# Smart Monitoring – Data structure and Optimal Experimental Design (OED) methods for (geo)physical data acquisition

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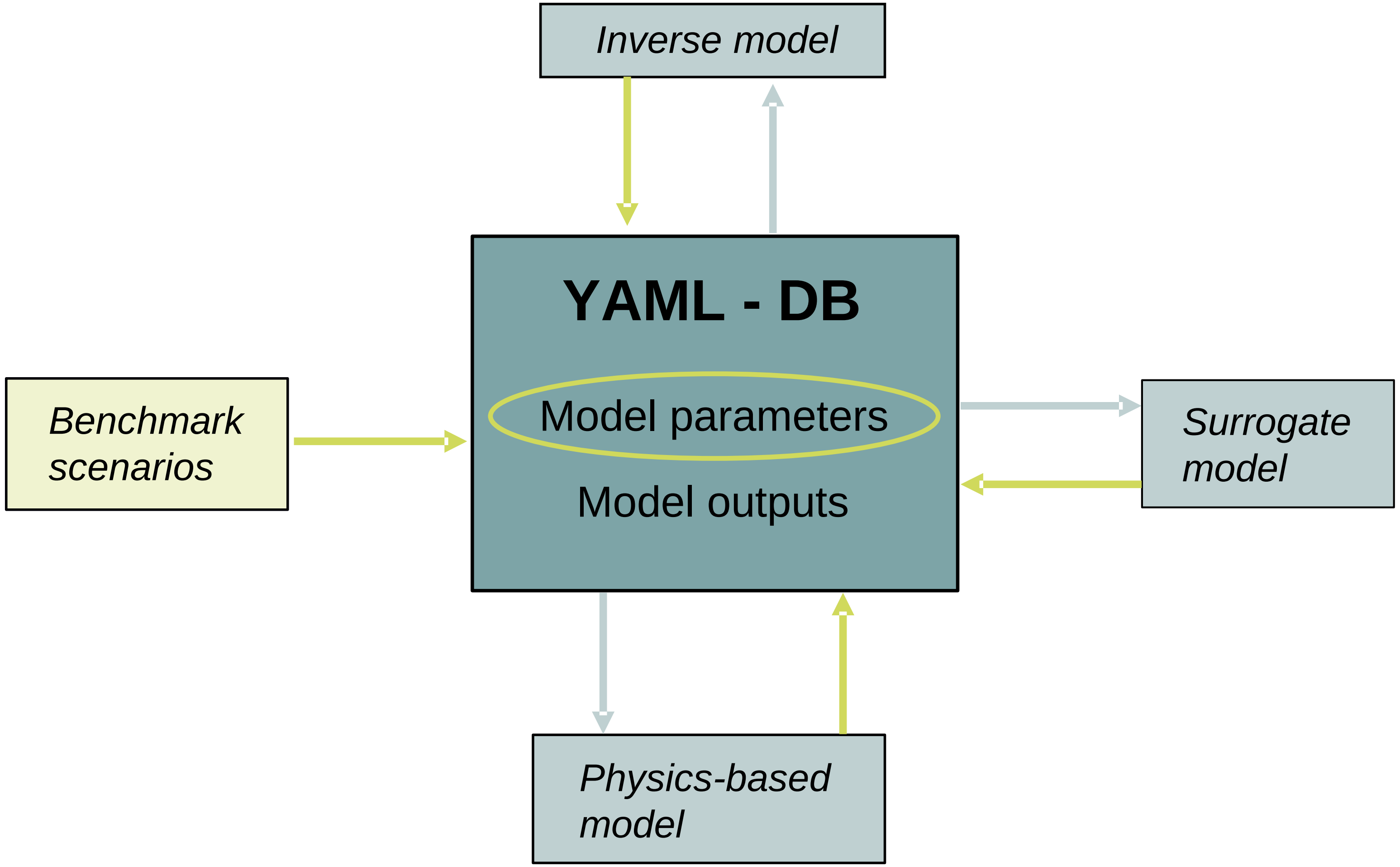
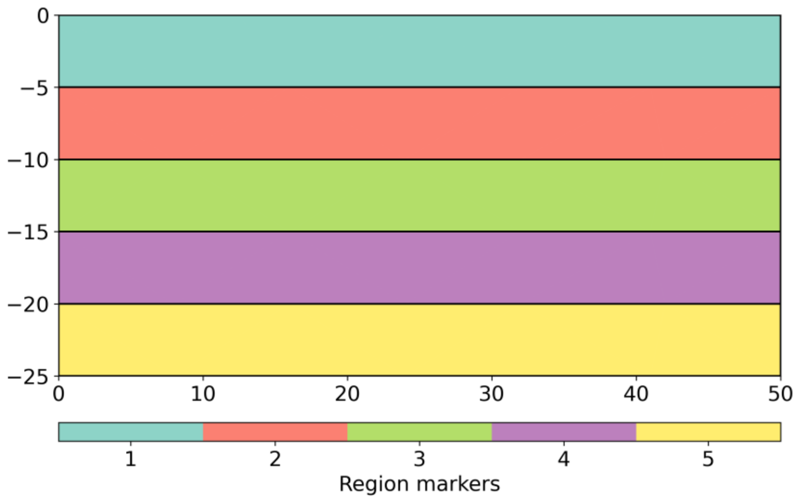
# Data structure – Overview and recap

- Model parameters are stored as **YAML files**
- **Input**: literature and field data from benchmark scenarios
- Referenced parameters can be utilized in **process models and inversions**
- Advantage: **simple, easily accessible** storage of important model parameters



