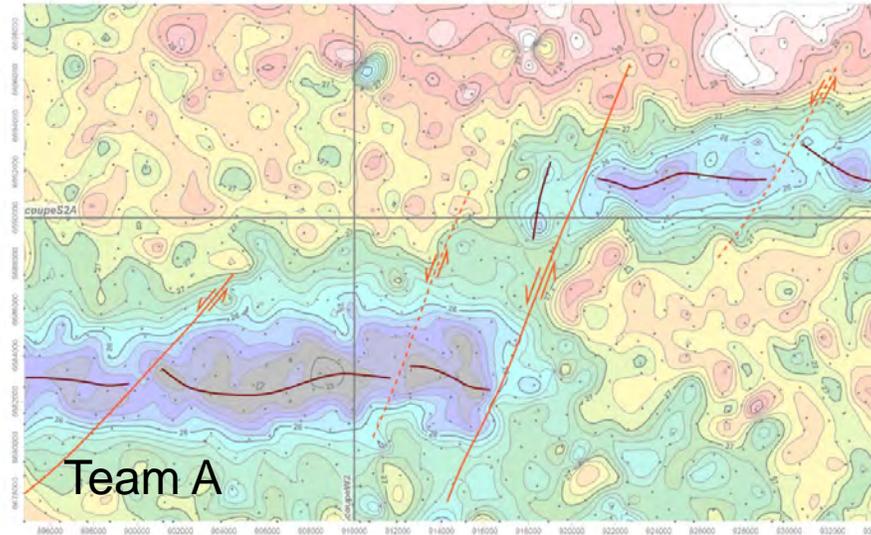
3. Inherent to the '**human nature**' of the interpreters

- Different **past experiences** (senior and mid career)
- Different **working practices** incl. tools
- **Different perceptions / understanding / biases** 

Data imperfection: noise

Interpretations of two teams of the map of Bouguer anomaly

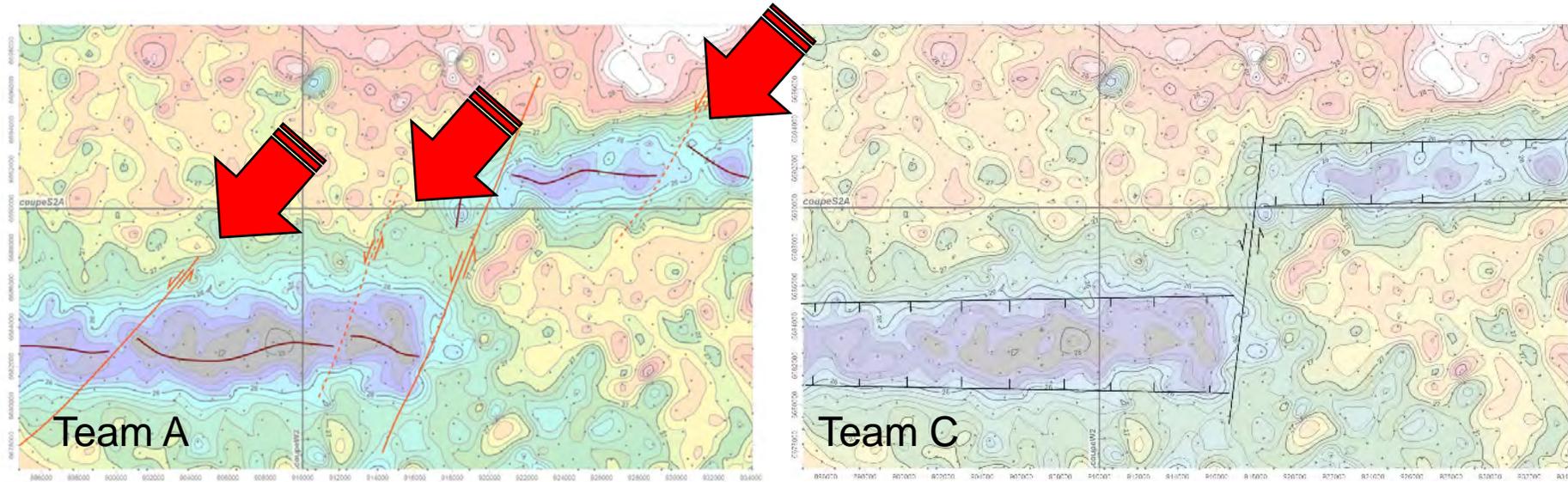
Large noise of $0.2 \mu\text{gal}$
= mimick the
processing of
gravimetry
measurements of early
1950s



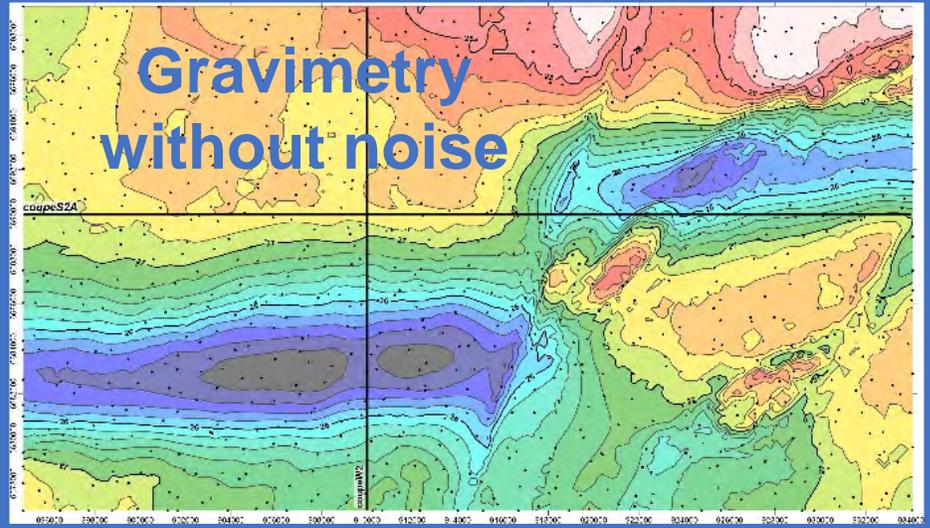
Data imperfection: noise

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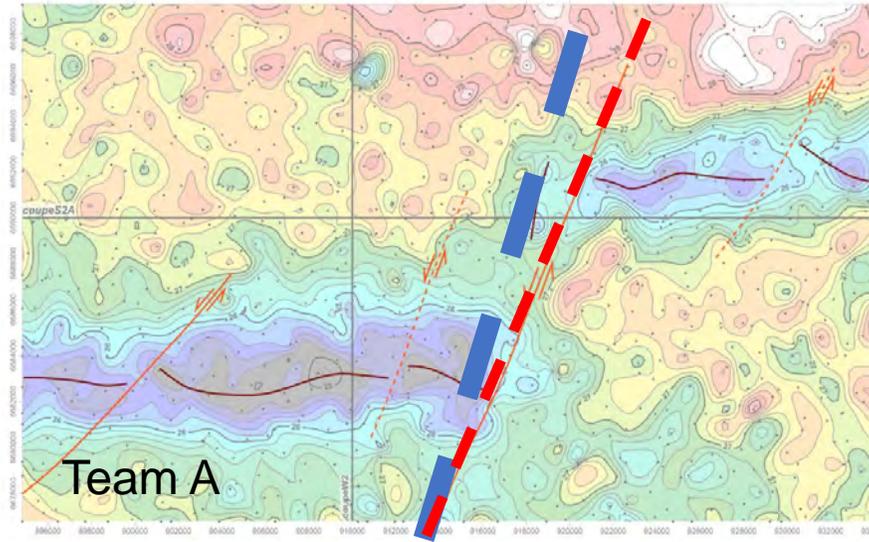
Gravimetry
without noise



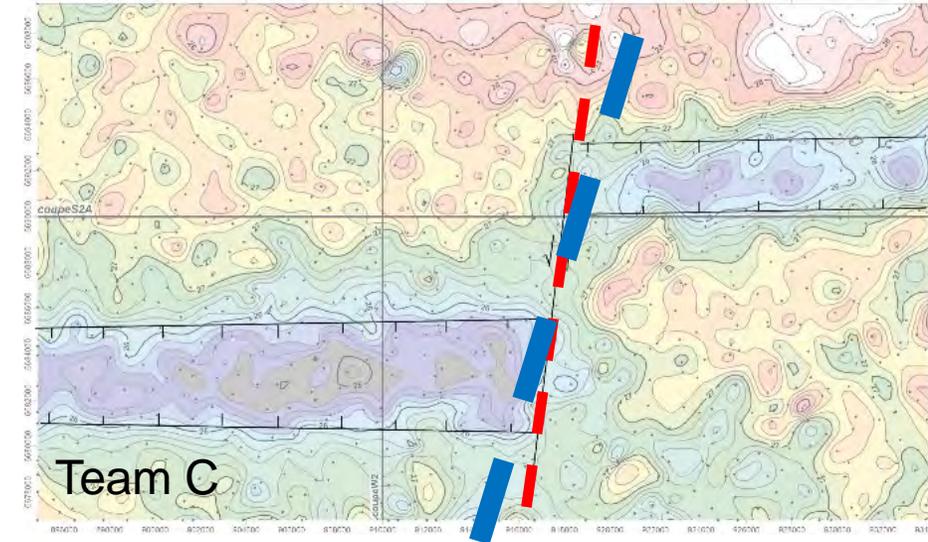
Some tendencies for **over-interpretation of small-scale structures** (<1km) that are purely related to noise

Data imperfection: noise

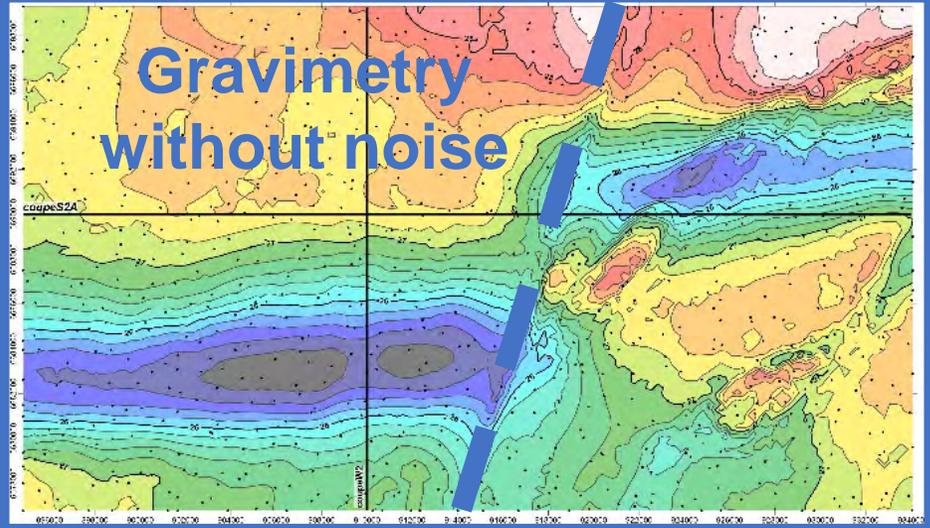
Large noise of $0.2 \mu\text{gal}$
= mimick the
processing of
gravimetry
measurements of early
1950s



Interpretations of the map of Bouguer anomaly



Gravimetry
without noise

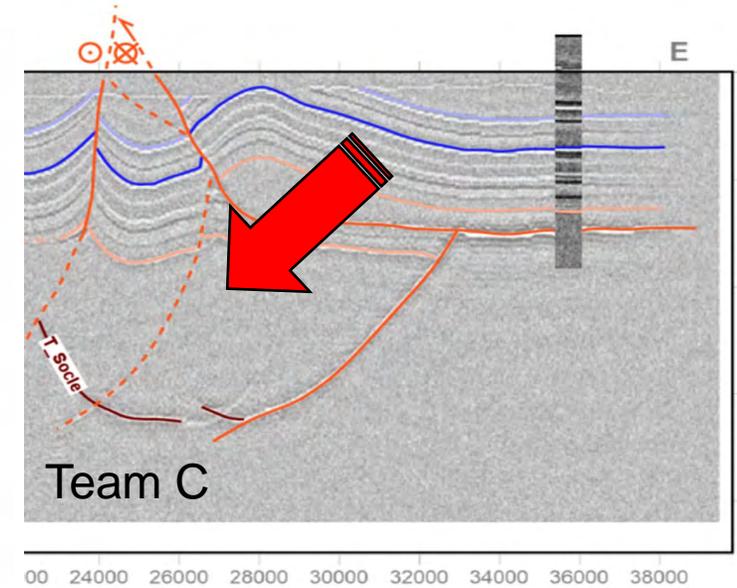
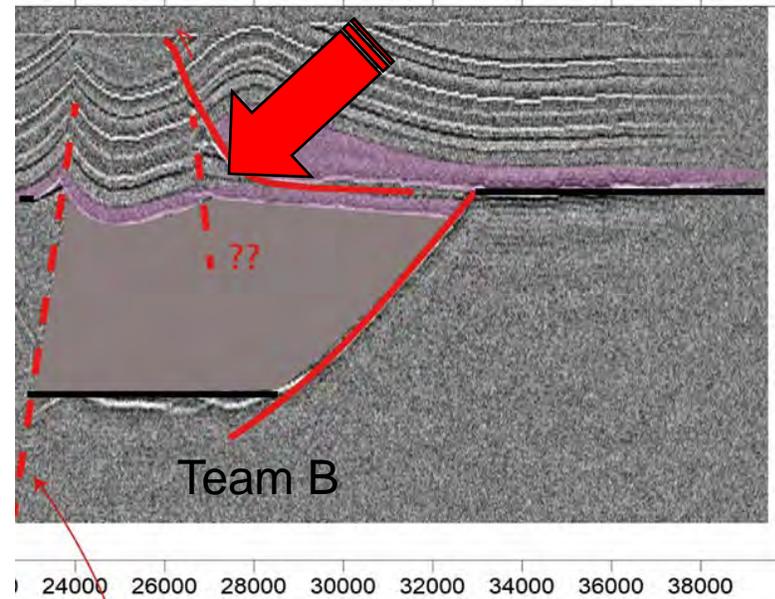


