

Focused Optimized Experimental Design strategies for geophysical subsurface flow monitoring campaigns

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1) The importance of optimizing survey designs

- Optimal Experimental Design (OED) aims at enhancing the efficiency and benefit of data collection by **maximizing the information content** of data sets while **limiting acquisition expenses and uncertainties**.
- OED commonly assumes that the quantitative **benefit** of a (geo)physical experiment is **proportional to the resolution or accuracy** of the parameters of interest.
- Overall goal is to **increase the benefit** of a survey, **before the actual measurement is conducted** by **improving the survey design** based on the goals of the specific field campaign.

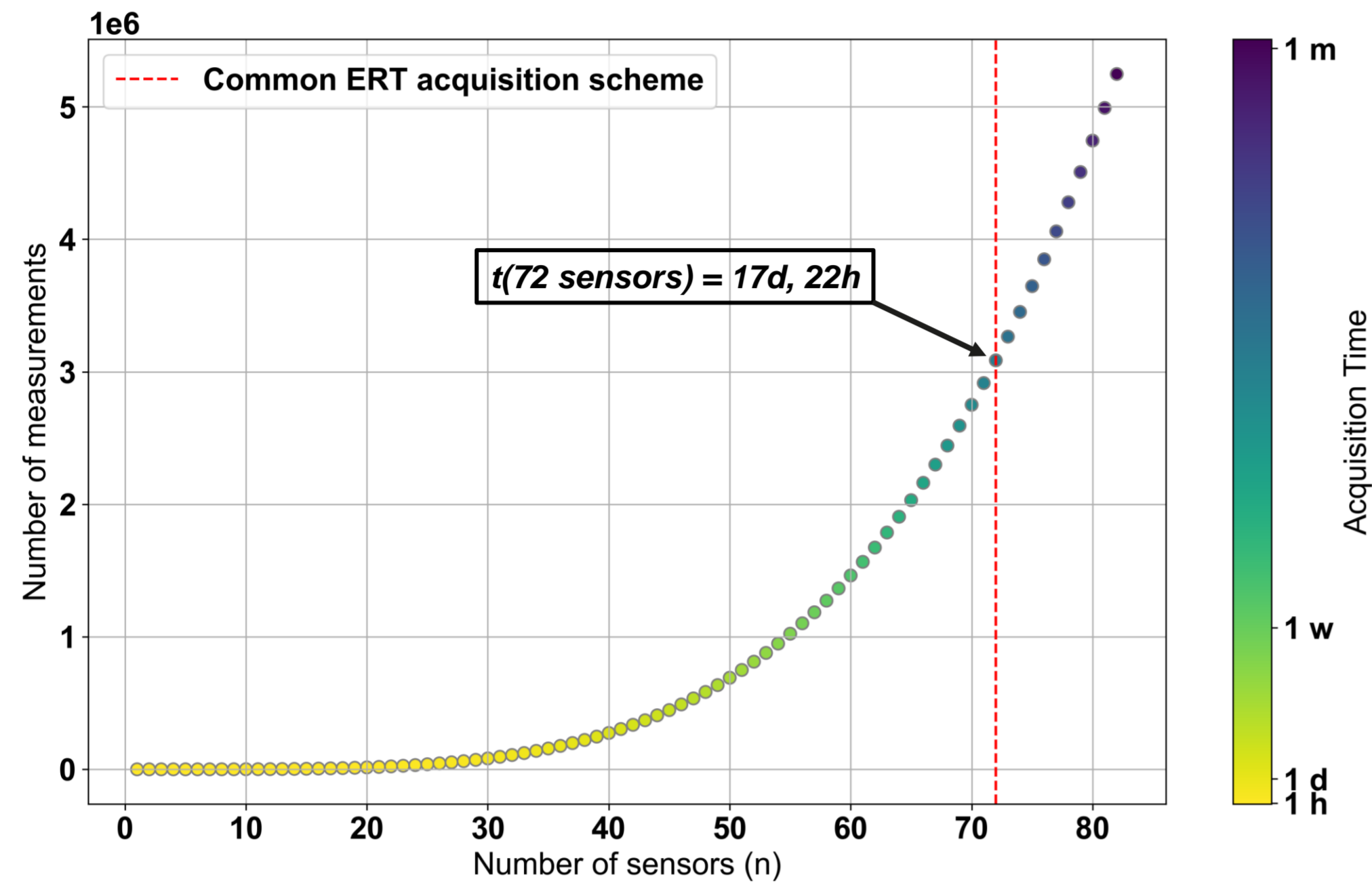
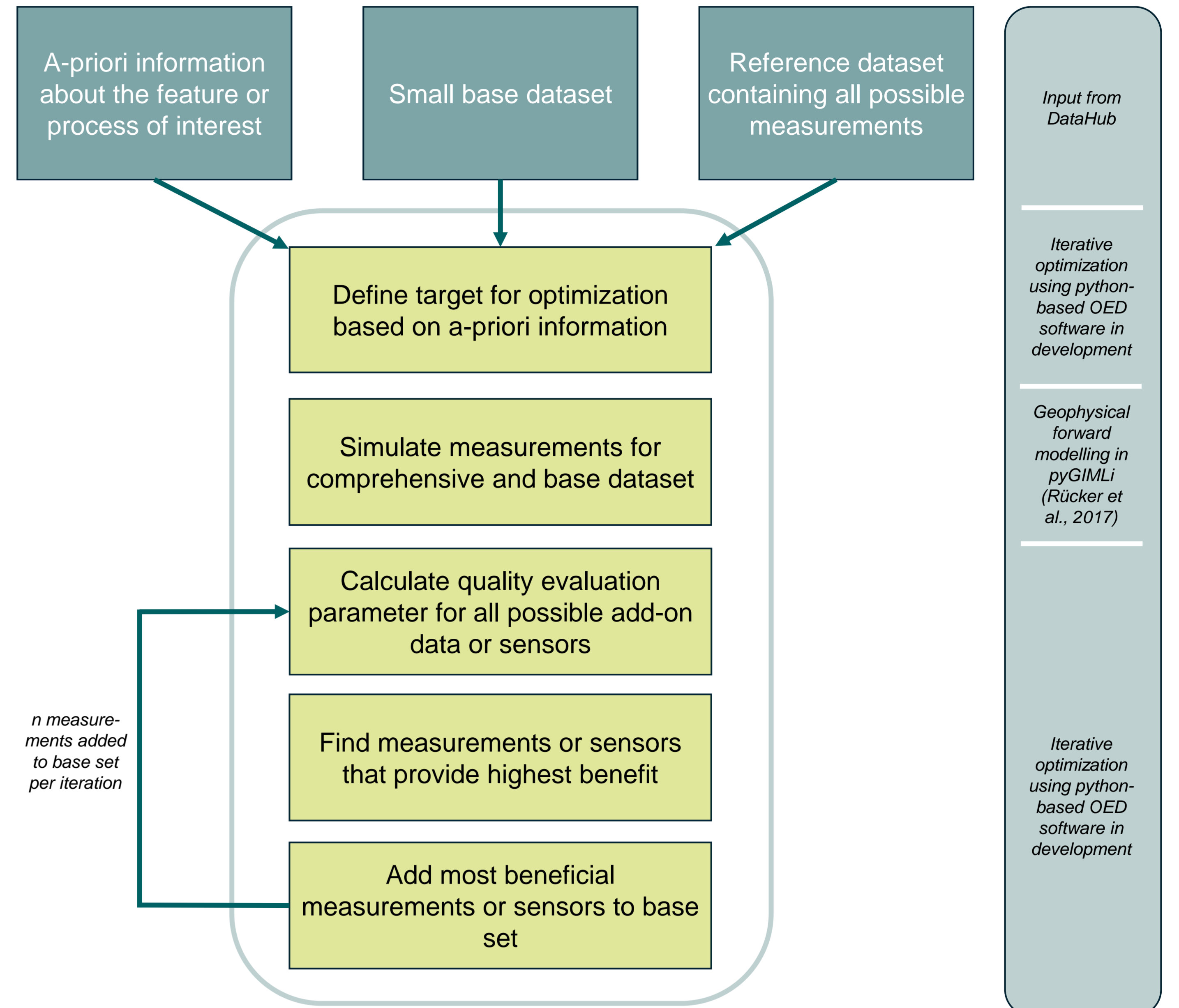


Fig. 1: Comparison of the number of sensors and the number of possible configurations in an ERT survey as well as the necessary acquisition time. The red line marks a commonly used number of electrodes for ERT surveys.