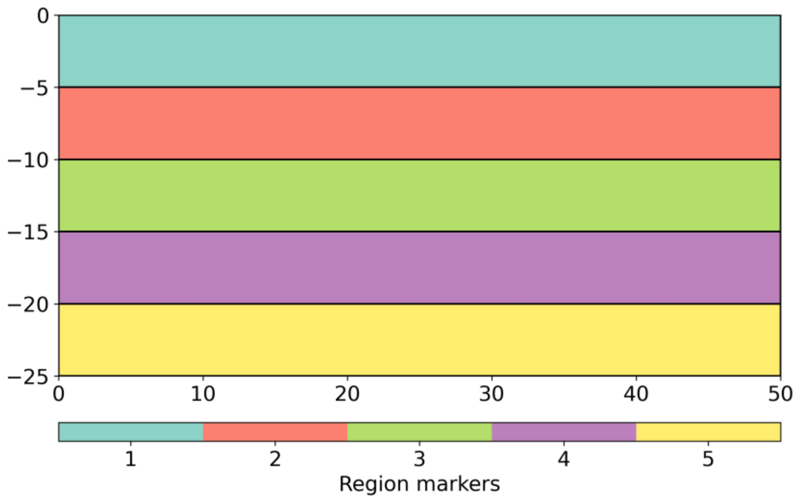
# Data structure – YAML-files




**OpalinusClay_MontTerri.yml**

- 1 Tertiary_sandstone.yml
- 2 UpperJurassic_sandstone.yml
- 3 MidJurassic_Opalinus_MontTerri.yml
- 4 LowerJurassic_claystone.yml
- 5 Bunter_sandstone.yml

# Data structure – YAML-files

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**MidJurassic_Opalinus_default.yml**

- Density_default
- Porosity_default
- HydraulicConductivity_default
- HeatCapacity_default
- ElectrResistivity_default

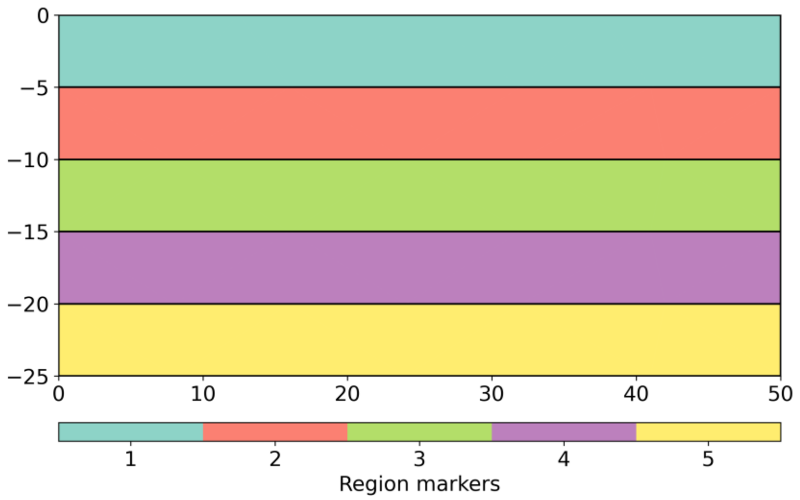
**3 MidJurassic_Opalinus_MontTerri.yml**

- HydraulicConductivity_MontTerri
- ElectrResistivity_MontTerri

**DEFAULT VALUES**

**SITE SPECIFIC VALUES**

# Data structure – YAML-files

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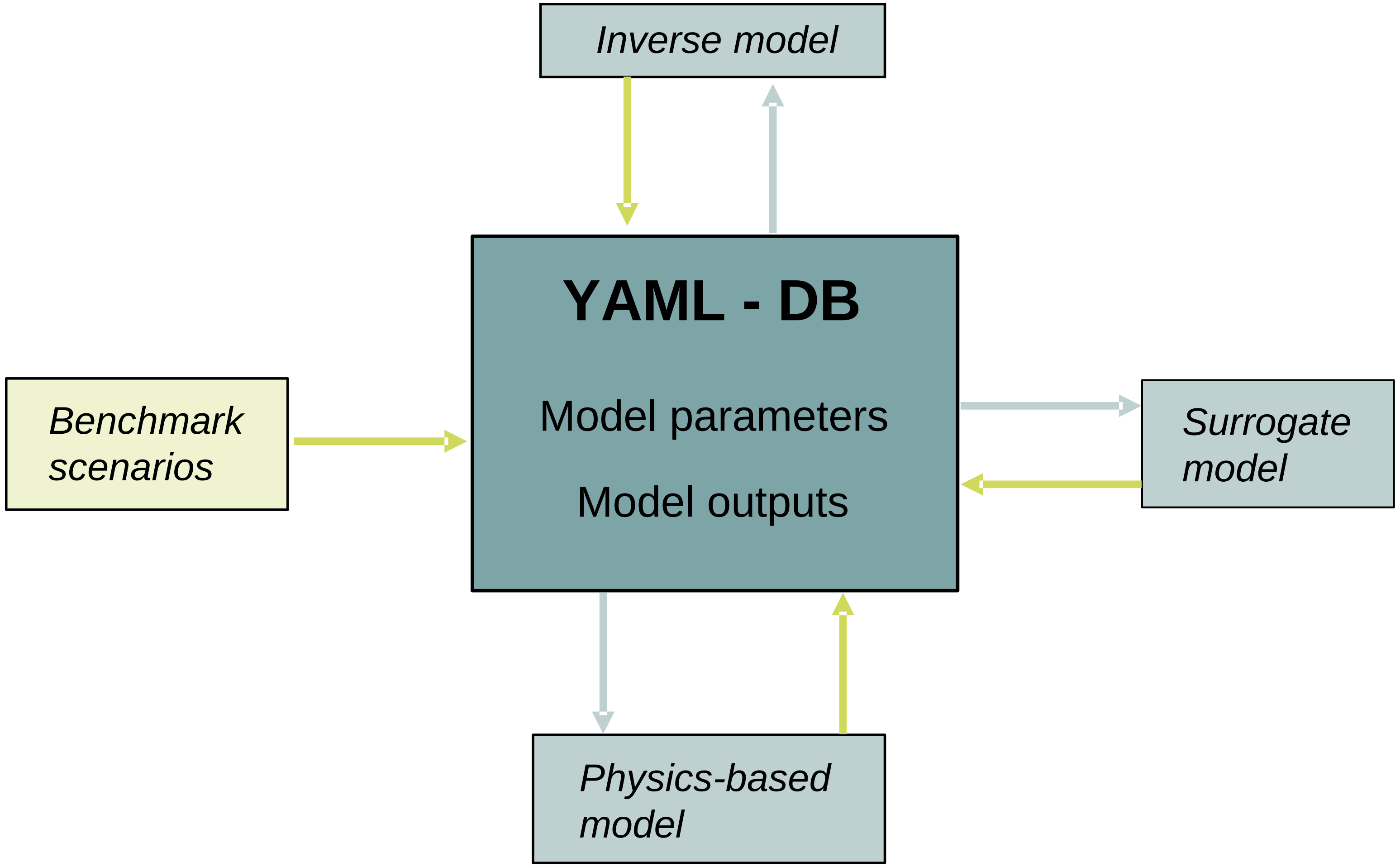
**3 MidJurassic_Opalinus_MontTerri.yml**

