Strategies for geoelectrical monitoring of subsurface fluid transport processes using Optimized Experimental Design

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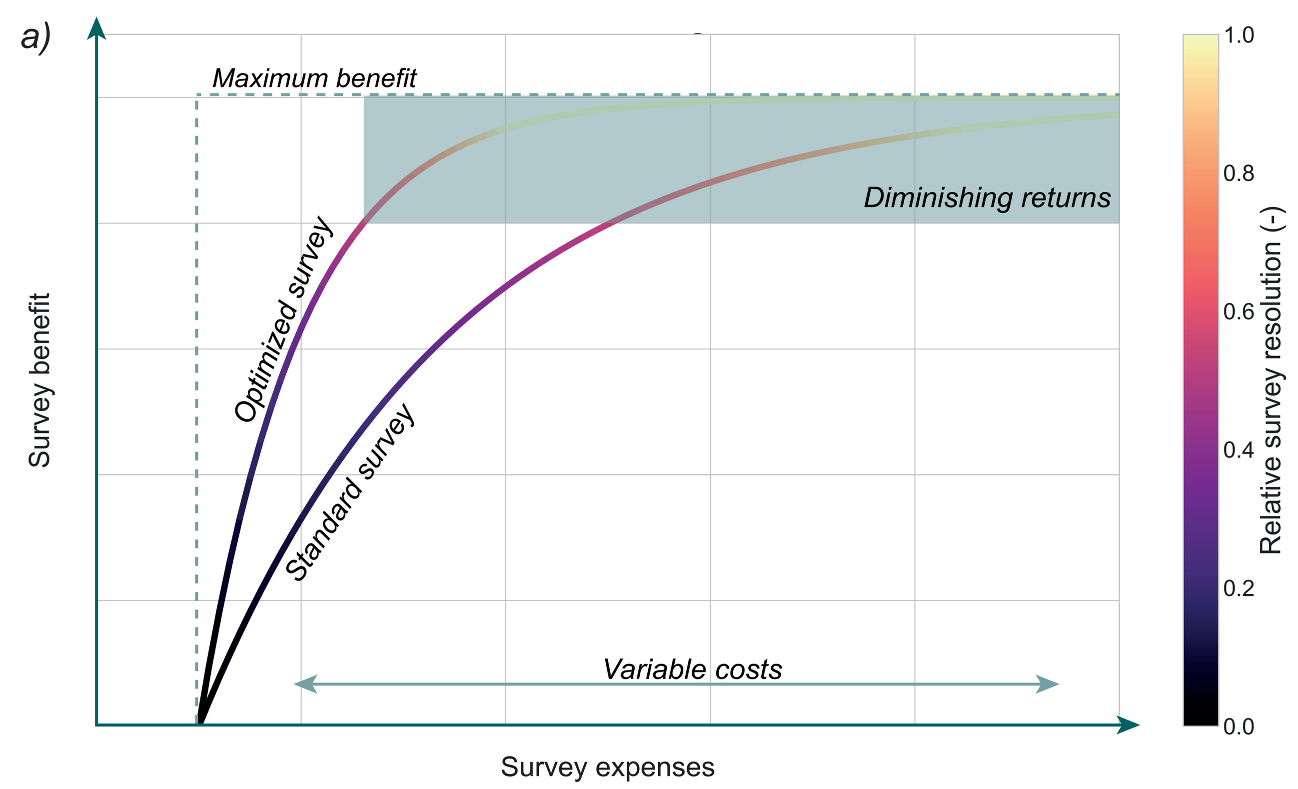
1) The importance of optimizing survey designs

- Optimized Experimental Design (OED) aims at **enhancing the efficiency** and precision 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.