Despite the large-but-realistic noise, gravimetry was useful
to **identify large scale structures**

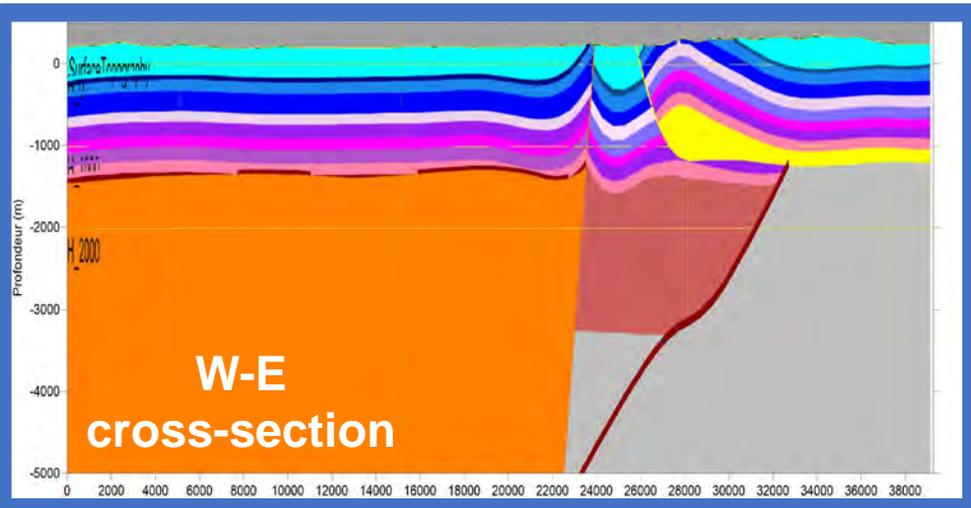
Uncertainty on the fault strike angle $\sim 15\text{-}20^\circ$

Data imperfection: noise

Interpretations of the seismic data



Truth

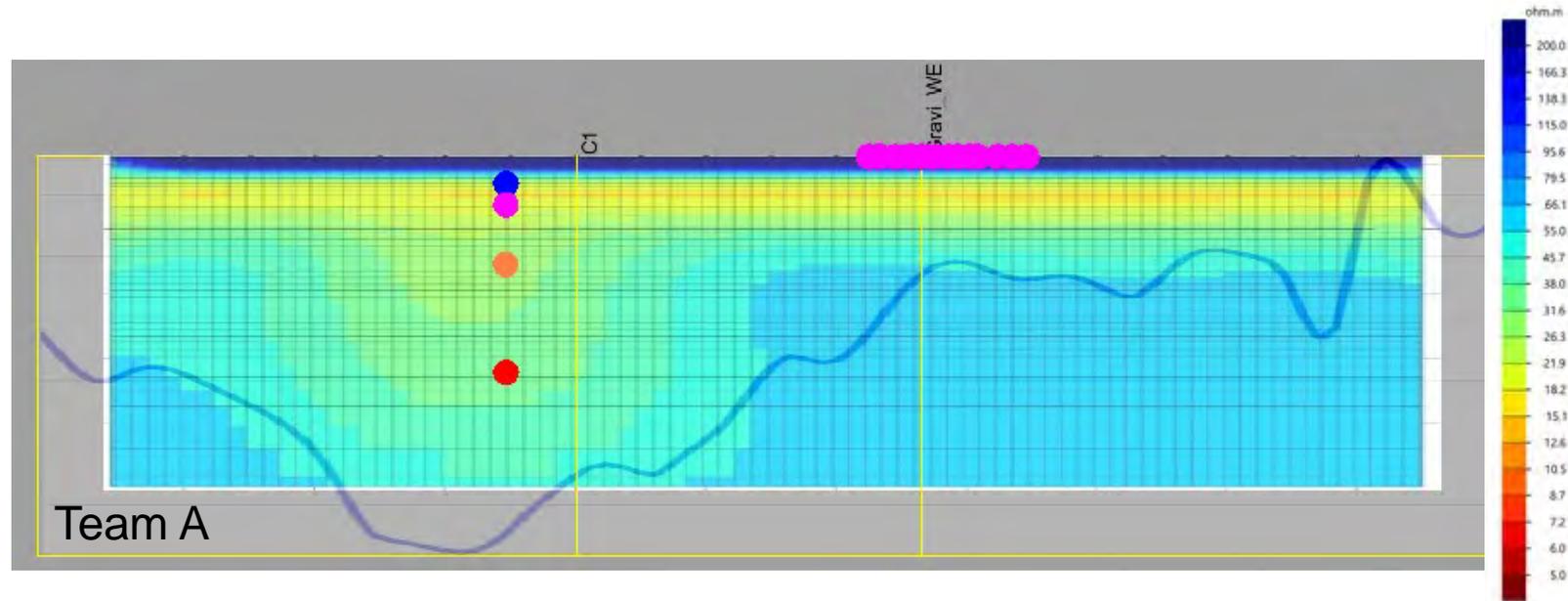


Some tendencies for over-interpretation of noise-related artefacts in seismic

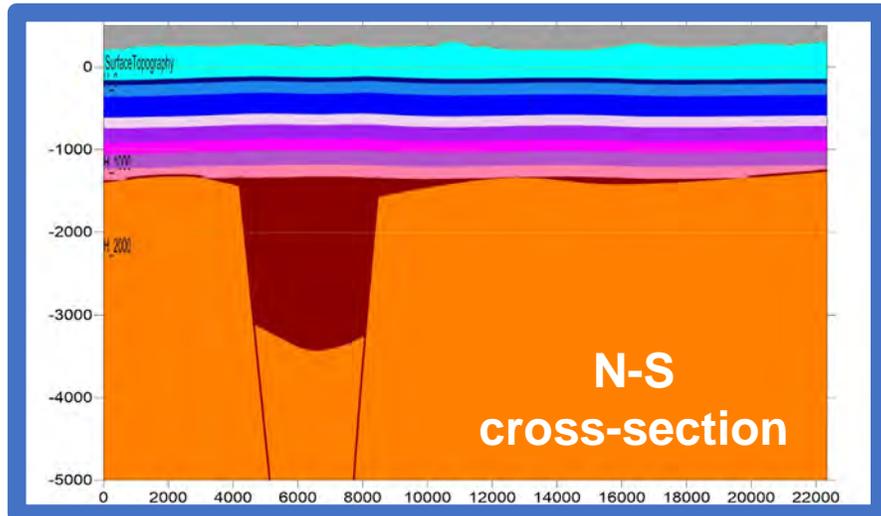
Data imperfection: resolution

MT was not corrupted with noise

By nature MT provides a 'blurry' vision



Truth

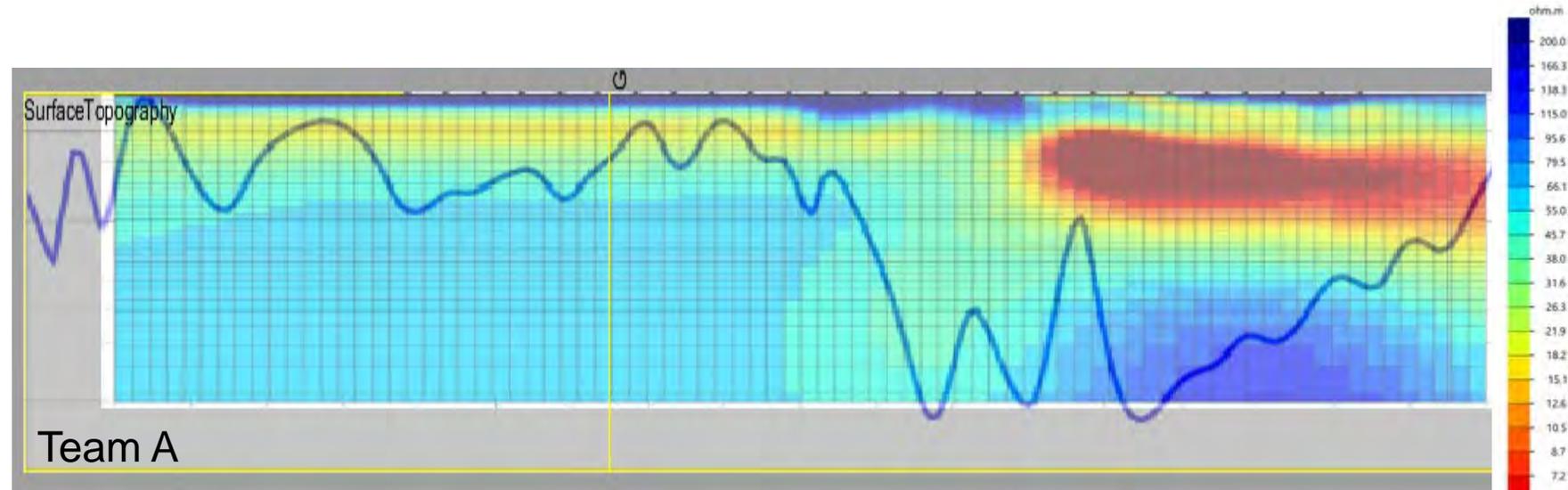


When **combined with gravimetry**, the 'blurry' imaging is alleviated and some hypotheses can be formulated

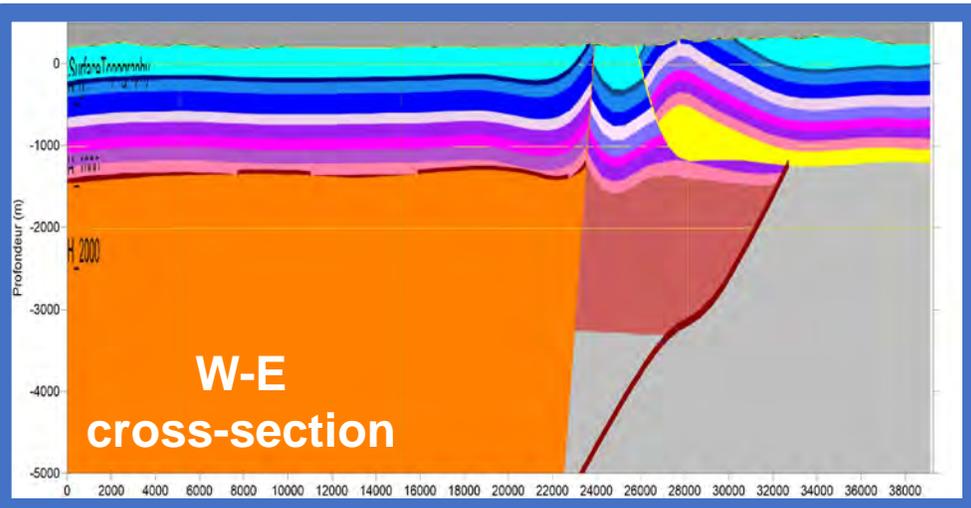
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Truth

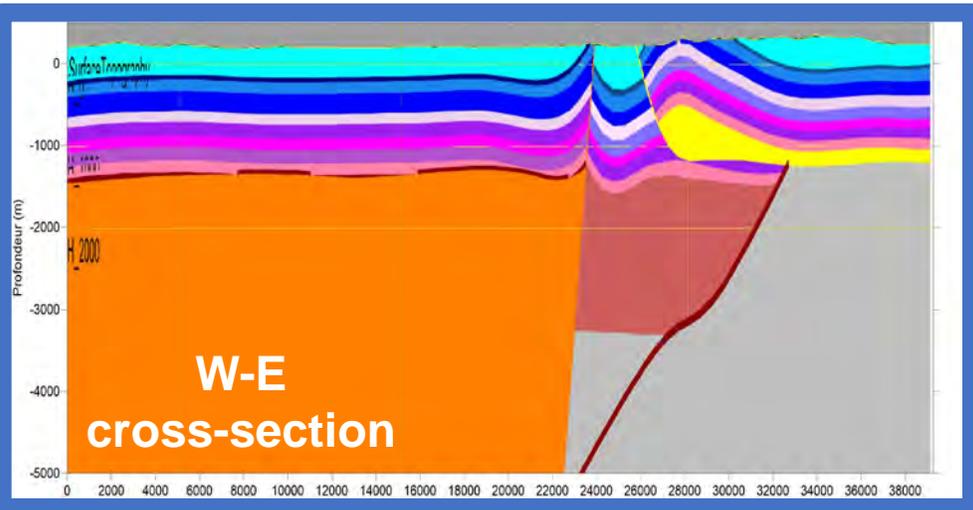


When **combined with gravimetry**, the 'blurry' imaging is alleviated and some hypotheses can be formulated