- Density_default
- Porosity_default
- HydraulicConductivity_MontTerri
- HeatCapacity_default
- ElectrResistivity_MontTerri

**COMBINED VALUES**

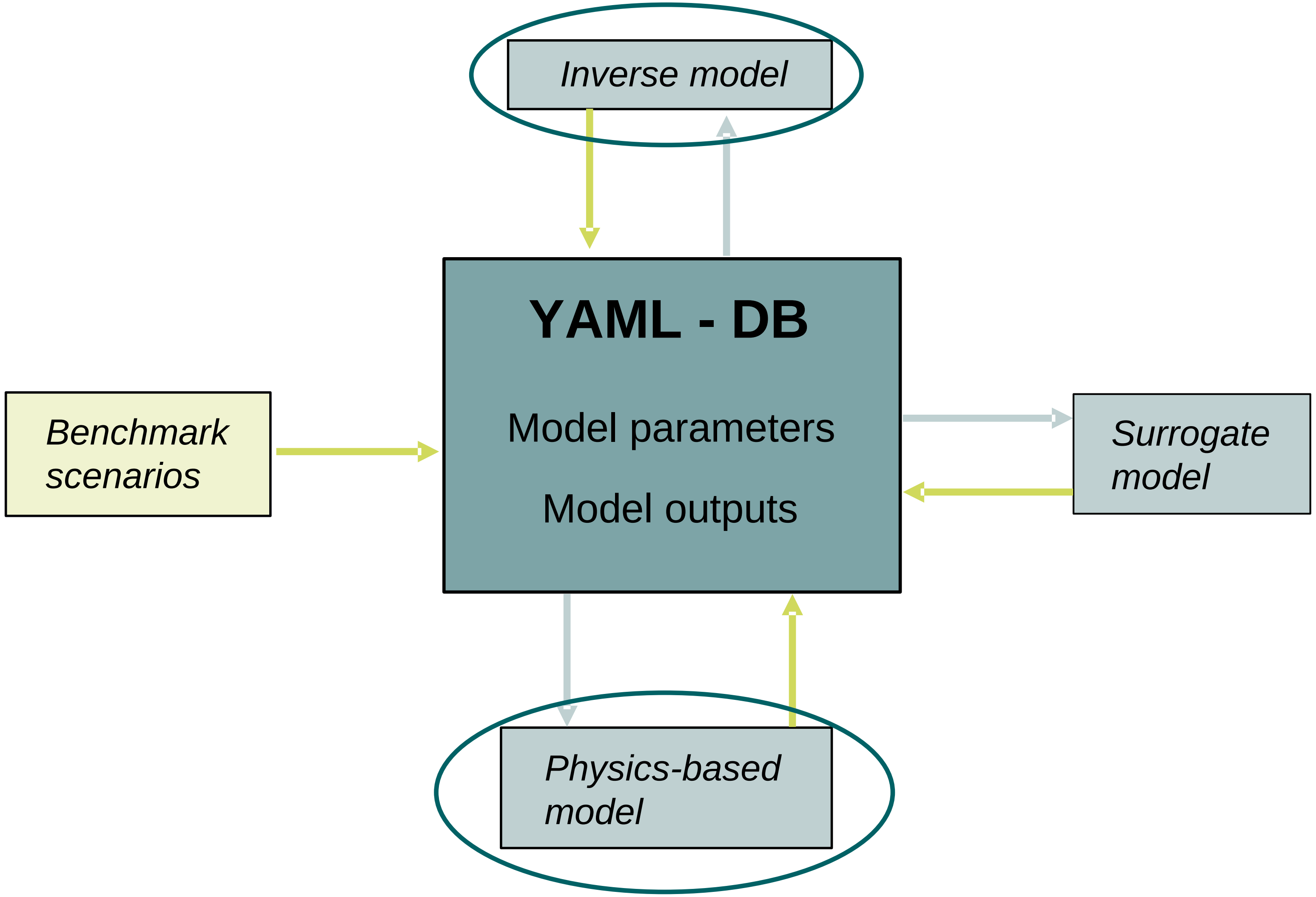
# Data structure – YAML-files

- Model parameters can be used as **input** for any kind of **simulation / model**
- **End Goal:** Library for simulation-relevant model parameters that **cover all benchmark scenarios** of possible repository sites.