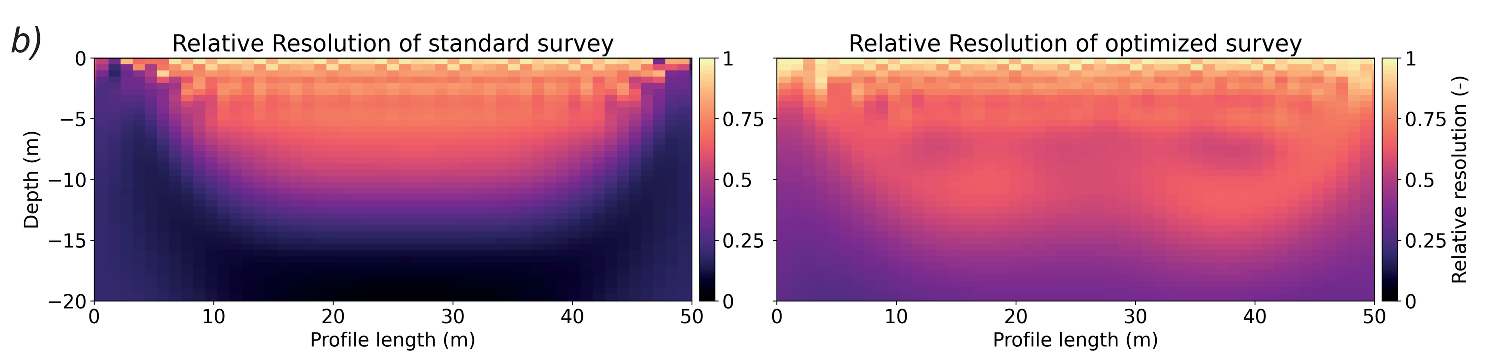


Fig. 1 a): *Cost - benefit diagram of a standard and an optimized ERT survey including the relative model resolution R_r. R_r represents the resolution capacity of the shown datasets normalized by the resolution of the comprehensive dataset. The latter contains the maximum possible number of four-point configurations for the chosen survey geometry.*
Fig. 1 b): *Corresponding plot of the relative model resolutions for both sets using 20 electrodes with 2.5 m spacing.*

A **broad variety of OED approaches** exist for different geophysical methods that were designed and tested in numerous past studies (e.g., Wagner et al., 2015, Uhlemann et al., 2018). However, 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 aims at:

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

2) Methodology and workflow

The **"Compare-R" method** (Wilkinson et al., 2012) is utilized as base for the optimization algorithms applied in the context of subsurface fluid transport monitoring. The approach is based on the **resolution matrix of a linearized Gauss-Newton solution** for an ERT problem, which is defined as:

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

where **G** is the Jacobian matrix and **C** the Constraint matrix. The **main diagonal elements** of R describe the **resolution of each model cell** *j* and range between 0 (unresolved) and 1 (perfectly resolved). Optimizing an ERT dataset is an iterative process that starts from a **small set of base measurements** *b* and adds *n* new measurements per iteration that hold the highest benefit for the parameters of interest. New configurations are chosen from a **dataset containing possible add-on measurements** (comprehensive dataset *c*). Every iteration includes the following steps:

*Calculate **change** in **resolution matrix** of the base set ΔR_b*

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***Rank** possible add-on configurations according to their **benefit** considering the weighting factor $\mathbf{w_t}$:*

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

*ε = Constant value, 1*10^{-12}*
q = Weighting exponent
$R_{c,j}$ = Resolution of compr. dataset

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*Check **Linear independency** – a measurement is only added, if it is linearly independent of previously added configurations*