Representation format: colorscale



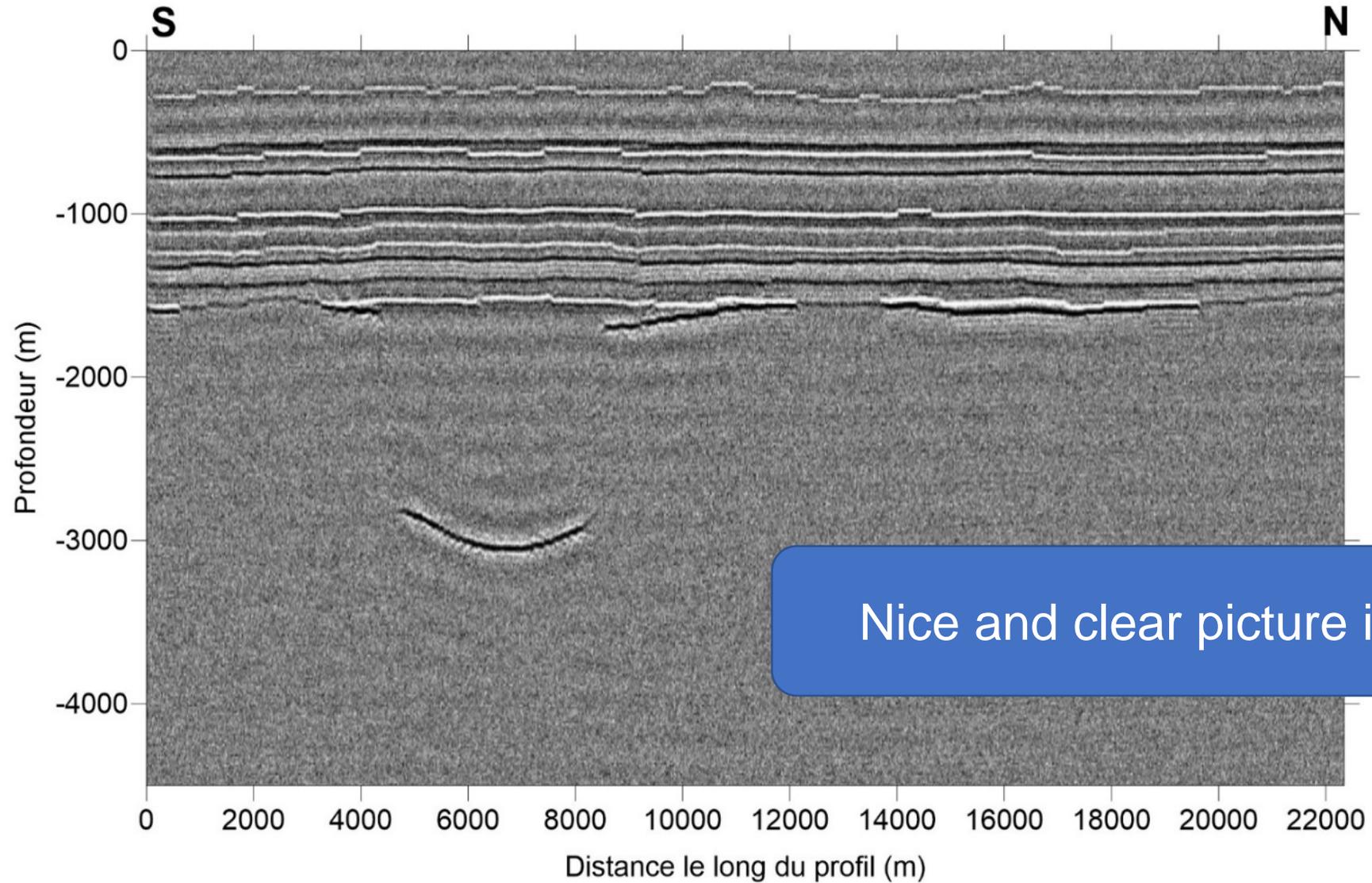
Truth



But made difficult by the choice of the **colorscale...**

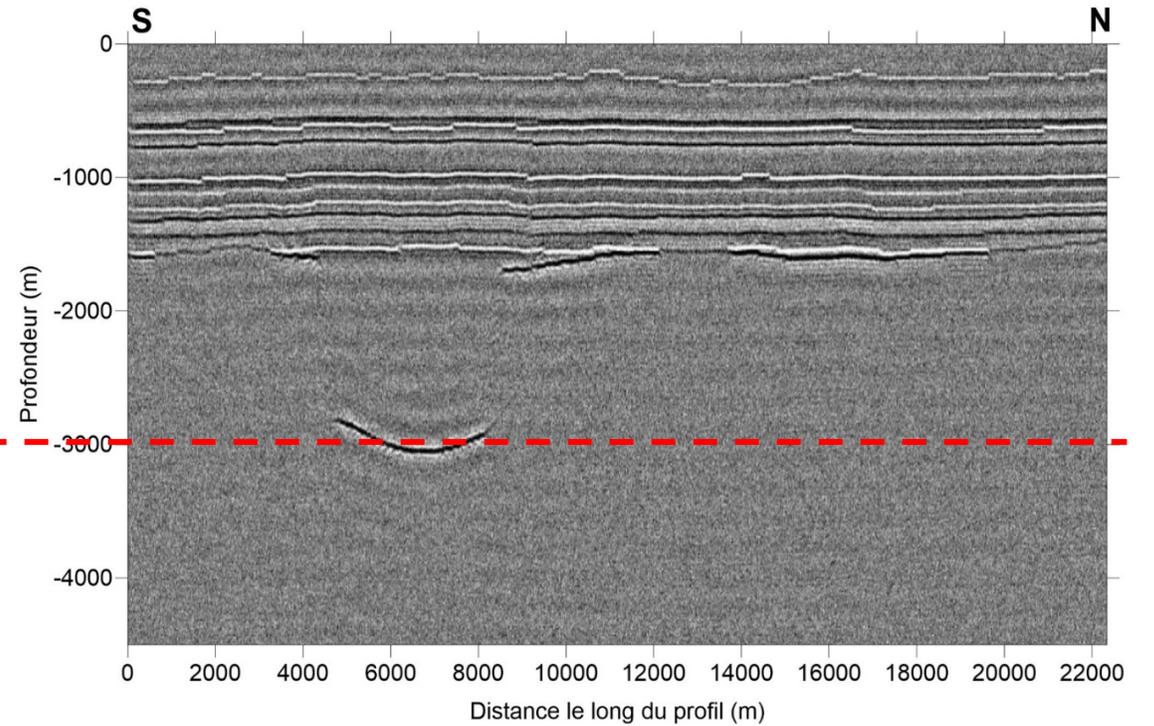
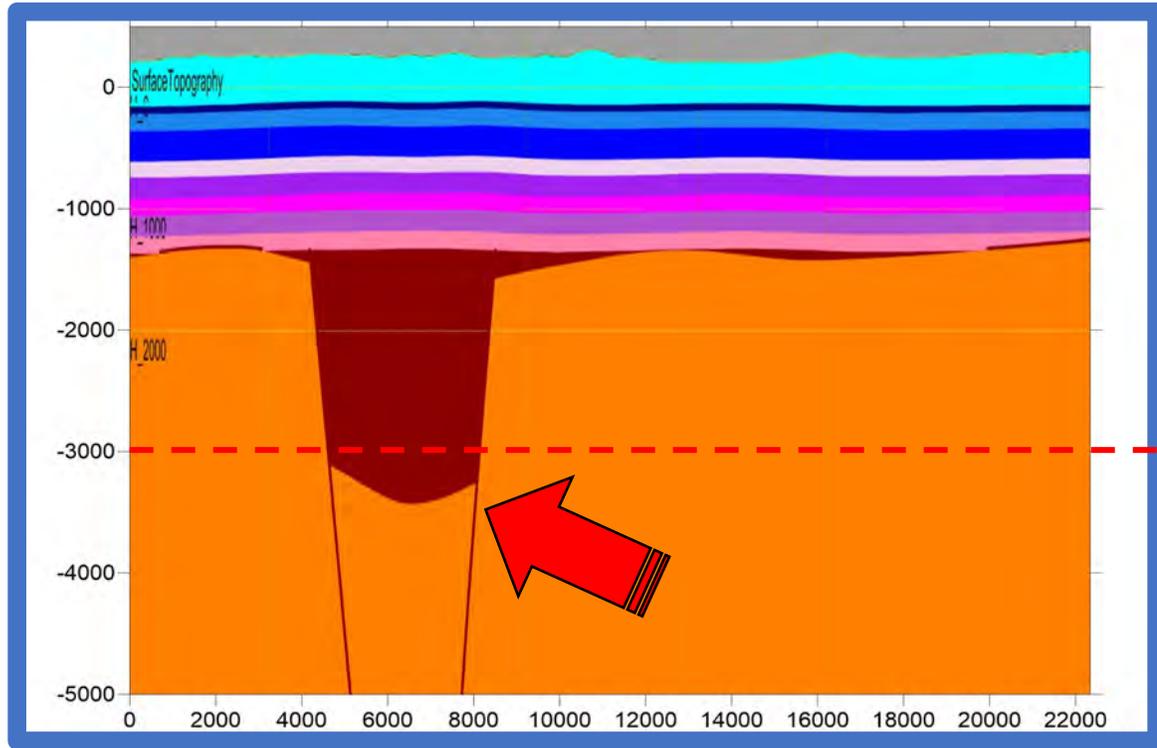
= 'dark-is-more' effect (Robinson et al. 1984)

Human-related difficulty



Human-related difficulty: misleading precision

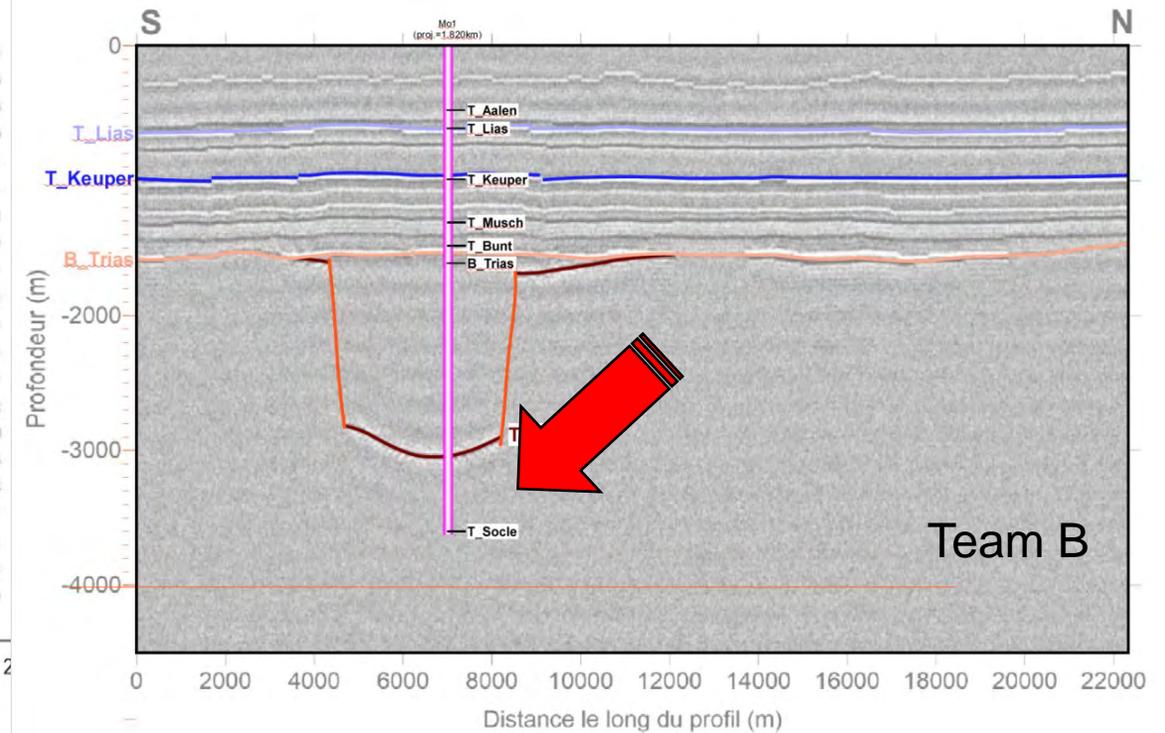
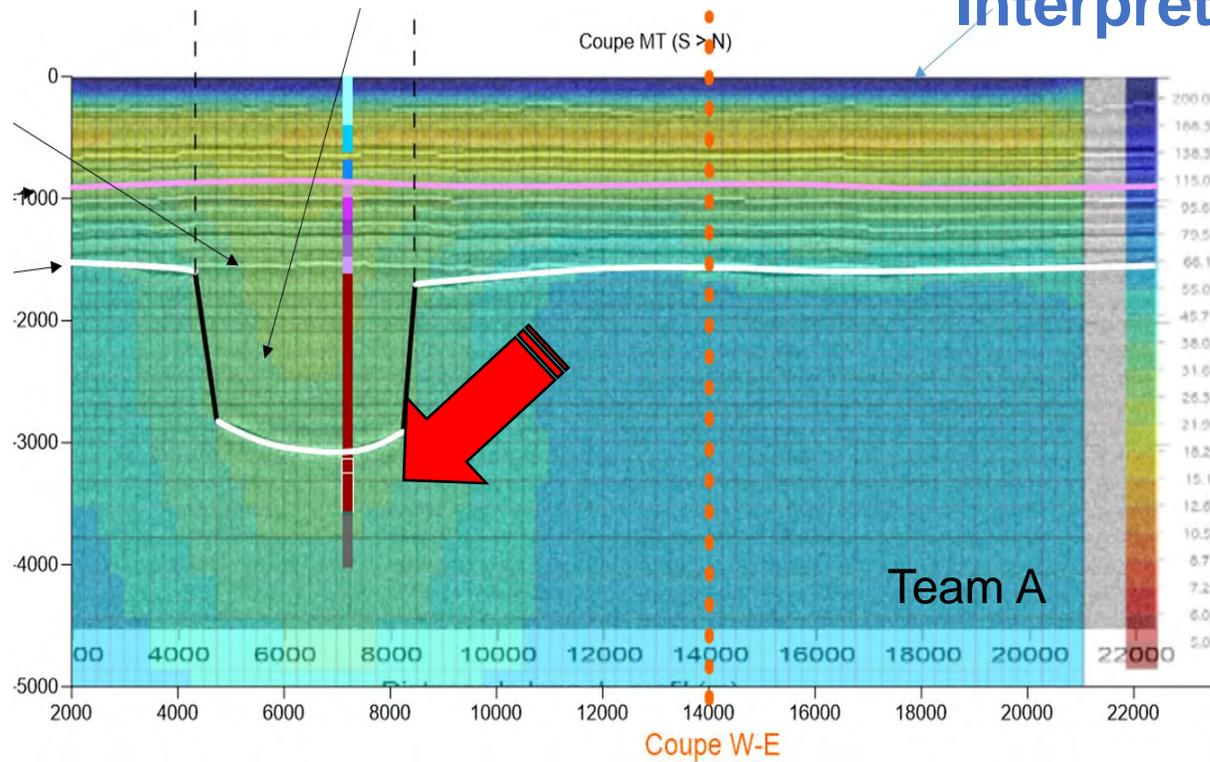
Truth