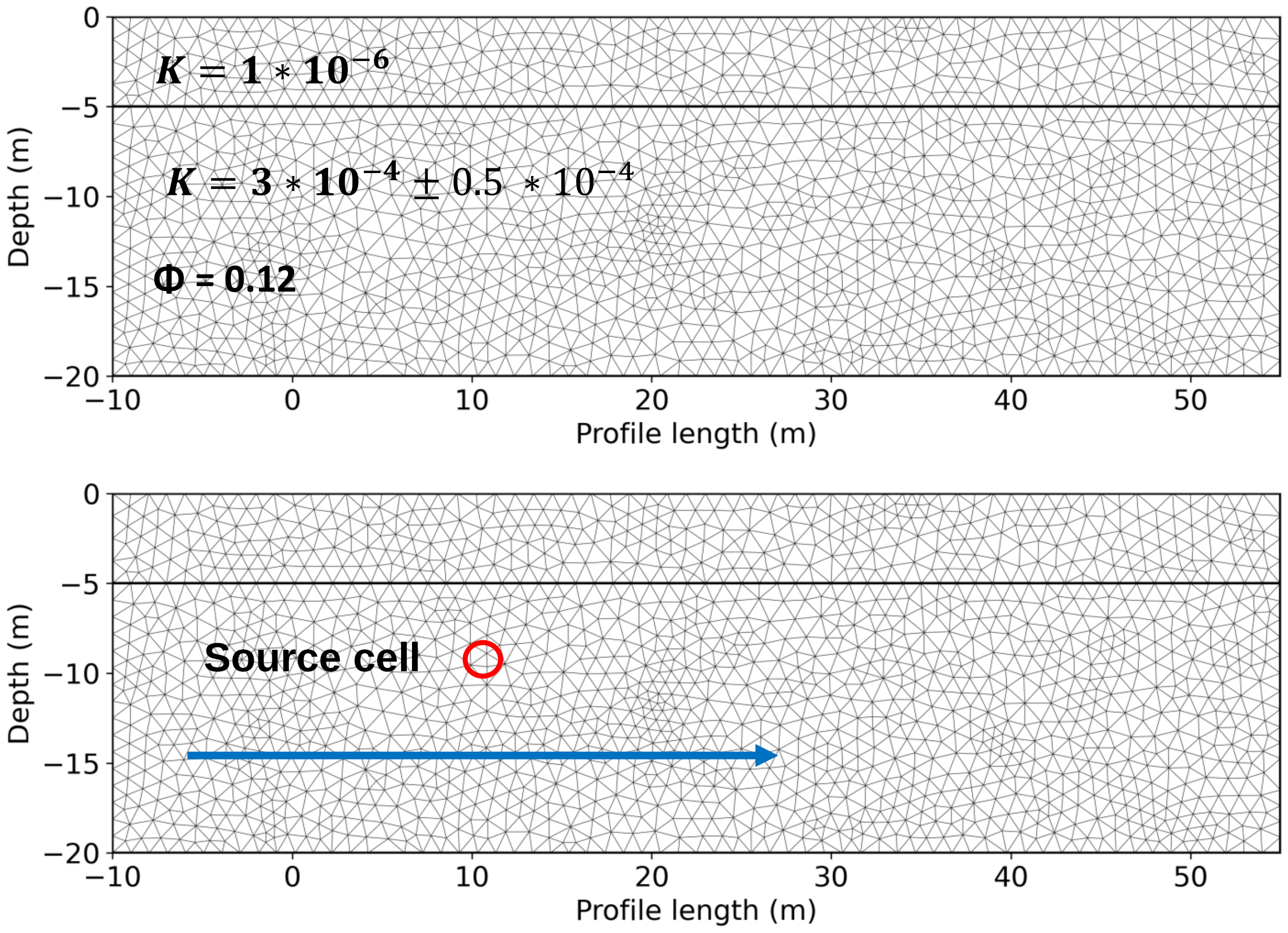
# Data structure – Integrating YAML DB into our workflow

**How can we incorporate the YAML-DB into a physics-based model?**



# Data structure – Integrating YAML DB into our workflow

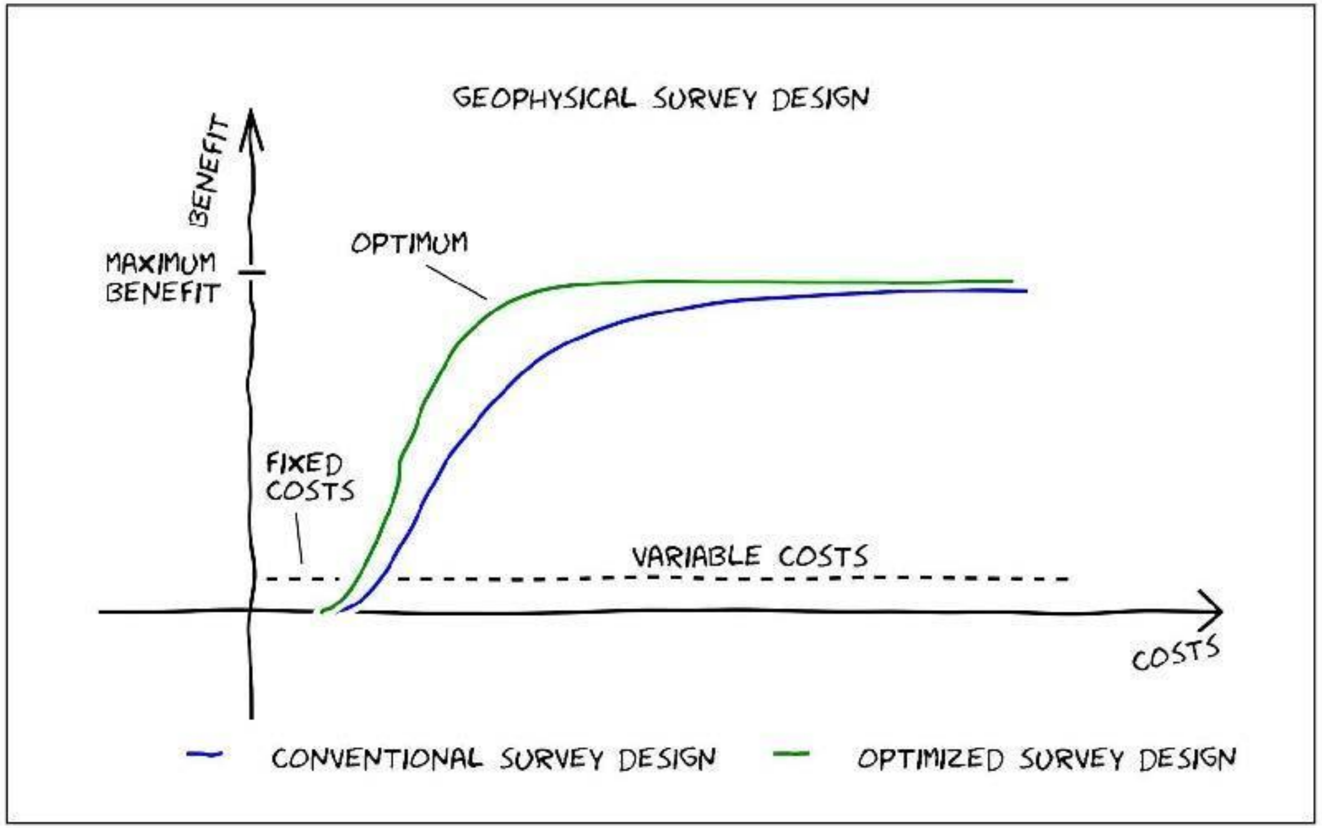
- **2D advective-diffusive** transport simulation in a simple geometry
- **Input** parameters for simulation: **Porosity, Hydraulic conductivity**
- Values are **imported** from YAML-files that are stored in the **YAML-DB**
- Parameter **uncertainties** can be included by importing **deviation value** from YAML file