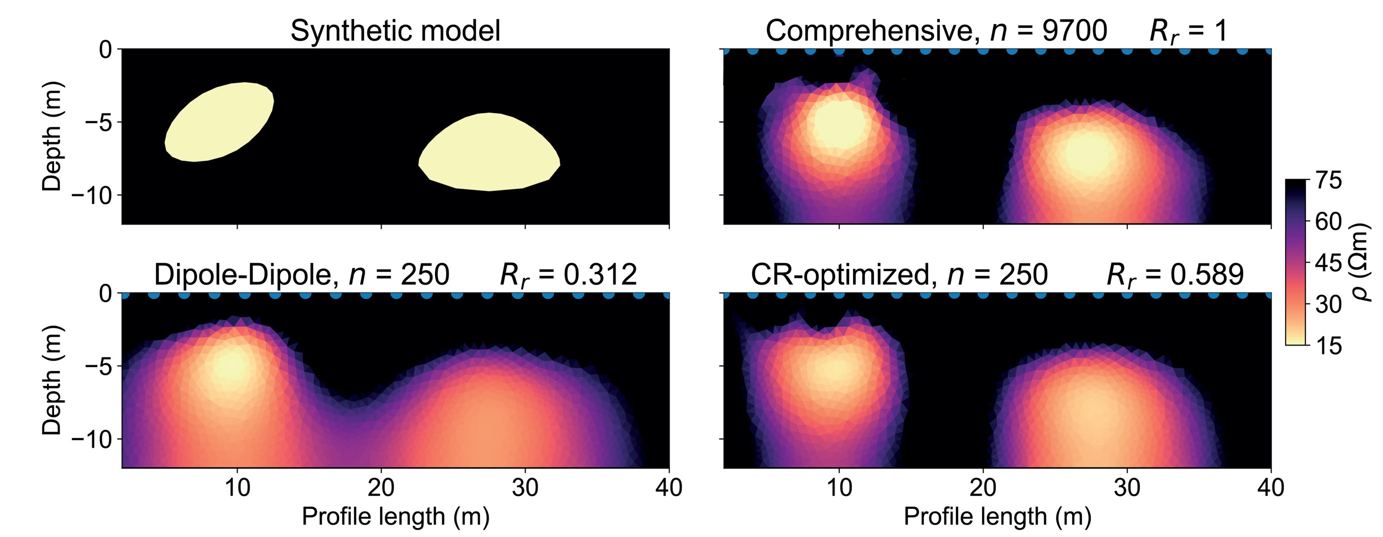


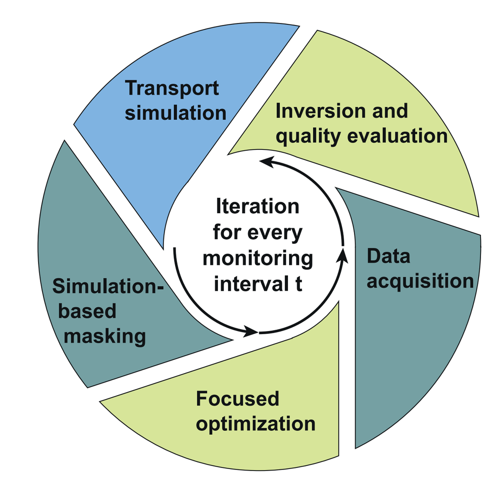
***Fig. 2**: True model and comparison of tomograms for the comprehensive, a standard Dipole-Dipole and a CR-optimized dataset.*

3) OED strategies for transport process monitoring

To visualize the OED strategies, a diffusive-advective tracer transport is simulated in a 2-layer geometry. All three presented approaches are applied to optimize ERT measurements at a single monitoring time t_n.

a) Model-driven approach:

- **Weighting factors** $w_{t,j}$ based on **concentration distribution** at t_n.
- Accounts for parameter uncertainties of transport model by **evaluating *m* model runs** with varying input parameters.
- $\mathbf{w_{t,j}}$ **incorporates probability** of exceeding predefined fluid concentration during *m* model runs **into ranking function** of OED approach.



