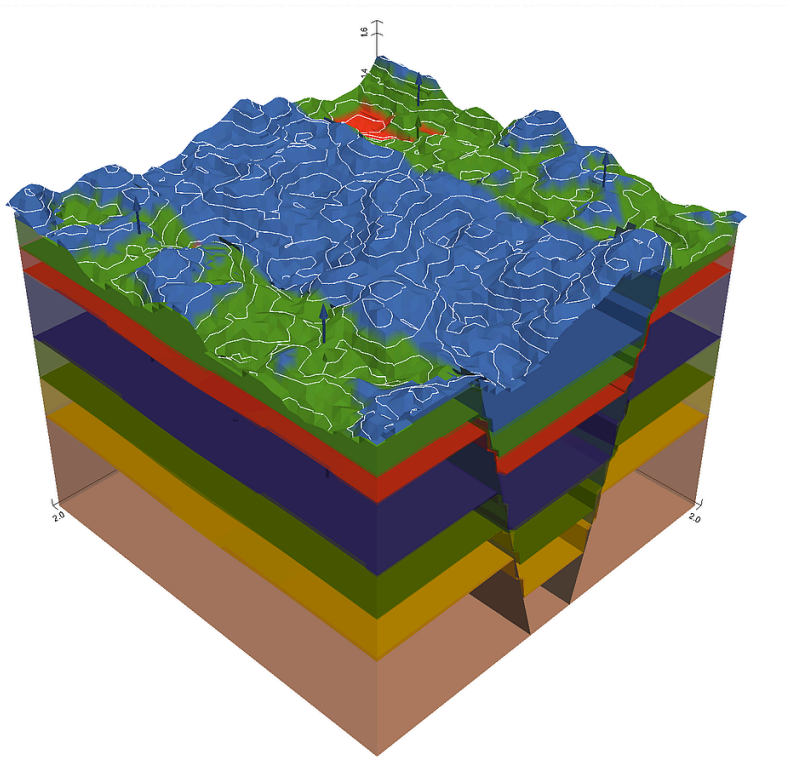




Geometry-Based Inversion of ERT data for Low-Dimensional Models of Complex Structures

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Overview: Conventional geophysical imaging

- Minimize objective function $\longrightarrow \psi(m) = \psi_d(m) + \lambda\psi_m(m)$
 - One term describes the difference between observed and estimated data
 - The second ,regularization' term enforces a smooth parameter distribution
 - Usually the simplest/smoothest model that fits the data within its error bounds is chosen
- Ill-posed problem: Usually infinitely many solutions
- Regularization reduces complexity

Conventional geophysical images

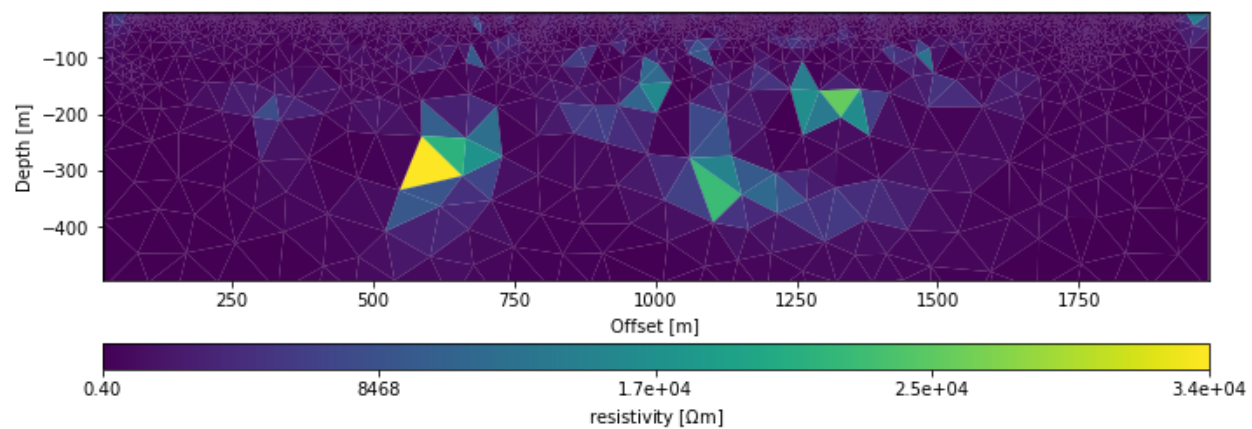
The following graphic will illustrate what typical geophysical images look like. They parameters that are inverted for are the values found in each mesh cell.