# Optimal Experimental Design - Recap

- Data processing can compensate for missing or inadequate data only to a certain extent
- Survey optimization aims at **optimizing the information content** of (geo)physical data sets while also **limiting acquisition expenses** (time and equipment)

**How can we reach the cost-benefit optimum?**




*Adapted from Maurer, 2010*

# Optimal Experimental Design - Recap

**"Compare-R" method** (Wilkinson et al., 2015)**:**

- Uses **resolution matrix** of linearized Gauss-Newton solution for ERT problem; defined as:

$$R = (G^T G + C)^{-1}\, G^T G$$

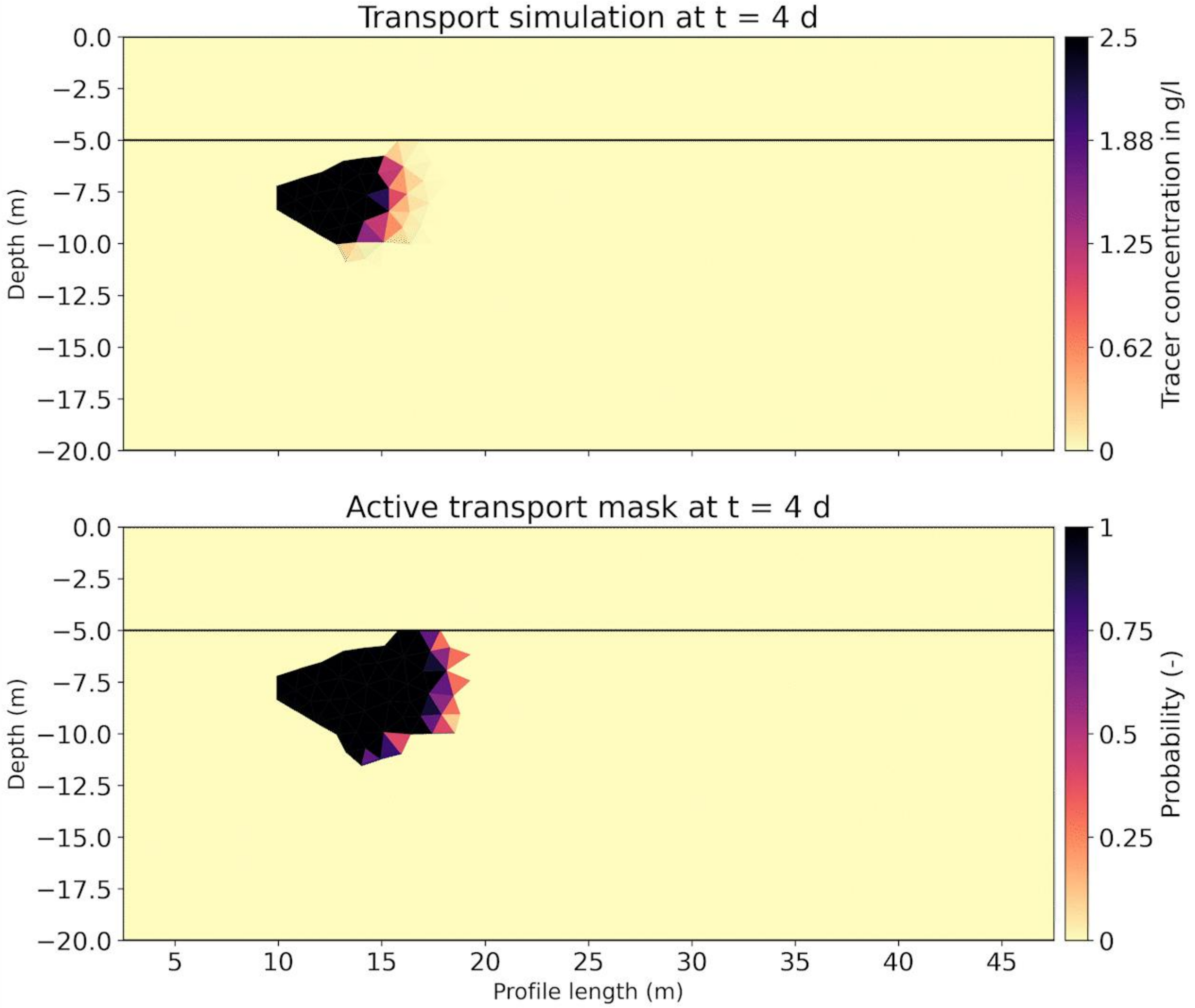
- Iterative optimization starts from a set of **base measurements** -> calculation of **change in resolution matrix** for each possible new measurement
- All additional measurements are **ranked according to improvement** of resolution matrix:

$$F_{CR} = \frac{1}{m}\sum_{j=1}^{m} \frac{w_{t,j}\, \Delta R_{b,j}}{R_{c,j}}$$

- Depending on chosen step size, **n measurements** with greatest benefit **are added to base set**