Utilizing OED algorithms to optimize surveys for **fluid transport process monitoring** over time has not been investigated yet. Due to its sensitivity to fluid saturation and temperature changes, **Electrical Resistivity Tomography (ERT)** is an **important geophysical tool** in this context. This study presents a **novel concept for OED strategies** for ERT surveys that aim at:

- monitoring** subsurface fluid transport processes over different time scales.
- incorporating** uncertainties of different physical properties into the optimization process.

2) Methodology and workflow



3) OED strategies for transport process monitoring

a) Model-driven approach:

- Target** for optimization is **defined based on model simulation result** at time t_i .
- If a model cell is **significantly affected by the underlying transport process**, it is incorporated into the focusing process.
- Accounts for **parameter uncertainties** of transport model by evaluating **m model runs** with varying input parameters.
- Masked area incorporates **probability of exceeding predefined fluid concentration** during m model runs.

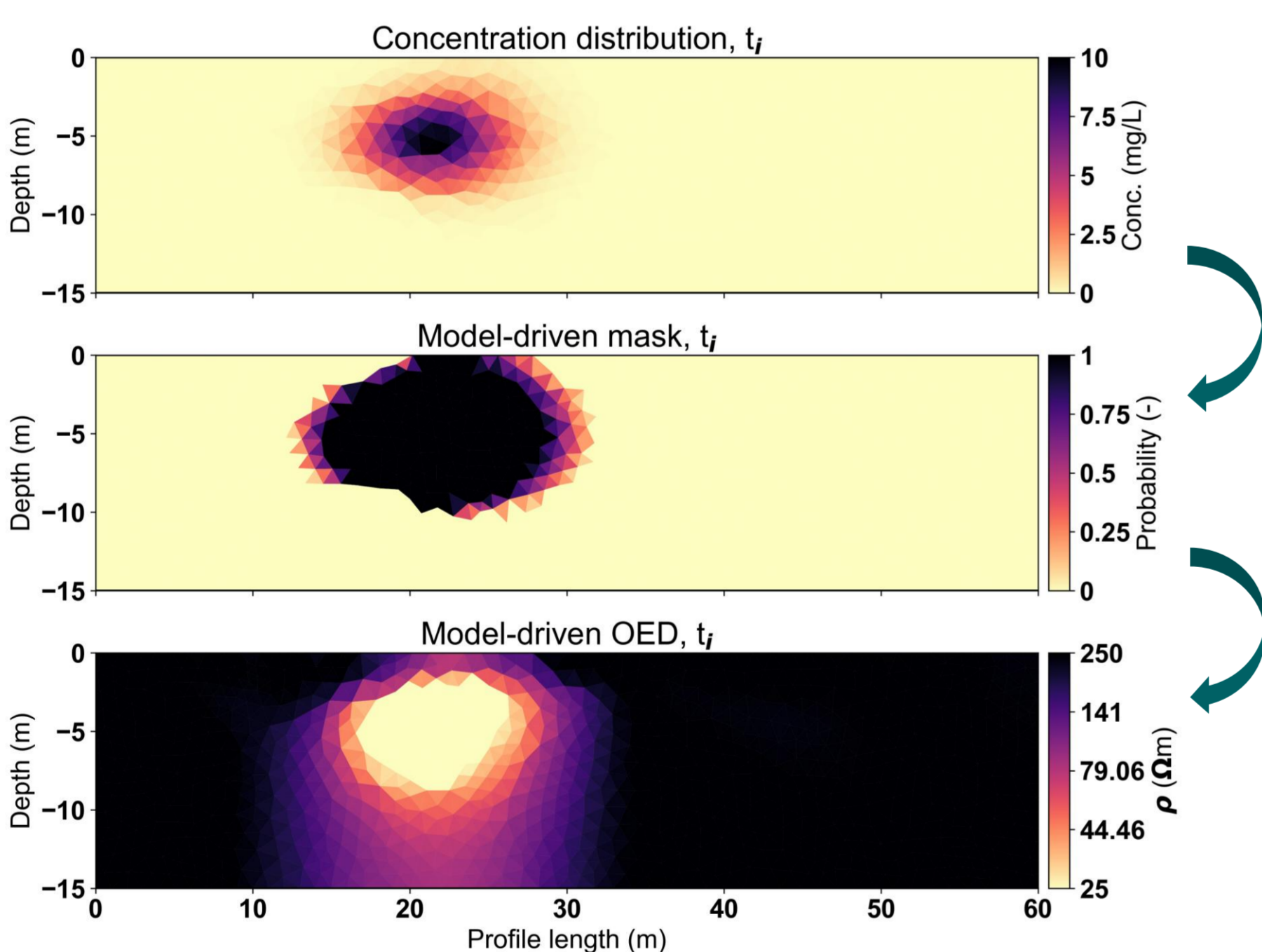


Fig. 2: Model-based OED approach using a weight distribution (middle) based on m transport model realizations for the current monitoring time step with varying simulation parameters (e.g. varying hydraulic conductivity).

- Accurate focusing** of the survey under the condition of a robust and reliable transport model simulation
- Solely relies on model predictions**, hence prone to error outside of considered uncertainty range during focusing

b) Data-driven approach:

- Optimization target** is chosen based on resistivity distribution in **inverse model** of **previous monitoring time** t_{i-1} .
- Survey focused on model regions where change of **electrical resistivities** at t_i is observed.
- Does not account for parameter uncertainties** since it only relies on acquired data at previous time steps of the monitoring campaign.