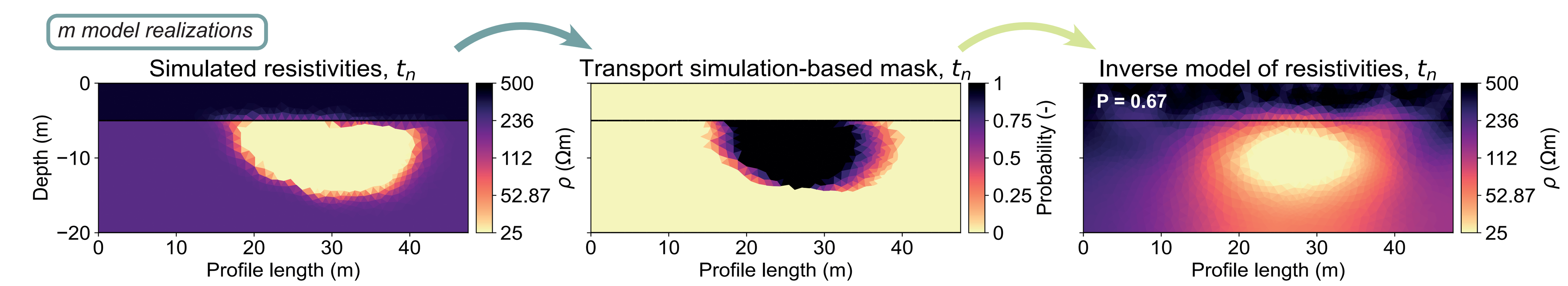
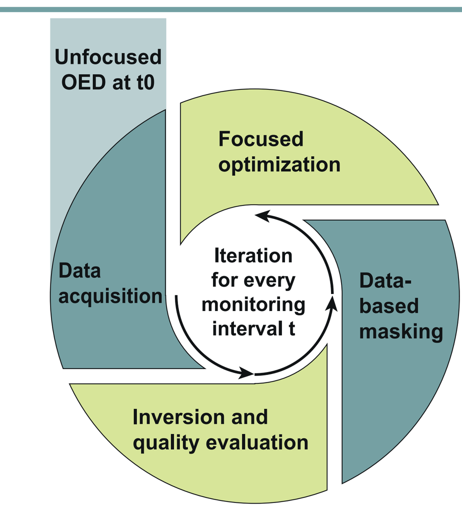


***Fig. 3:** Model-based OED approach using a weight distribution (middle) based on m transport model realizations for the current monitoring time step with varying simulation parameters (e.g. varying hydraulic conductivity). The left image displays the fluid concentration distribution at time t_n, the right image shows the inverse model of the optimized dataset including the Pearson number P as quality evaluation criterion.*

b) Data-driven approach:

- **Weighting factors** $w_{t,j}$ are chosen based on **resistivity distribution** in inverse model of previous monitoring time t_{n-1}.
- Survey focused on model regions where **change of electrical resistivities** at t_{n-1} is observed.
- **Focusing** of survey might be **spatially delayed**, since mask corresponds to parameter distribution of t_{n-1}.