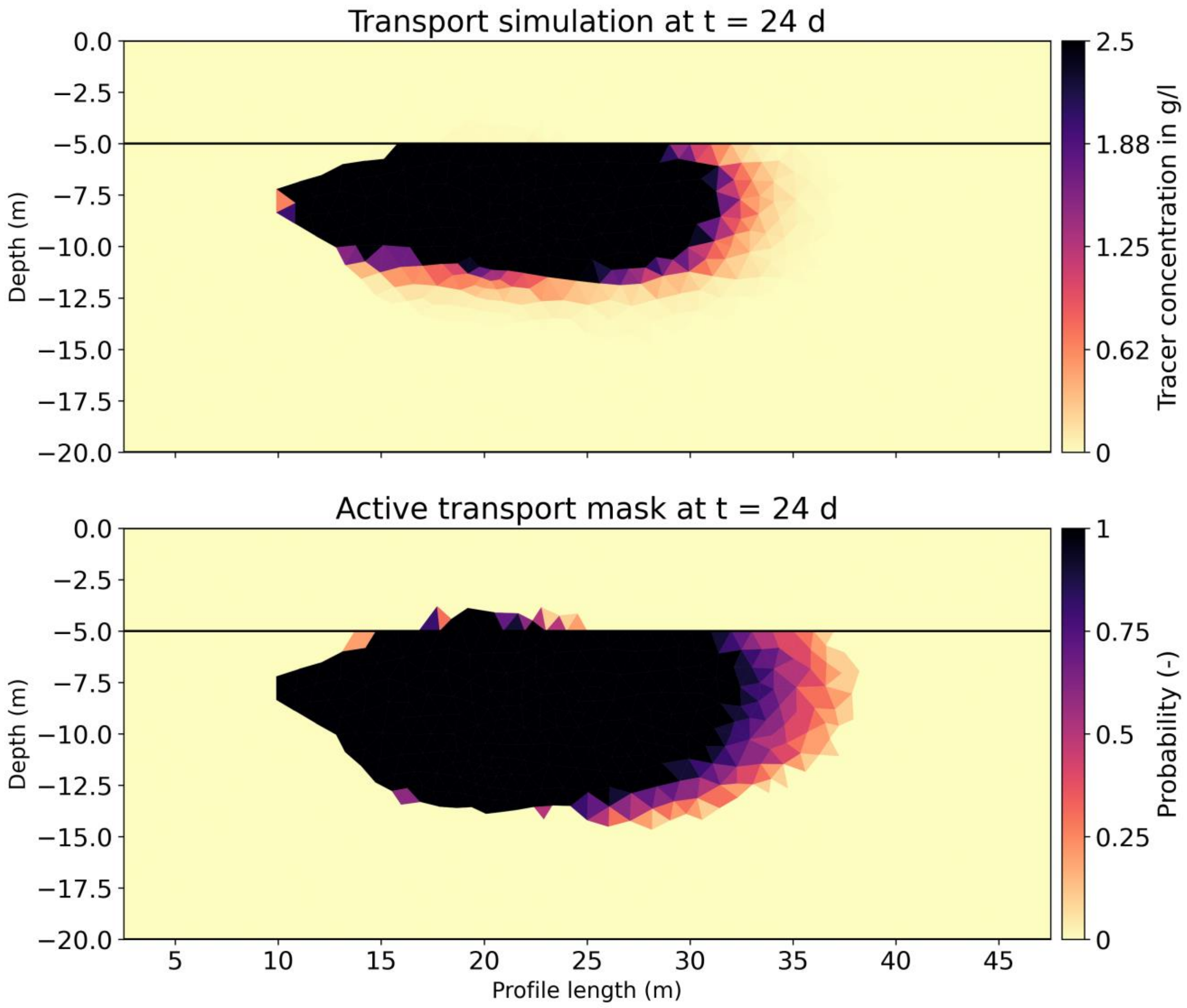
# Optimal Experimental Design – Model-driven OED

- Algorithm aims at giving “**extra resolution”** to regions that are influenced by transport process
- Underlying transport simulation is taken for creation of **focusing mask** at each time step
- If the simulated **fluid concentration** in a model cell is **above a set threshold**, it is considered “relevant”.



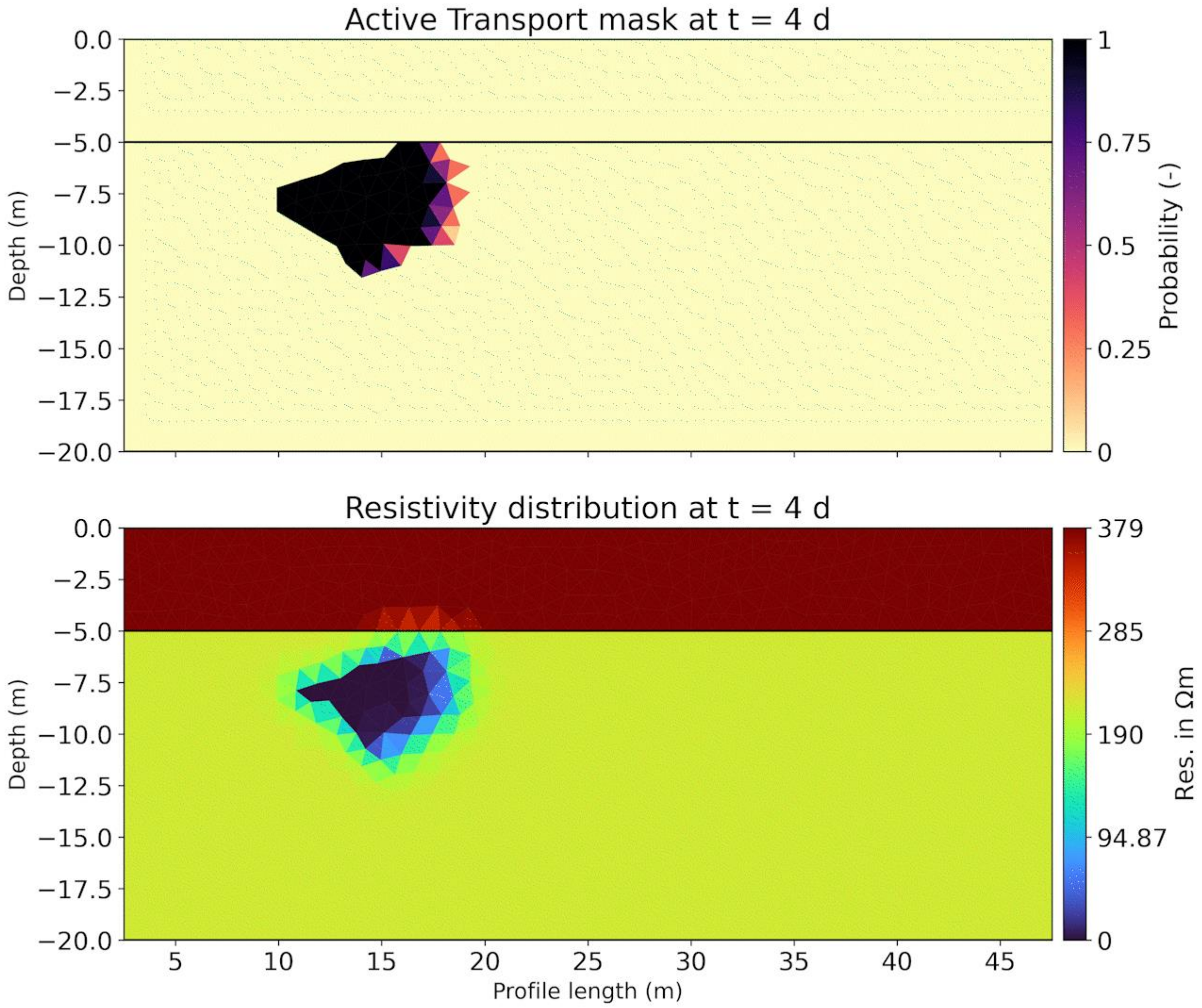
# Optimal Experimental Design – Incorporating uncertainties