A mismatch of several hundreds of meters

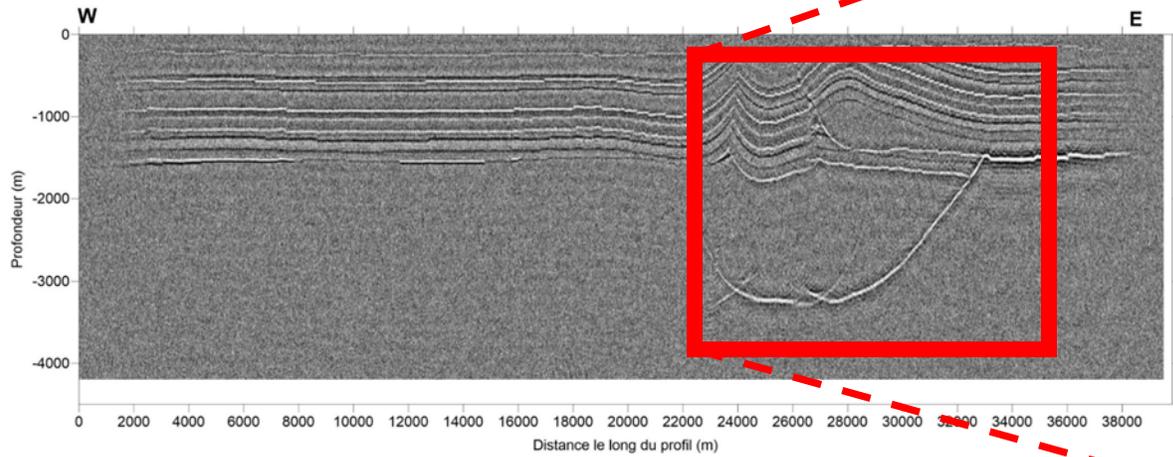
Human-related difficulty: misleading precision

Interpretations

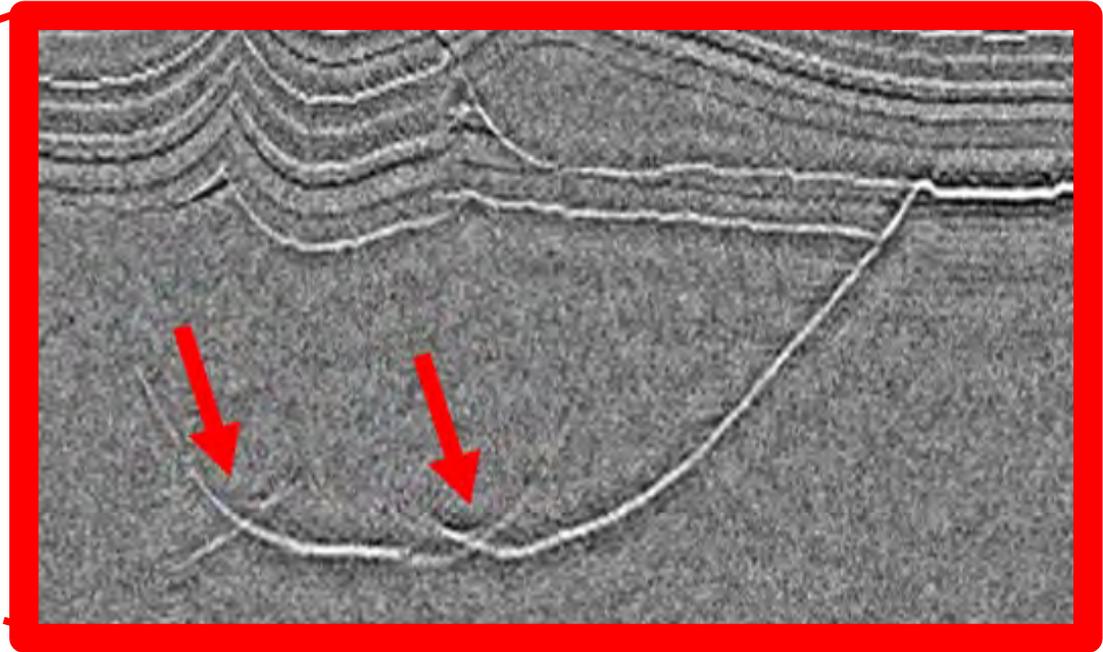


A clear discrepancy betw.
borehole and seismic was
highlighted BUT **little**
discussed...

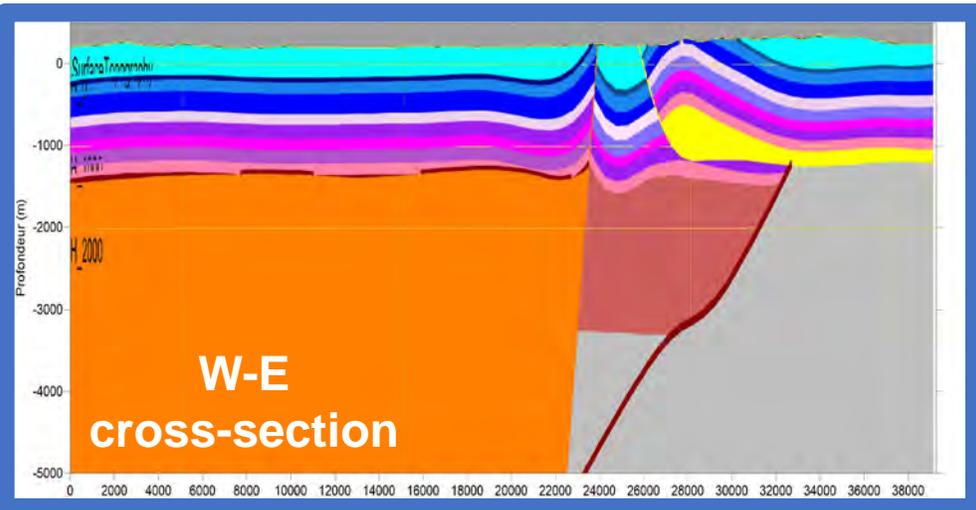
Human-related difficulty: misleading precision



Truth



... although artefacts in W-E cross sections should have indicated **mis-specifications** in the time-to-depth conversion



Summary

The blind exercise gives **confidence** in the ability of the interpreters to **formulate hypotheses to support discussions on further characterization campaigns**



Despite:

- **The time constraint of the exercise:** <6 hours
- **The 3D effect:** cross sections not necessarily orthogonal to the structures
- **The differences in practices** and tools of each team of interpreters
- **The cascade of different types of error** (noise, #borehole, resolution)

Summary

The blind exercise gives **confidence** in the ability of the interpreters to **formulate hypotheses to support discussions on further characterization campaigns**

Despite:

- **The time constraint of the exercise:** <6 hours
- **The 3D effect:** cross sections not necessarily orthogonal to the structures
- **The differences in practices** and tools of each team of interpreters
- **The cascade of different types of error** (noise, #borehole, resolution)

- Seismic was perceived as the **'perfect' dataset** although some artefacts were present
- Being able to question his/her first guess is not straightforward = linked to **'anchoring' bias [1,2]**
- Forstering **exchanges betw. interpreters and data providers = key**



Thank you for your attention!

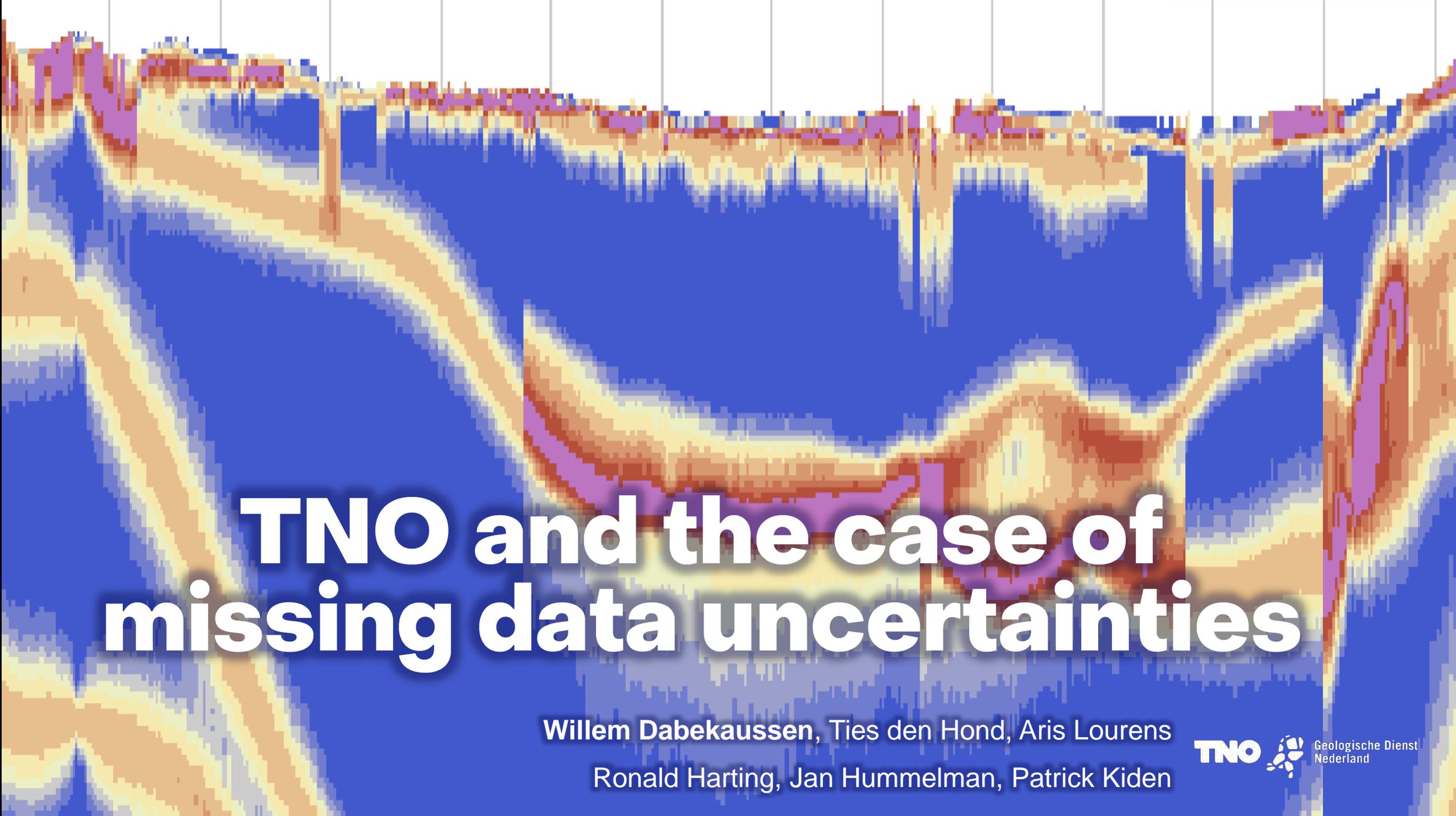
We acknowledge financial funding by
ANR-HOUSES
(grant number: **ANR-22-CE56-0006**)

<https://anrhouses.github.io/>

As well as the BRGM funded research
project PEX 'incertitudes'



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agence nationale
de la recherche



TNO and the case of missing data uncertainties

Willem Dabekaussen, Ties den Hond, Aris Lourens
Ronald Harting, Jan Hummelman, Patrick Kiden

Uncertainty of 2D maps

www.dinoloket.nl

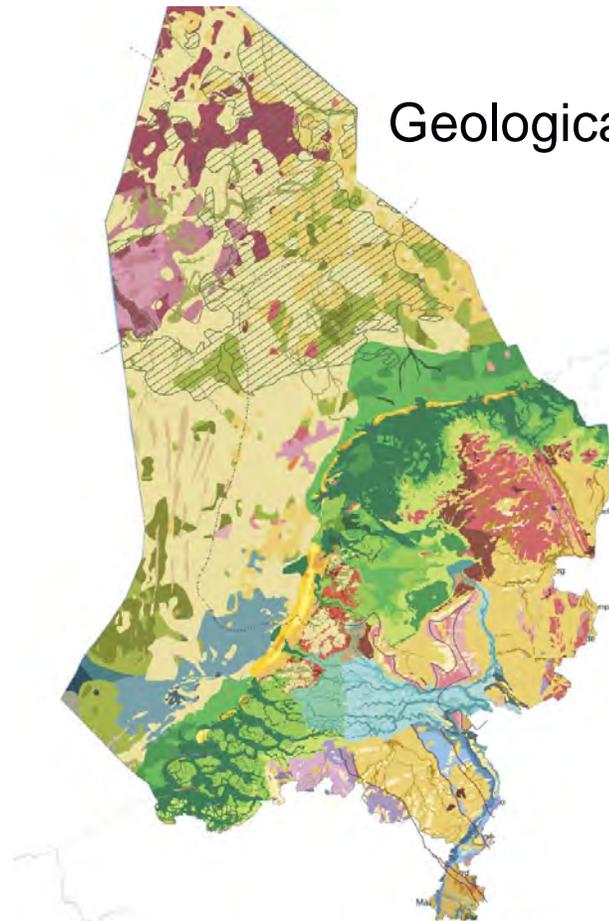
DINOloket

Data and Information on the Dutch Subsurface

Select model of interest

BRO data only:

- BRO DGM v2.2
- BRO REGIS II v2.2.1
- BRO GeoTOP v1.6
- BRO Geomorphology 2023-01
- BRO Soil map 2023-01
- BRO Groundwater level depth 2023-02
- Geological map 2021
- Seabed sediment
- DGMdeep v5.0



Geological map

No uncertainty
information

Uncertainty of 2D maps (2)

www.dinoloket.nl

DINOloket

Data and Information on the Dutch Subsurface

Select model of interest

BRO data only:

BRO DGM v2.2

BRO REGIS II v2.2.1

BRO GeoTOP v1.6

BRO Geomorphology 2023-01

BRO Soil map 2023-01

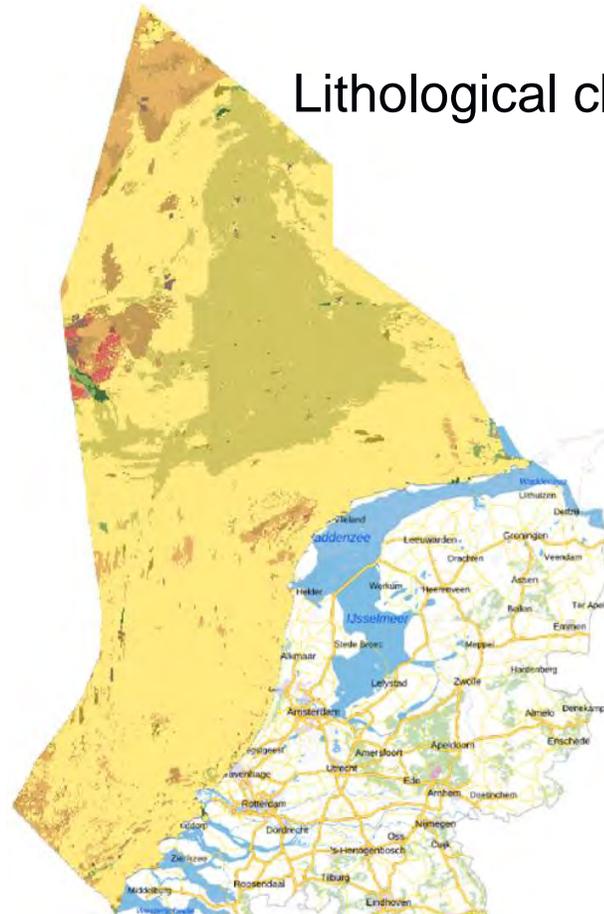
BRO Groundwater level depth 2023-02

Geological map 2021

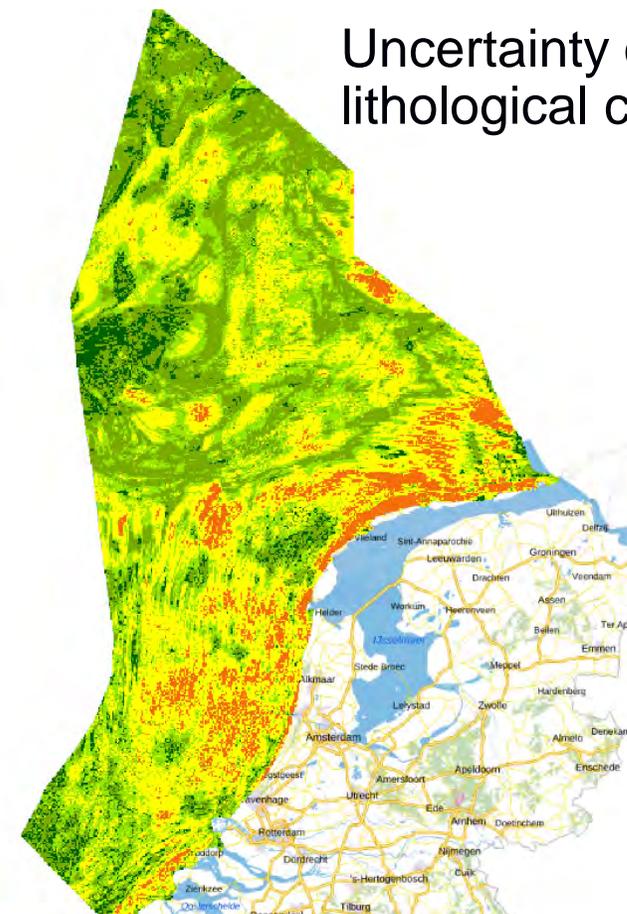
Seabed sediment

DGMdeep v5.0

Lithological class



Uncertainty of lithological class



Legend Likelihood class [%]

■ Almost certain ($P > 95$)

■ Highly likely ($80 < P \leq 95$)

■ Likely ($65 < P \leq 80$)

■ About as likely as not ($35 < P \leq 65$)

■ Unlikely ($P \leq 35$)

Uncertainty of 2.5D stratigraphic layer models

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DINOloket

Data and Information on the Dutch Subsurface

Select model of interest

BRO data only:

BRO DGM v2.2

BRO REGIS II v2.2.1

BRO GeoTOP v1.6

BRO Geomorphology 2023-01

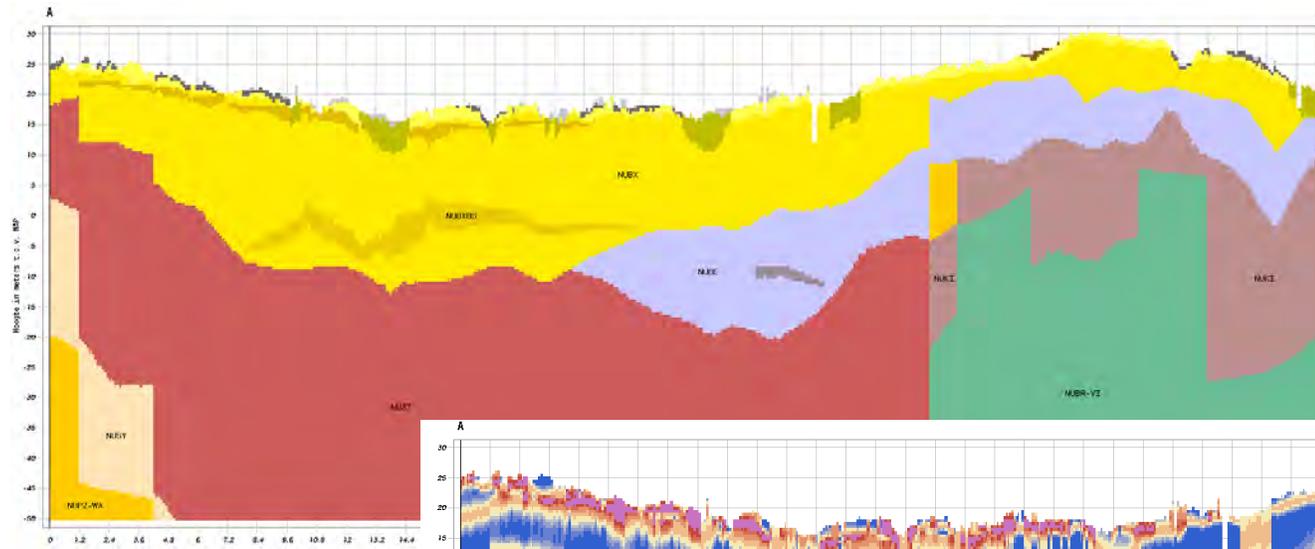
BRO Soil map 2023-01

BRO Groundwater level depth 2023-02

Geological map 2021

Seabed sediment

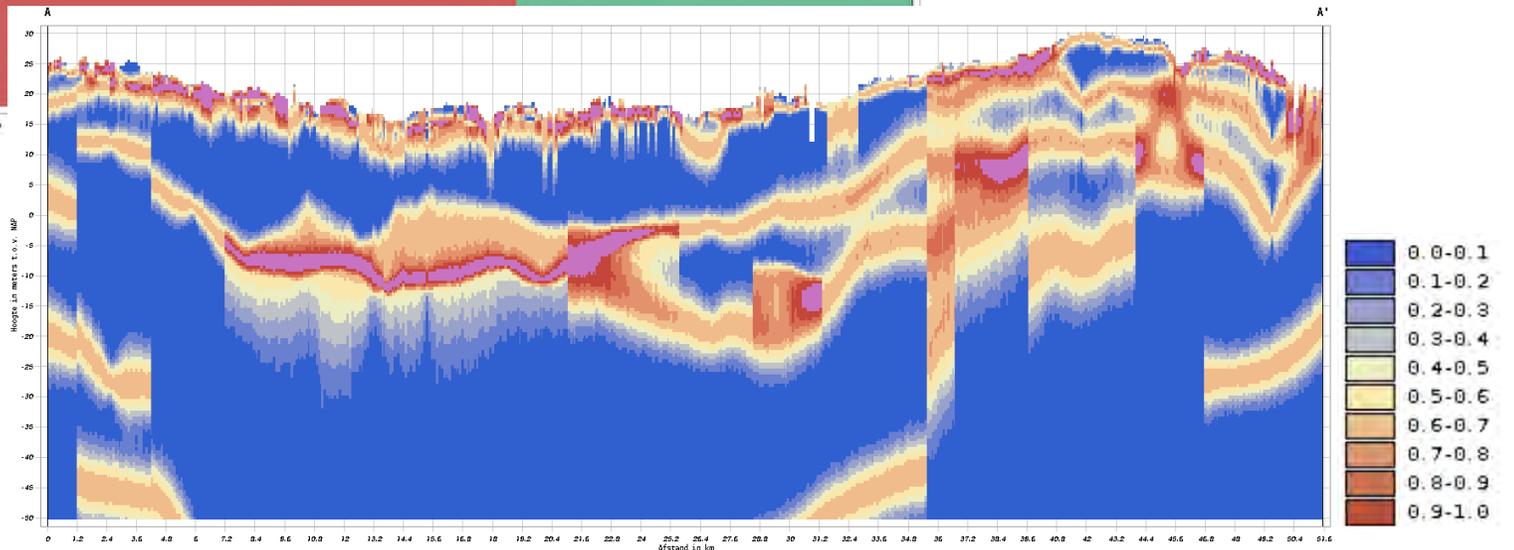
DGMdeep v5.0



Layer model

Stratigraphic units

Uncertainty
Stratigraphic unit



Uncertainty of 3D voxel models

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DINoloket

Data and Information on the Dutch Subsurface

Select model of interest

BRO data only:

BRO DGM v2.2

BRO REGIS II v2.2.1

BRO GeoTOP v1.6

BRO Geomorphology 2023-01

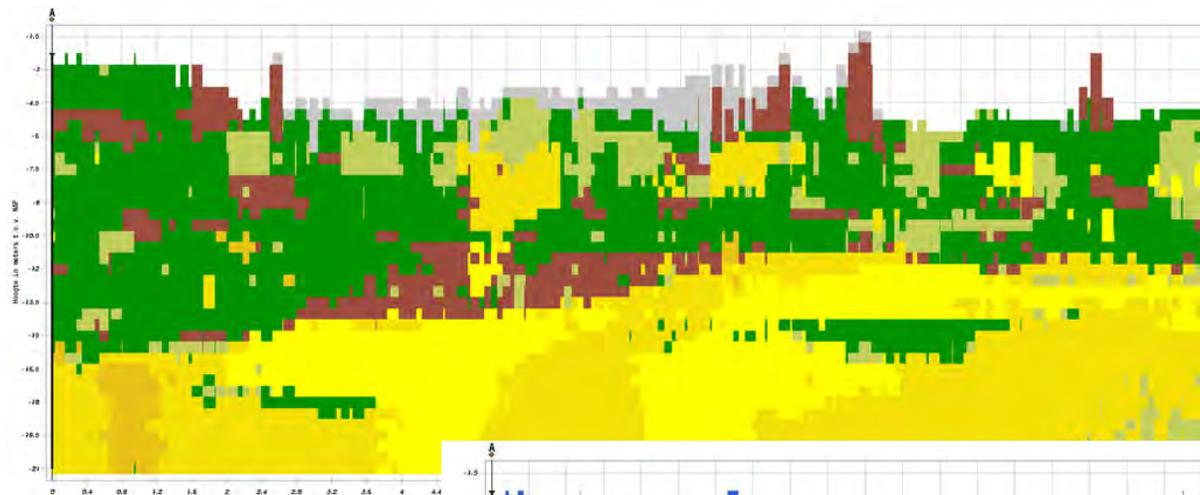
BRO Soil map 2023-01

BRO Groundwater level depth 2023-02

Geological map 2021

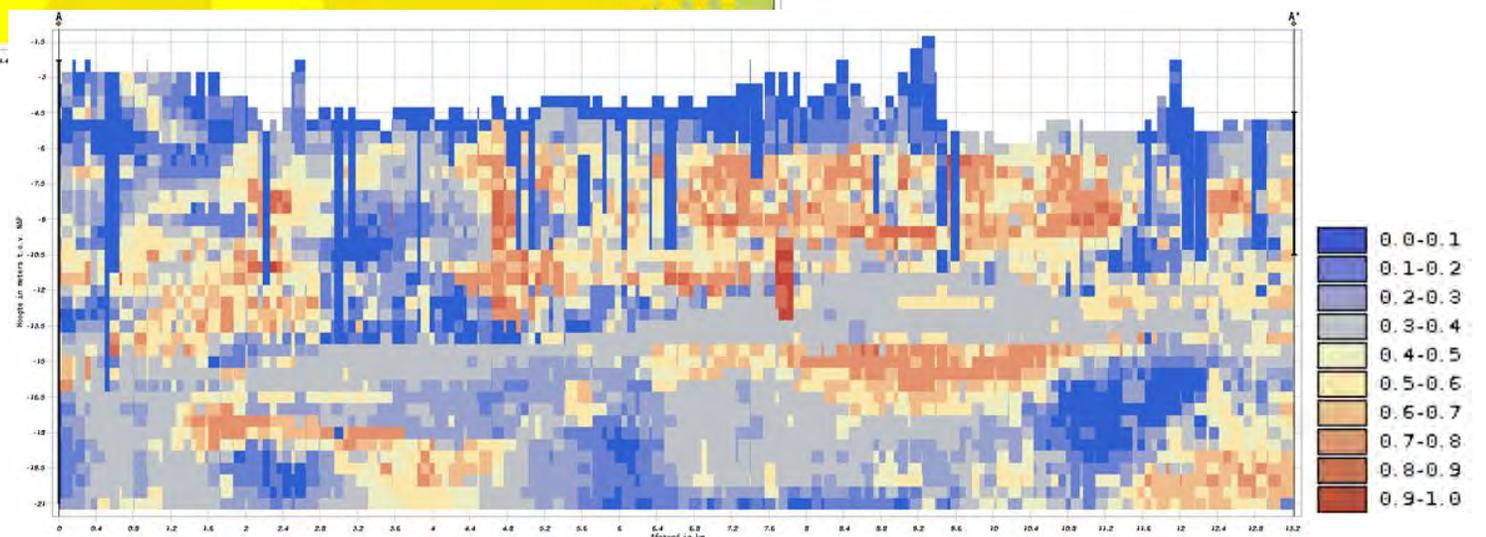
Seabed sediment

DGMdeep v5.0

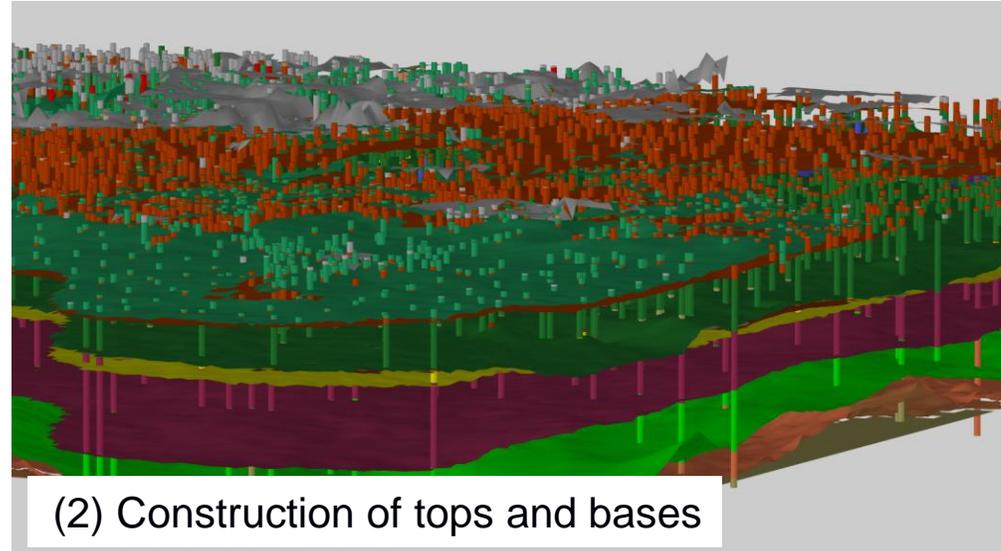
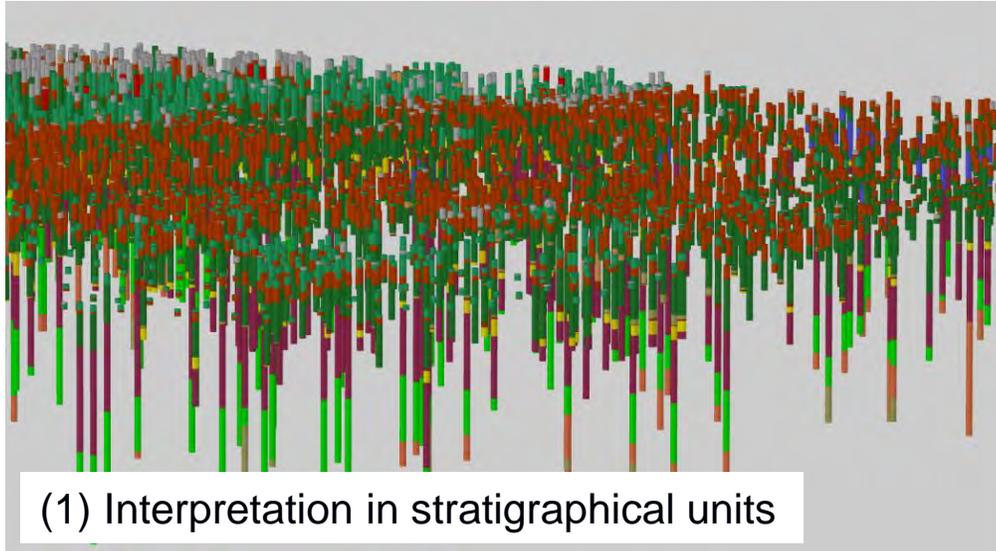


Voxel model
lithological class

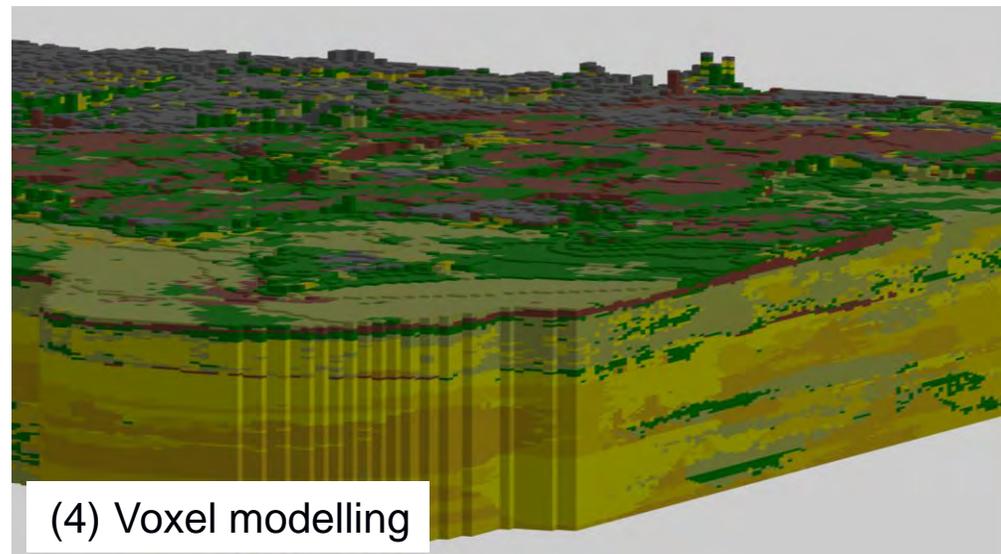
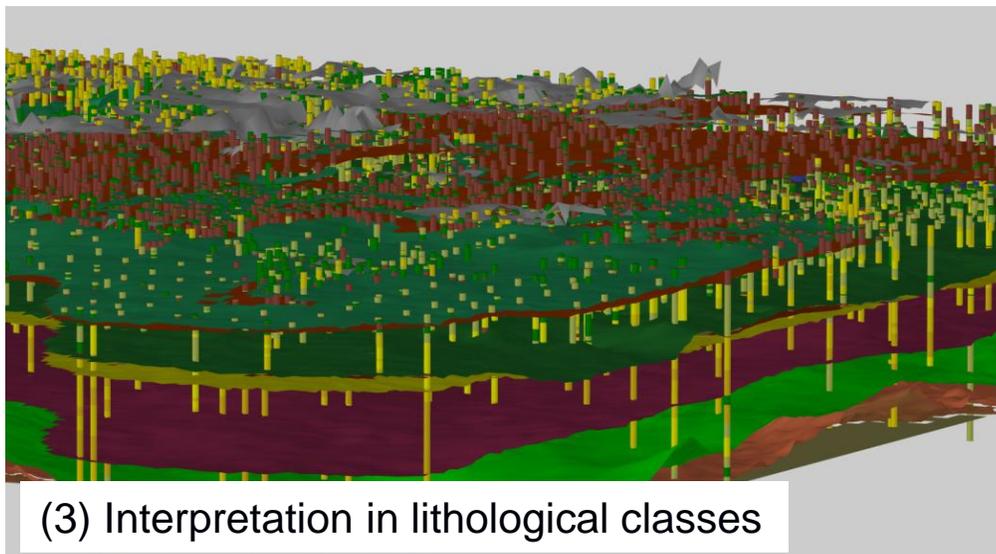
Uncertainty
lithological class



Shallow modelling workflow



Stratigraphical
units
+
uncertainties



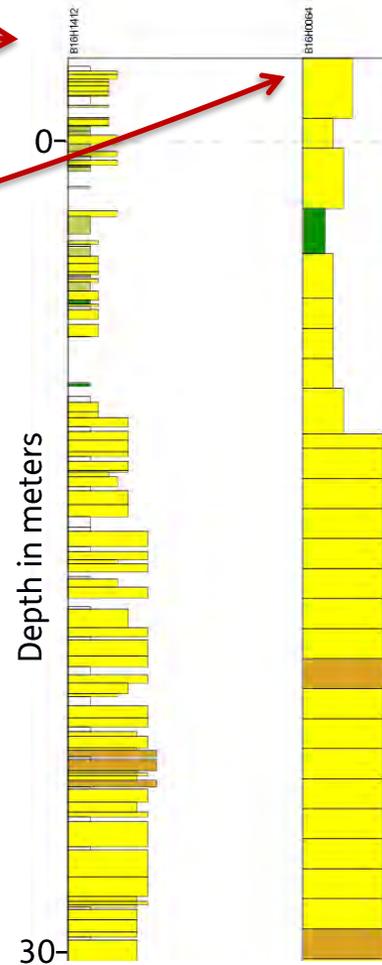
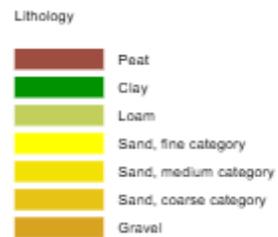
Lithological
classes
+
uncertainties

Sources of uncertainty

Many factors influence uncertainty of the geological model:

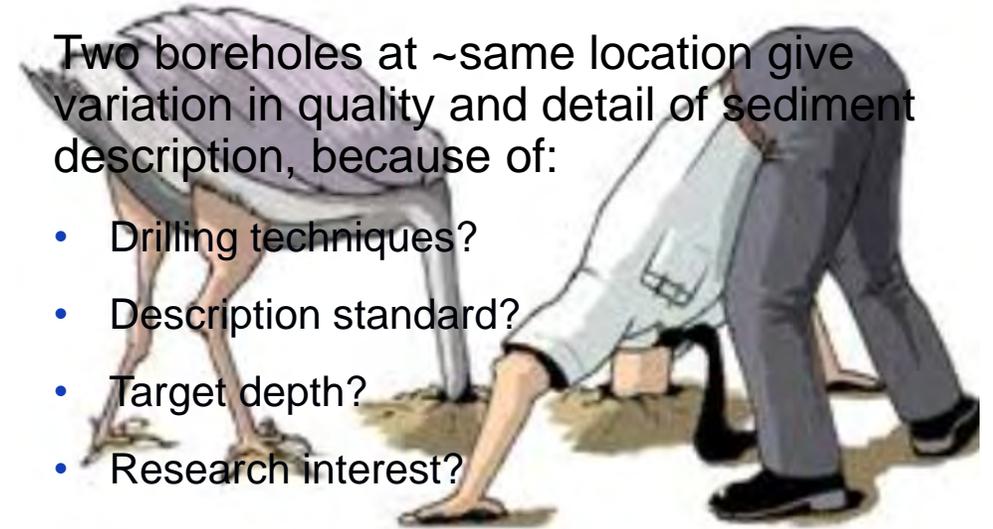
- XY-location
 - Depth of borehole sample
 - Sediment description
 - Conceptual model
 - Fault positions
 - Stratigraphic interpretations
 - Expected areal extent of stratigraphic units
 - ...
 - Interpolation of point data to 3D model
- ← Our model uncertainty represents only this one!
- Diagram annotations:
- A blue bracket groups the first three items (XY-location, Depth of borehole sample, Sediment description) and is labeled 'raw data'.
 - A green bracket groups the next four items (Conceptual model, Fault positions, Stratigraphic interpretations, Expected areal extent of stratigraphic units) and is labeled 'Geological knowledge'.