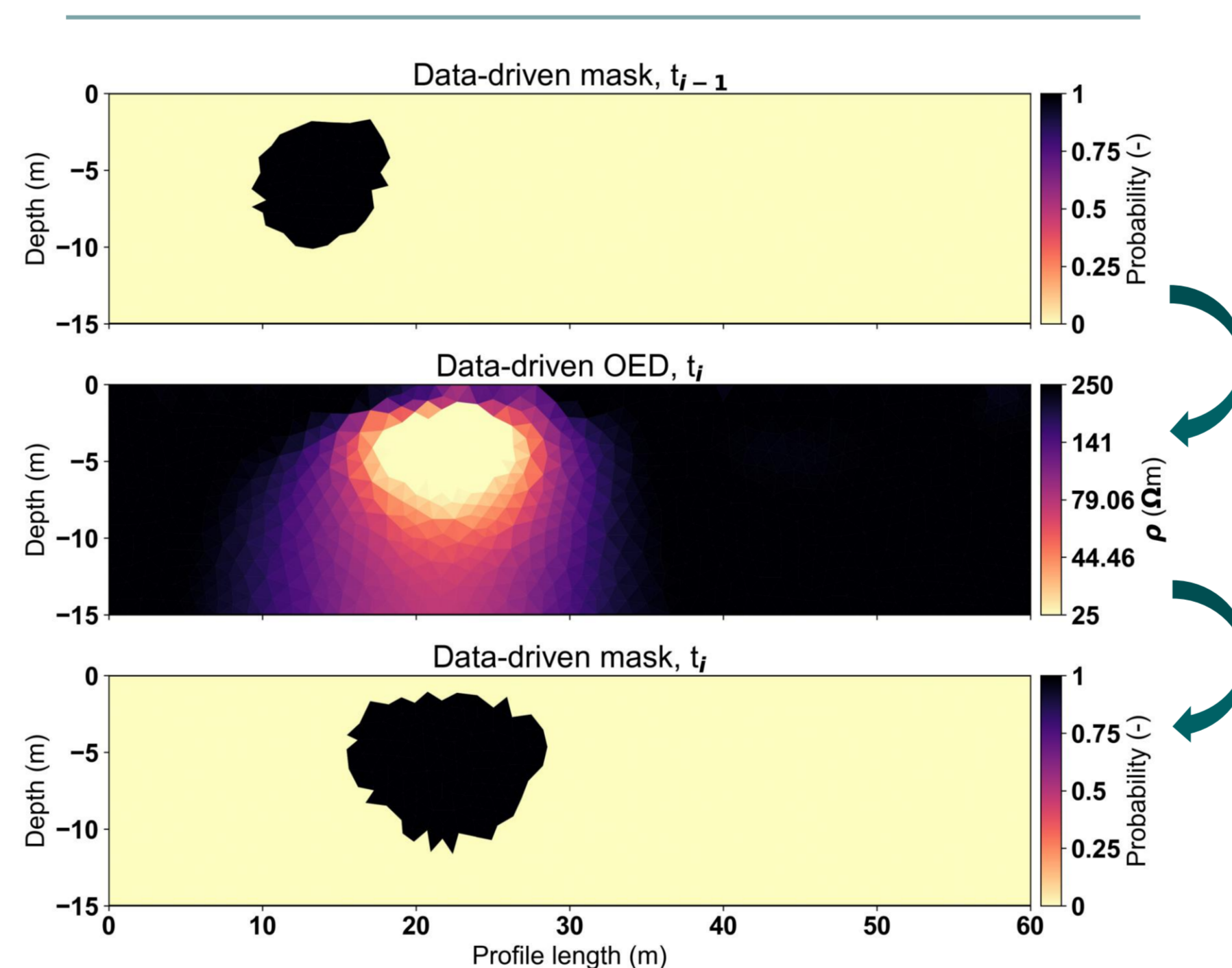


Fig. 3: Data-driven OED using a focusing method based on the inverse ERT model of the previous time step (up). The right image presents the mask that is created using the inverse model of the resistivity distribution at time t_i (middle).

- More robust** focusing method compared to model-driven approach
- Misfocusing**, if the time between two monitoring intervals is large (**temporal smearing**)

c) Hybrid approach:

- Model-driven survey focusing** and uncertainty estimation.
- Acquired data** at time t_i are compared to several simulated datasets using varying transport model parameter sets, but the same optimized dataset from t_i .
- If inverse model **deviates** from predicted distribution at t_i , the **simulation parameters** for later time steps are **adapted** to refine the transport model predictions (**Transport parameter evaluation**).