- OED algorithm allows for **incorporation of uncertainties,** e.g., for hydraulic conductivity
- **Multiple simulation runs** for different **K** values in defined range
- **Value** of the cell inside the mask reflects **probability of concentration > threshold** for simulation runs with variable K
- Incorporated in weighting factor of **ranking function** of OED



# Optimal Experimental Design – Model-driven OED

- “**Petrophysical link**” via **Archie** (1943) allows for estimation of **electrical resistivities** for a given fluid concentration
- Necessary for **geophysical** forward modelling and inversion

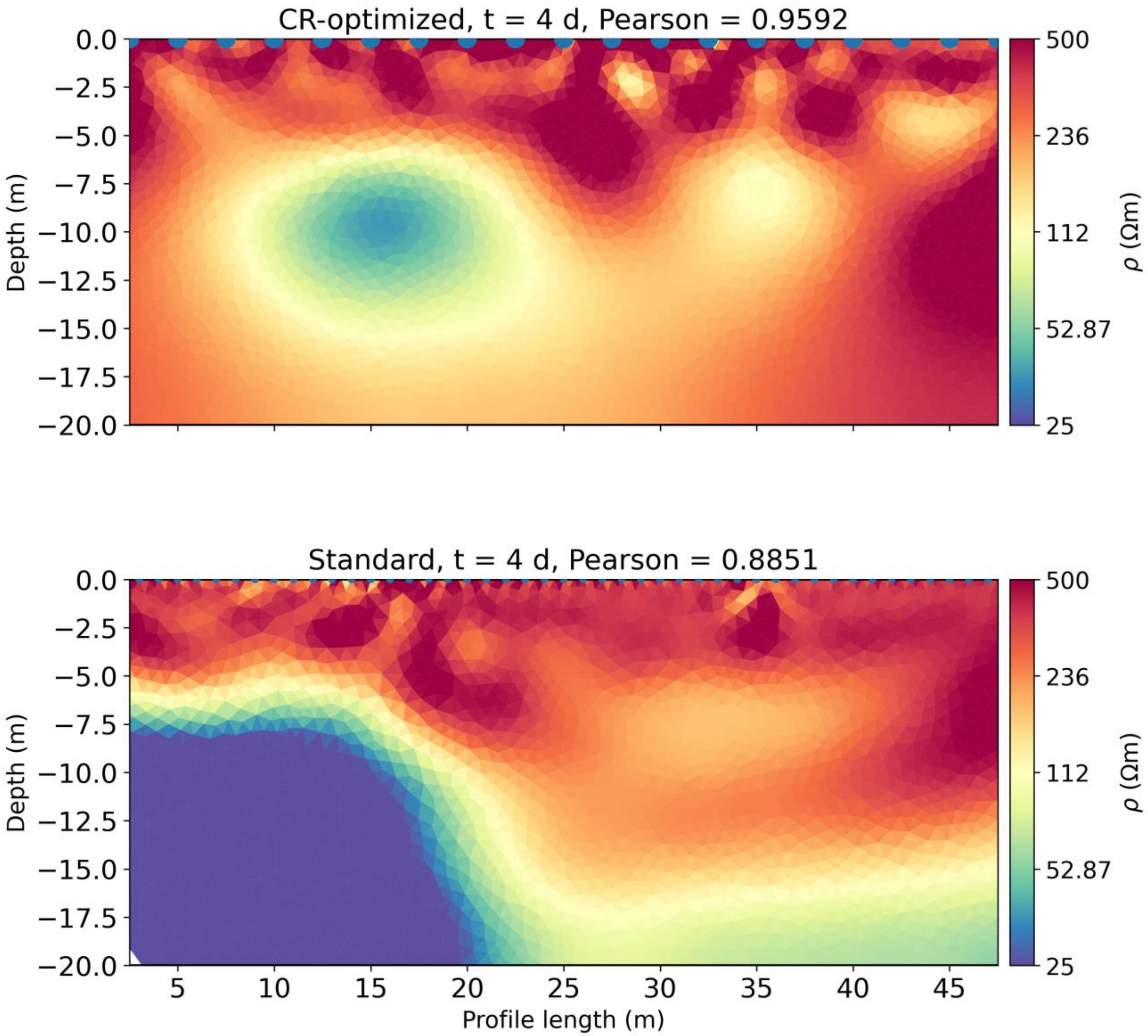


# Optimal Experimental Design – Model-driven OED

- Two geophysical surveys presented:

1. **Optimized** dataset using **25 electrodes** and 950 measurement points
2. **Standard** Dipole-Dipole configuration using **50 electrodes** and > 1100 measurements