Sample description differences

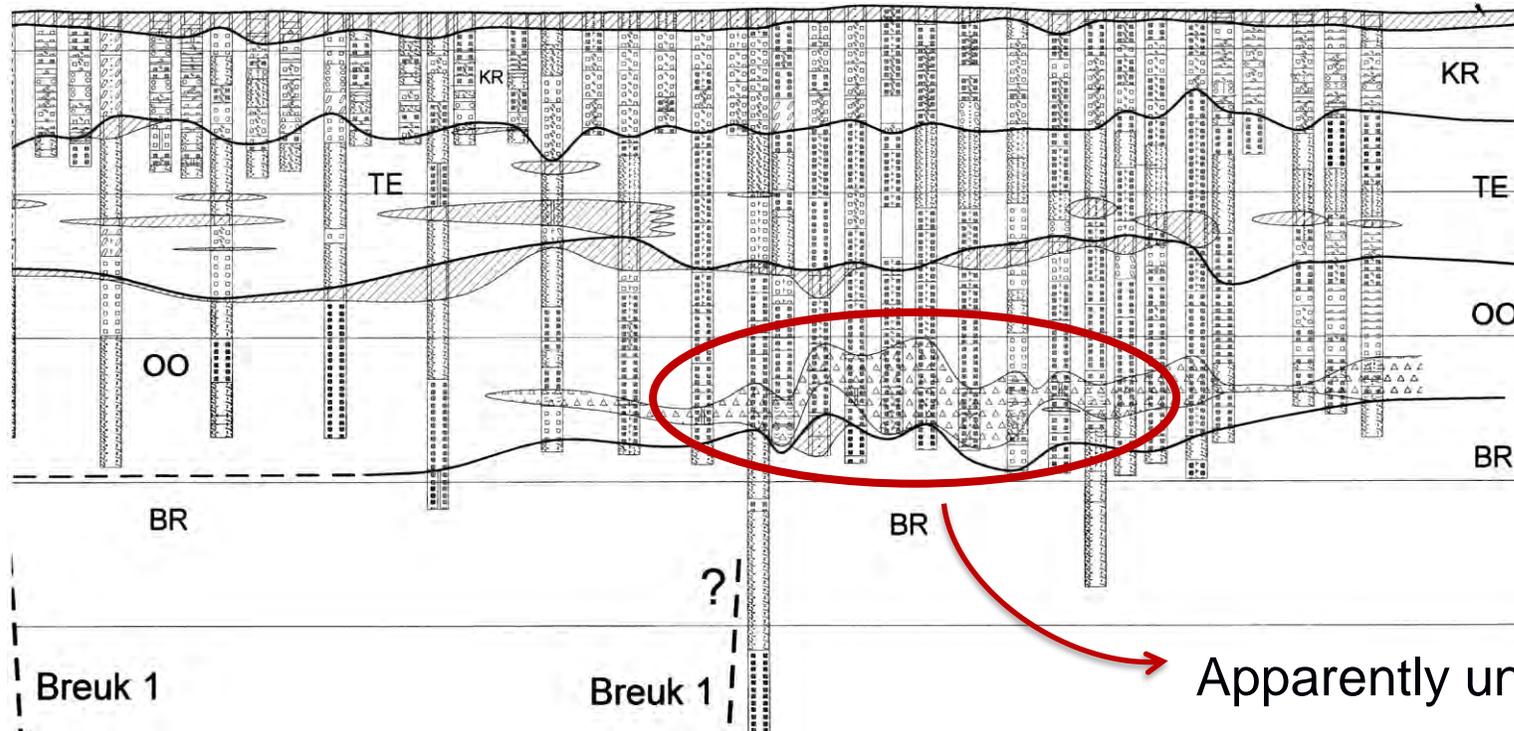


Two boreholes at ~same location give variation in quality and detail of sediment description, because of:

- Drilling techniques?
- Description standard?
- Target depth?
- Research interest?
- Personnel mood?
- ...



Sample description differences (2)



Apparently undulating surface:
Due to differences in sediment
description between drilling
companies

The software is ready for uncertain data



Special Options

<input type="checkbox"/> Collocated cokriging	<input type="checkbox"/> Use local anisotropies	<input type="checkbox"/> Use customized block sizes	<input type="checkbox"/> Reset negative weights to zero
<input type="checkbox"/> Rescaled cokriging	<input checked="" type="checkbox"/> Use uncertain data	<input type="checkbox"/> Use sampling density variance	
<input type="checkbox"/> Filtering model components	<input type="checkbox"/> Take faults into account	<input type="checkbox"/> Multiple kriging	



RandomForestRegressor

`fit(X, y, sample_weight=None)` [source]

Build a forest of trees from the training set (X, y).

Parameters:

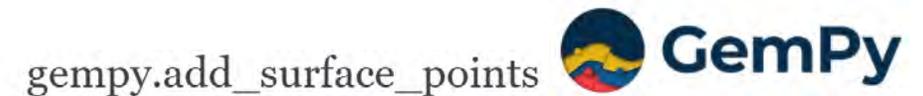
- X** : (array-like, sparse matrix) of shape (n_samples, n_features)
The training input samples. Internally, its dtype will be converted to `dtype=np.float32`. If a sparse matrix is provided, it will be converted into a sparse `csc_matrix`.
- y** : array-like of shape (n_samples,) or (n_samples, n_outputs)
The target values (class labels in classification, real numbers in regression).
- sample_weight** : array-like of shape (n_samples,), default=None
Sample weights. If None, then samples are equally weighted. Splits that would create child nodes with net zero or negative weight are ignored while searching for a split in each node. In the case of classification, splits are also ignored if they would result in any single class carrying a negative weight in either child node.



```
print("Fit with sample weight")
model = get_compiled_model()
model.fit(x_train, y_train, sample_weight=sample_weight, batch_size=64, epochs=1)
```

If per-sample uncertainty is known:

- Kriging can incorporate variance per sample
- Machine Learning can use sample weight
- Regardless of method: run simulations on possible variations of input data



`gempy.add_surface_points(geo_model: GeoModel, x: Sequence[float], y: Sequence[float], z: Sequence[float], elements_names: Sequence[str], nugget: Sequence[float] | None = None) + StructuralFrame` [source]

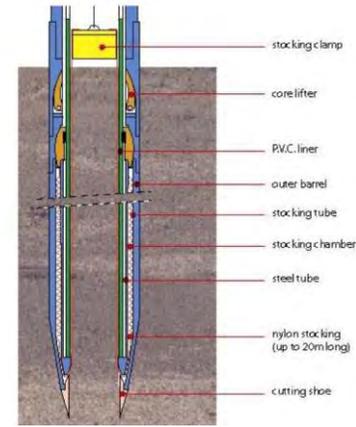
Add surface points to the geological model.

This function adds surface points to the specified geological elements in the model. The points are grouped by element names, and optional nugget values can be specified for each point.

- Parameters:
- **geo_model** (`GeoModel`) – The geological model to which the surface points will be added.
 - **x** (`Sequence[float]`) – Sequence of x-coordinates for the surface points.
 - **y** (`Sequence[float]`) – Sequence of y-coordinates for the surface points.
 - **z** (`Sequence[float]`) – Sequence of z-coordinates for the surface points.
 - **elements_names** (`Sequence[str]`) – Sequence of element names corresponding to each surface point.
 - **nugget** (`Optional[Sequence[float]]`) – Sequence of nugget values for each surface point. If not provided, a default value will be used for all points.

Where to start... uncertainty related to drilling techniques

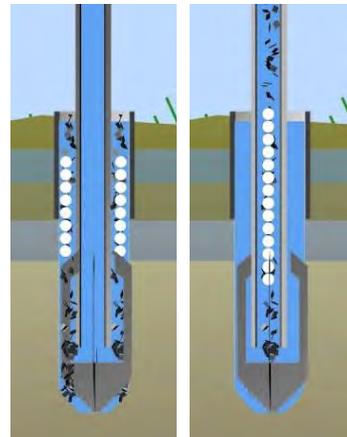
Different drilling techniques



Undisturbed sampling



Sample per meter interval



Can we quantify uncertainty of sample depth?

We have available:

- Quality classes per drilling method in *Standaard Boorbeschrijving (borehole description standard)*
- Drilling-expert opinion: estimated uncertainty of depth of sediment sample per drilling method

Before declaring data uncertain with value x , how to get confidence in our uncertainty values? We need a double-blind experiment...

Drilling method	SBB Quality label	Expert std dev [m]
Steekboring	A	0.1
Pulsboring	A	0.15
Counter-flushboring	A/B	0.75
Luchtlift-/zuigboring	B	1.5
Zuigboring	B	1.5
Luchtliftboring	B	1.5
Ro-flushboring	C	1.5
Sputboring	C	3.0
Straight-flushboring	C	3.0
Spoelboring	C	3.0

Sediment description vs. well log

Goal

- Determine uncertainty in depth of sediment descriptions interval (layer) boundaries

Data

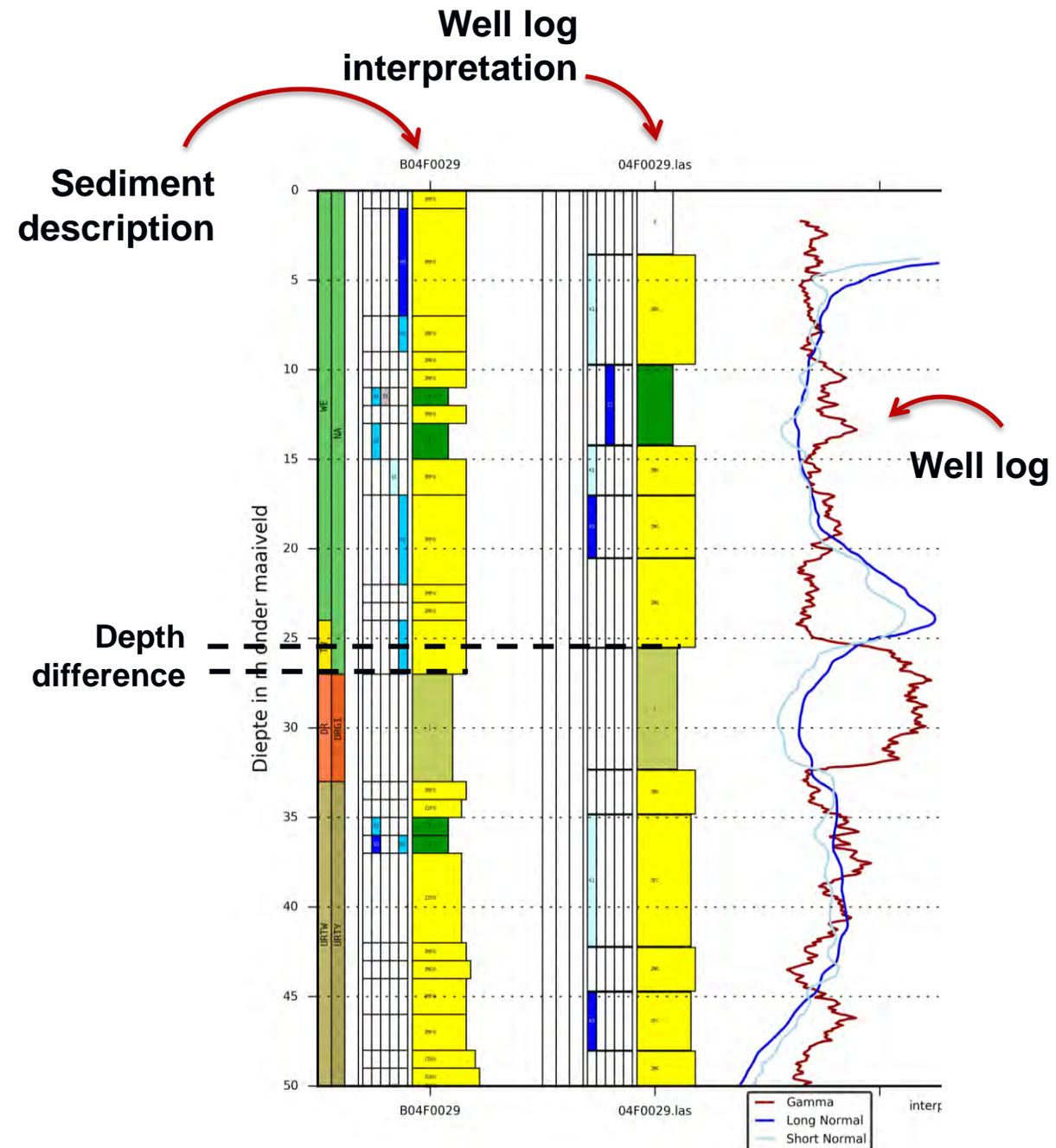
- We have sediment descriptions per borehole interval
- We have a well log and its lithological interpretation

Assumption

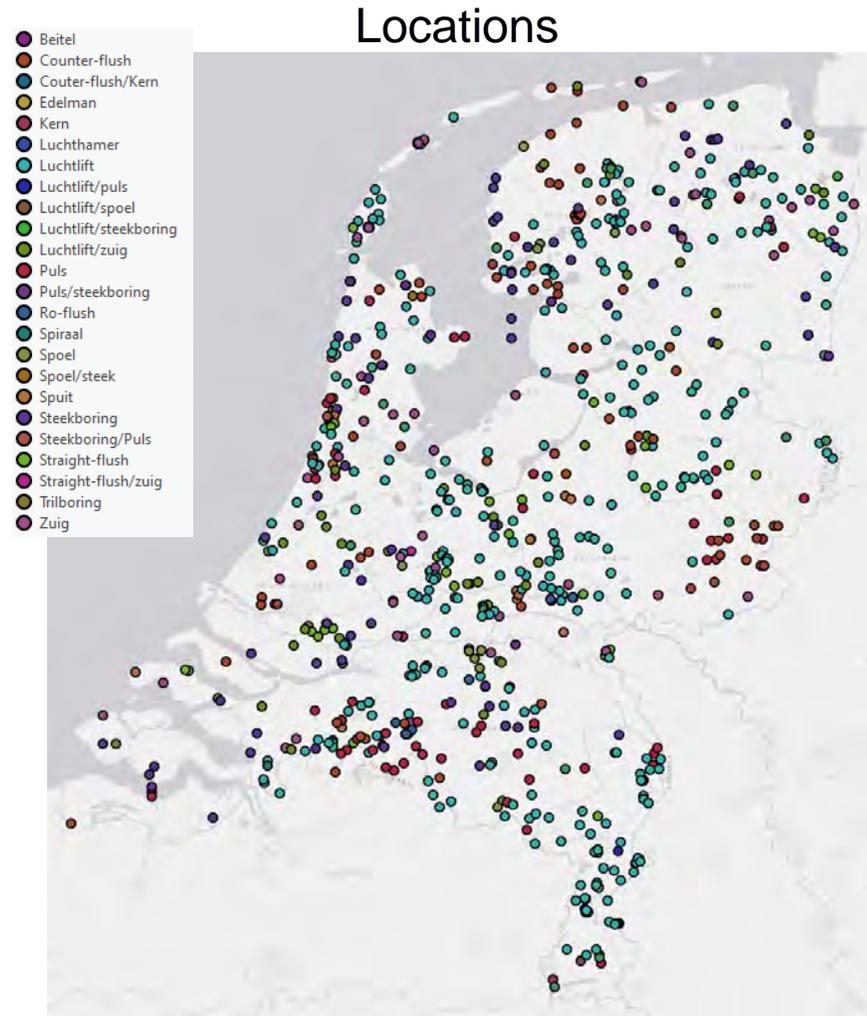
- Well logs are of constant quality, sediment description quality will show variation

Experiment design

- Note difference in depth of tops and bases of clayey intervals
- Analyse systematic differences in depth.