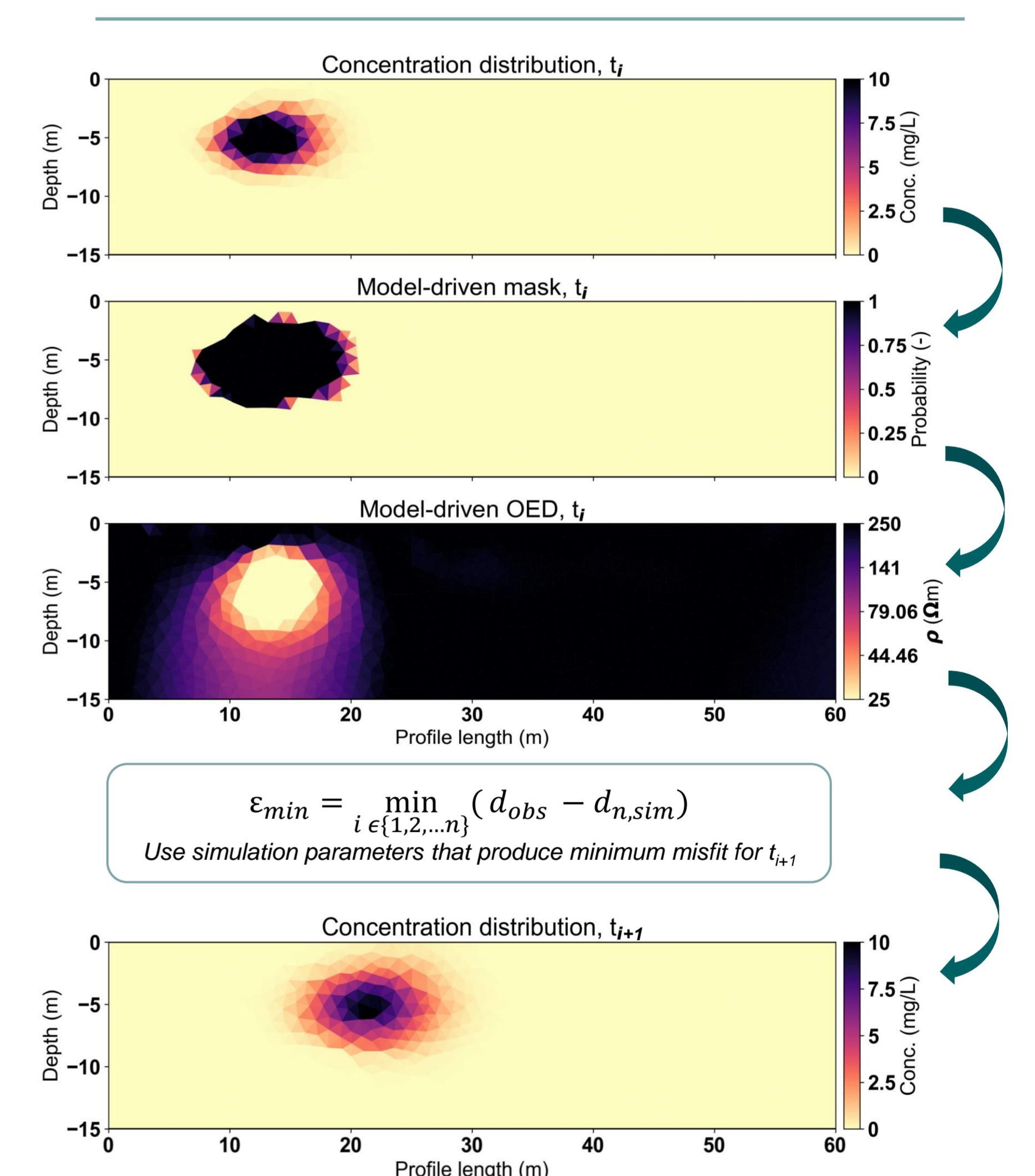


Fig. 4: Hybrid OED using a transport simulation-based focusing for the current monitoring time. After each iteration, the inverse electrical resistivity distribution is compared to the simulated distribution and the transport simulation parameters are adapted if a deviation is detected.

4) Outlook and conclusion

Optimal Experimental Design (OED) helps to **time- and resource-efficiently acquire geophysical datasets** in a variety of situations:

- Enhancing the resolution around **static and moving features of interest**, such as geological structures or radionuclide transport plumes in the subsurface by **approximately 40%** without additional resources