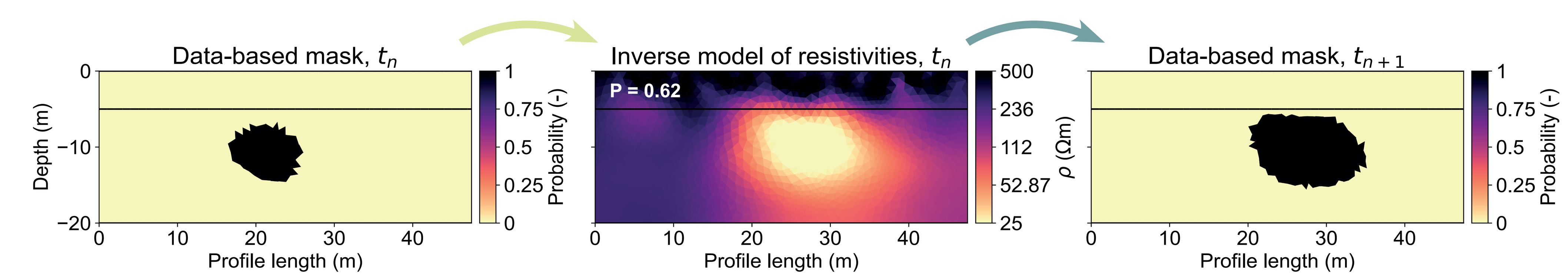
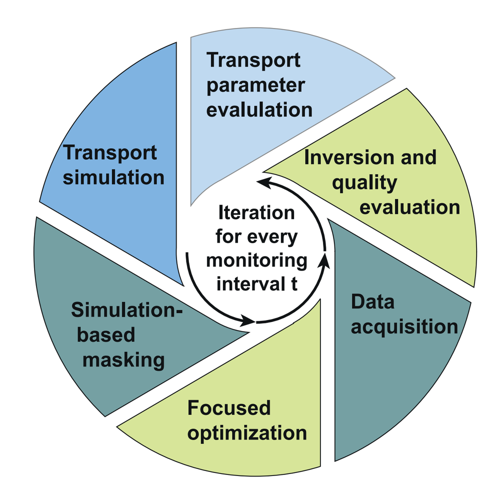
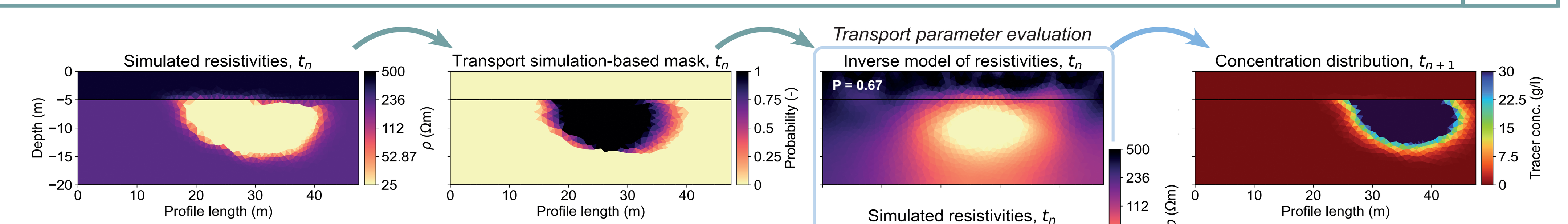


***Fig. 4**: Data-driven OED using a focusing method based on the inverse ERT model of the previous time step (left). The right image presents the mask that is created using the inverse model of the resistivity distribution at time t_n (middle). The resistivity distribution at time t is evaulated using the Pearson coefficient P.*

c) Hybrid approach:

- Survey focusing and uncertainty estimation **similar to model - driven approach.**
- The **inverse model** of resistivity distribution at t_n is **compared to simulated resistivities** of same time step.
- **If inverse model deviates** from predicted distribution at t_n, the **simulation parameters** for later time steps **are adapted** to refine the transport model predictions (*Transport parameter evaluation*).





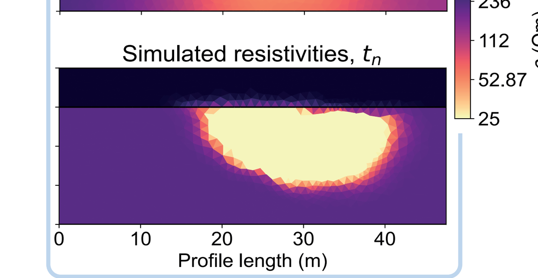


***Fig. 5**: Hybrid OED using a transport simulation-based focusing including uncertainties for the current monitoring time step based on m model runs. After each iteration, the inverse electrical resistivity distribution is compared to the simulated distribution and the transport simulation parameters are adapted if a deviation is detected.*

Sharing is encouraged

Uhlemann, S., Wilkinson, P. B., Maurer, H., Wagner, F. M., Johnson, T. C., & Chambers, J. E. (2018). Optimized survey design for electrical resistivity tomography: combined optimization of measurement configuration and electrode placement. *Geophysical Journal International*, 214(1), 108–121.
Wagner, F., Günther, T., Schmidt-Hattenberger, C., Maurer, H. (2015): Constructive optimization of electrode locations for target-focused resistivity monitoring. *Geophysics*, 80, 2, 29-40.
Wilkinson, P. B., Loke, M. H., Meldrum, P. I., Chambers, J. E., Kuras, O., Gunn, D. A., & Ogilvy, R. D. (2012). Practical aspects of applied optimized survey design for electrical resistivity tomography: Applied optimised ERT survey design. *Geophysical Journal International*, 189(1), 428–440.

Link to institute website

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