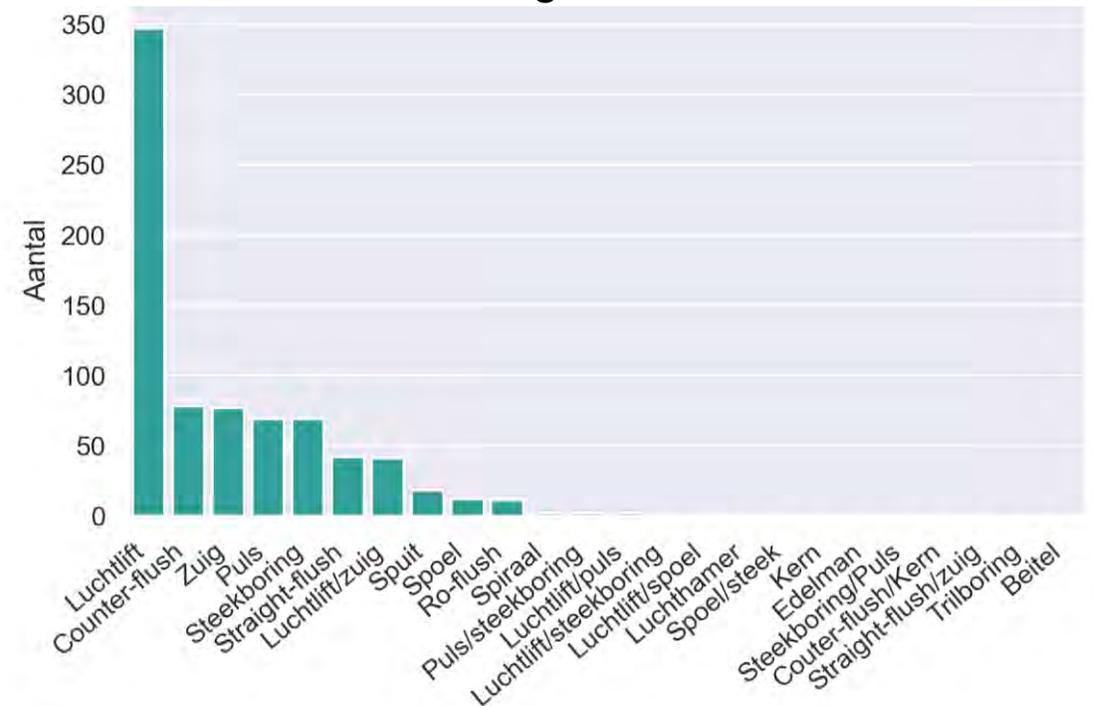
Well log data



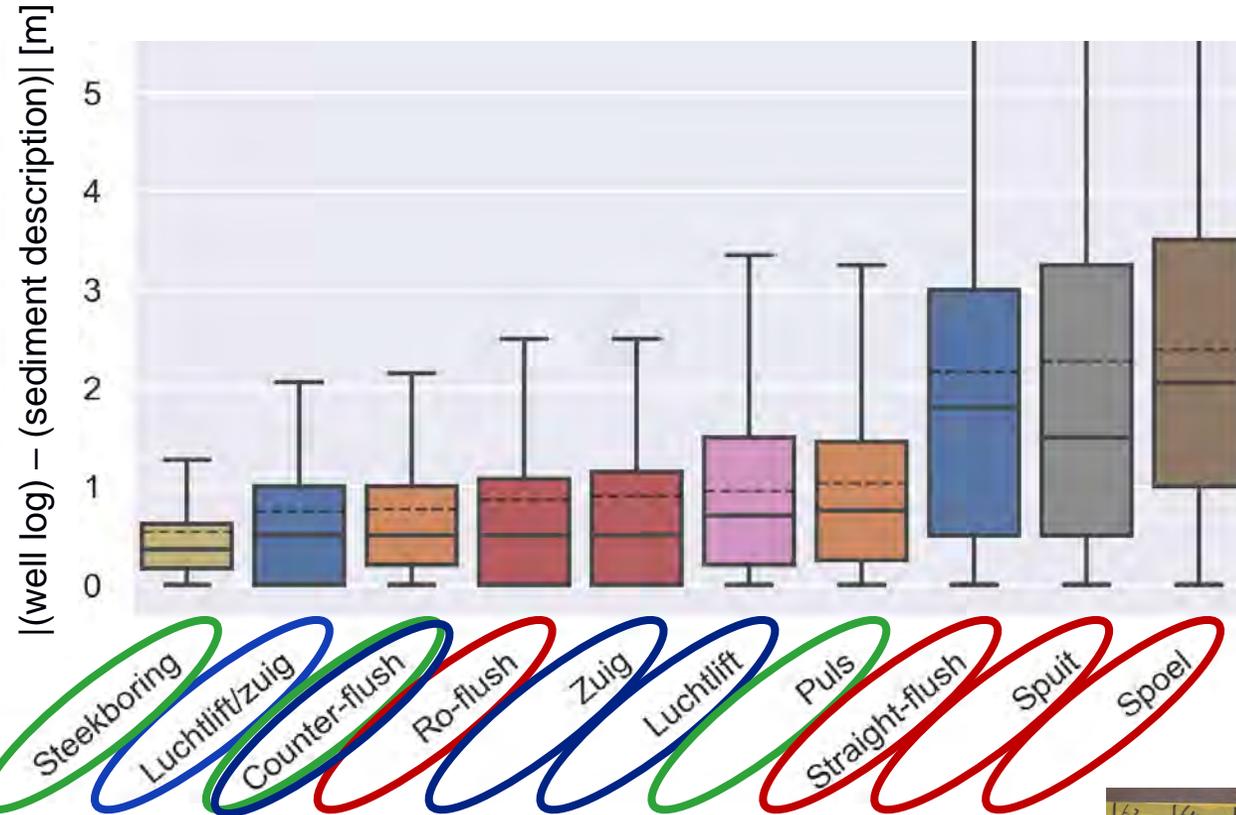
Data

- N=783
- Overrepresentation of specific drilling methods (e.g. airlift)
- Only few logs deeper than 100m

Drilling method



Differences in depth per drilling method



- N=3782 correlated boundaries (!)

SBB quality label: **A** **B** **C**



Drilling method uncertainty quantification

Drilling method	SBB Quality label	Expert Std dev [m]	Calculated mean deviation [m]	Calculated std dev [m]
Steekboring	A	0.1	0.00	0.00
Pulsboring	A	0.15	0-0.5	1-1.5
Counter-flushboring	A/B	0.75	0-0.5	0.5-1
Luchtlift-/zuigboring	B	1.5	0-0.5	1-1.5
Zuigboring	B	1.5	0-0.5	1-1.5
Luchtliftboring	B	1.5	0-0.5	1-1.5
Ro-flushboring	C	1.5	0-0.5	1-1.5
Sputboring	C	3.0	1-2	2-3
Straight-flushboring	C	3.0	1-2	2-3
Spoelboring	C	3.0	1-2	2-3

calculation

- Assume well logs have ~constant uncertainty, while sediment description uncertainty varies with drilling method
- Well log measurements have uncertainty as well...
- Assume undisturbed coring has zero uncertainty, then we can calculate minimum uncertainty for other drilling methods

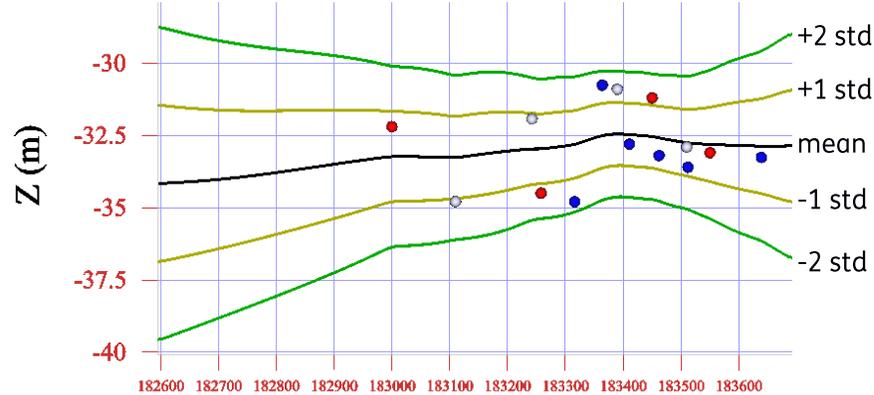
result

- Good match between expert estimates and well-log based experiment outcome

The benefit of knowing your data uncertainty

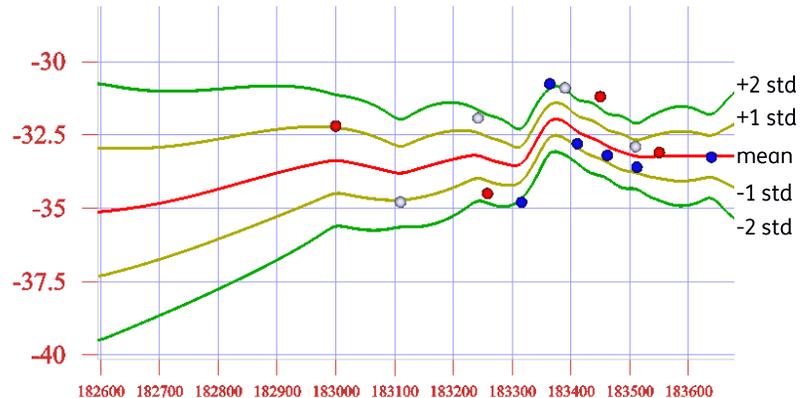
Current practice:

kriging with global variogram nugget



Future practice:

Kriging without global variogram nugget, with sample variance



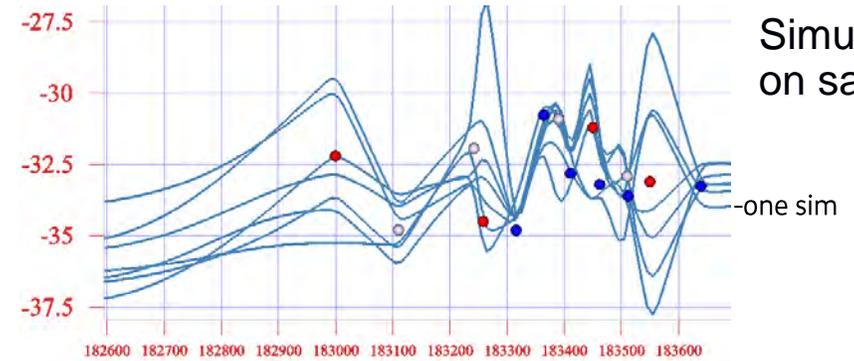
Sample std dev

- High
- Mid
- Low

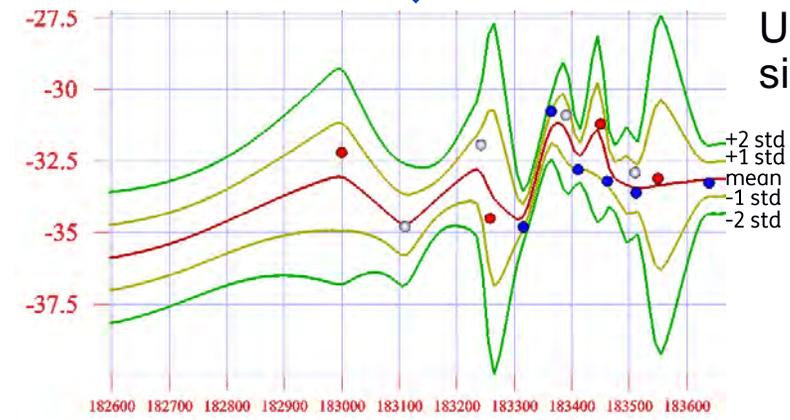
X (m)



Adding sample uncertainty
reduces model uncertainty!



Simulations based on sample draws



Uncertainty of simulations

X (m)

Conclusions

- Quantifying data uncertainty is possible!
- But a lot of work, and this was just **one** source of uncertainty.
- Good match between expert estimate and quantified uncertainty for *most* drilling methods
- Next step: implement in stratigraphical layer models e.g. DGM+, REGIS, GeoTOP...
- Further steps: quantify and implement other sources of data uncertainty, e.g. XYZ-coordinates
- We have different geology but use the same kind of data. Setting-up a data uncertainty framework is a nice case for European collaboration?