- Accurately track fluid distributions** over time and space based on data- and / or model-driven focusing and optimization techniques

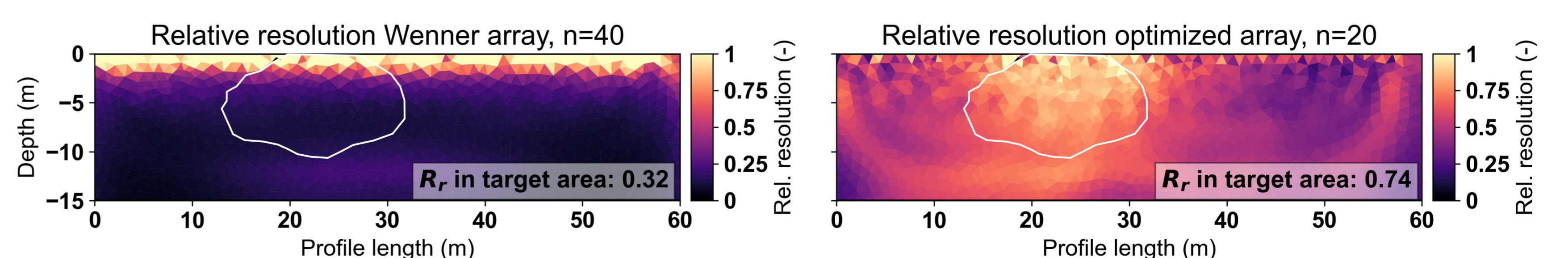


Fig. 5: Representation of the relative model resolution ($R_{rel,j} = R_{rest,j}/R_{comprehensive,j}$) for a conventional survey using 40 electrodes with 1.5 m spacing (left) and the relative model resolution of an optimized dataset using half of the electrodes with 3 m spacing (right). Both datasets consist of approximately 500 four-point configurations. The white outline marks the targeted (transport model-affected area). This figure visualizes the resolution improvement that is achieved by using optimized datasets for geoelectrical measurements.

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