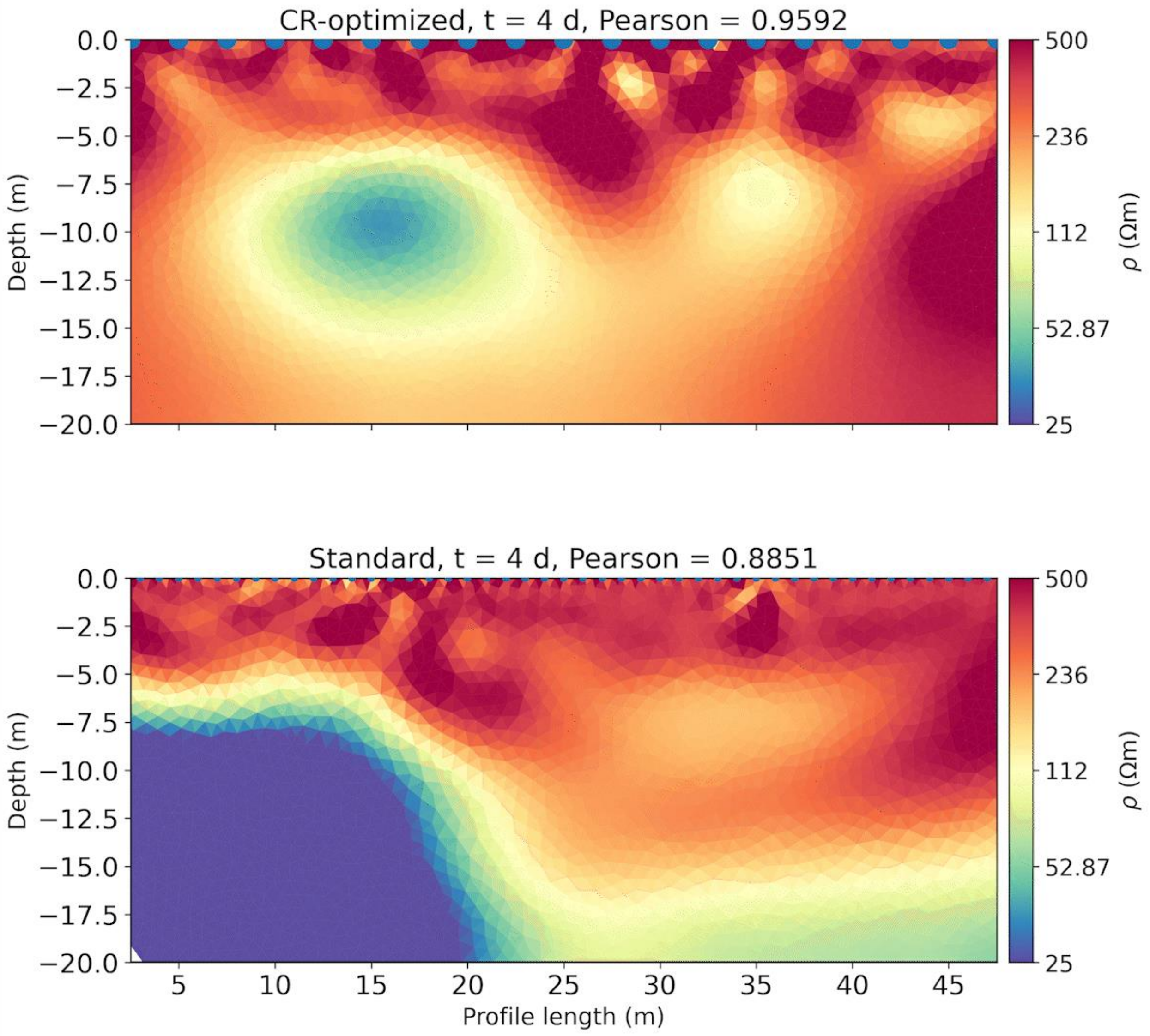
- **More electrodes -> more costs**



# Optimal Experimental Design – Model-driven OED

- Created **probability mask** is used in OED algorithm: gives **extra resolution** to masked area with **significant fluid concentrations**
- Allows **focusing** of measurements to **relevant areas** of model domain

**->** We aim at **optimizing the information content** of (geo)physical data sets while also **limiting acquisition expenses** (time and equipment)



# Smart Monitoring – Outlook and next steps

**Data management:**

- Continue with literature research and **fill YAML-DB**
- **Unify** existing YAML files and datasets and **integrate** them into our workflows

**Optimal Experimental Design:**

- **Implement data-driven OED** and compare to model-driven approach (idea of hybrid OED algorithm?)
- Adapt OED to **other (geo)physical parameters** and optimize datasets for **joint inversions**

# Thanks for your attention!

**LITERATURE:**

ARCHIE, G. E. (1942). The electrical resistivity log as an aid in determining some reservoir characteristics. *Transactions of the AIME, 146(01), 54-62.*

MAURER, H., CURTIS, A., & BOERNER, D. E. (2010). Recent advances in optimized geophysical survey design. *Geophysics, 75(5), 177-194.* https://doi.org/10.1190/1.3484194

WILKINSON, P. B., UHLEMANN, S., MELDRUM, P. I., CHAMBERS, J. E., CARRIÈRE, S., OXBY, L. S., & LOKE, M. H. (2015). Adaptive time-lapse optimized survey design for electrical resistivity tomography monitoring. *Geophysical Journal International, 203(1), 755–766*. https://doi.org/10.1093/gji/ggv329

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# Optimal Experimental Design – Application to transport processes

**Data driven** active OED**:**

Makes use of **the acquired data** at a certain time **to focus** the survey on the region of the model where changes occur.

**Model driven** active OED:

Utilizes an **underlying transport simulation** to focus the measurements on the region of the model that shows **transport-induced changes.**

# Optimal Experimental Design - Recap

**Compare-R" method** (Wilkinson et al., 2015)**:**

- Uses **resolution matrix** of linearized Gauss-Newton solution for ERT problem; defined as:

$$R = (G^T G + C)^{-1} G^T G$$

- Iterative optimization starts from a set of **base measurements** -> calculation of **change in resolution matrix** for each possible new measurement:

$$\Delta R_b = \frac{z}{1+(g*z)}(g^T - y^T) \quad \text{where} \quad z = \left(G_b^T g_b + C\right)^{-1} g, \quad y = \left(G_b^T G_b\right) z$$

- All additional measurements are **ranked according to improvement** of resolution matrix:

$$F_{CR} = \frac{1}{m} \sum_{j=1}^{m} \frac{w_{t,j}\, \Delta R_{b,j}}{R_{c,j}}$$

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