Different results of the inversion of one dataset for different smoothing strengths λ are presented. Very weak constraints lead to models that do not look physical but instead explain the data by emphasizing the resistivity value of a single cell.

Constraint strengths around 10 lead to realistic looking results, the presence of two distinct layers can be discerned. The main issue with this model is that the interface between layers is smoothed over and no distinct boundaries can be identified.

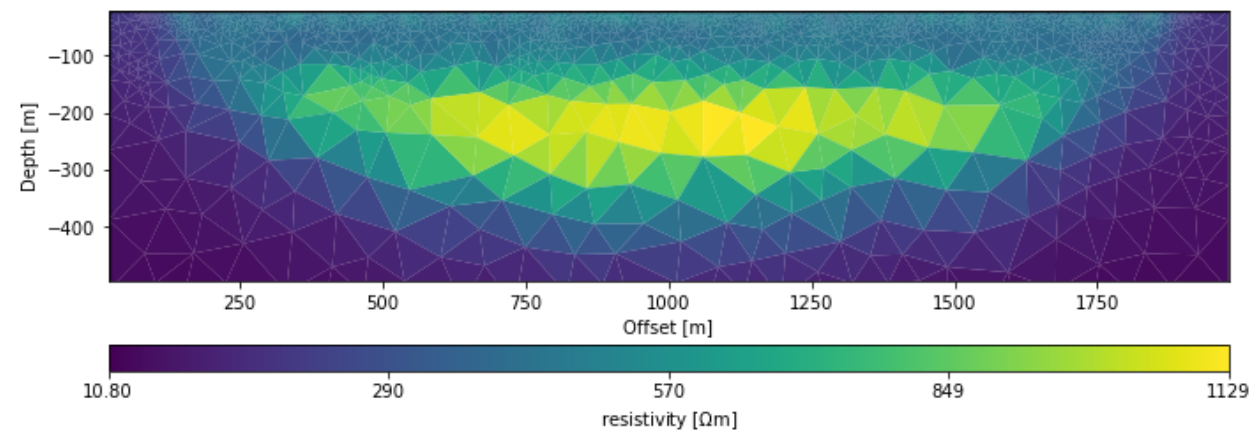
Under-regularized model

Lambda = 0.001, Data misfit (χ^2) = 1.02



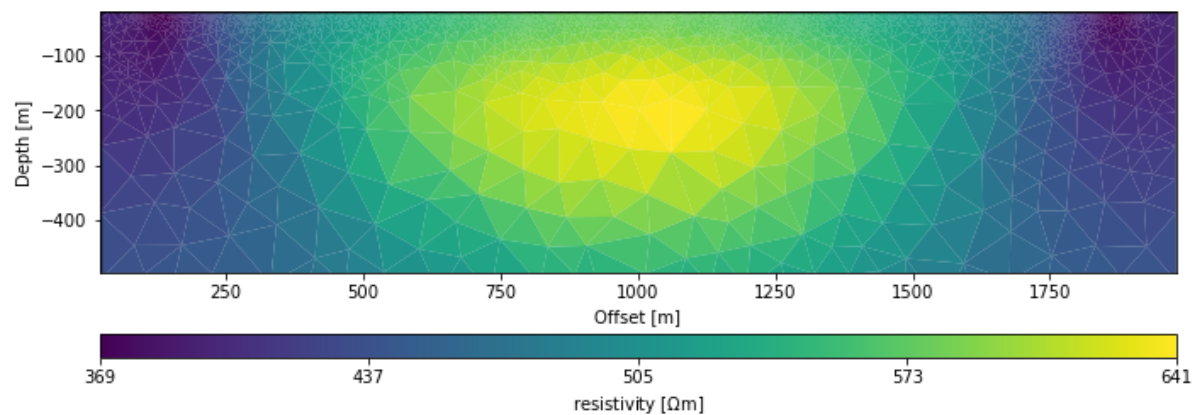
Appropriately regularized model

Lambda = 10, Data misfit (χ^2) = 0.76

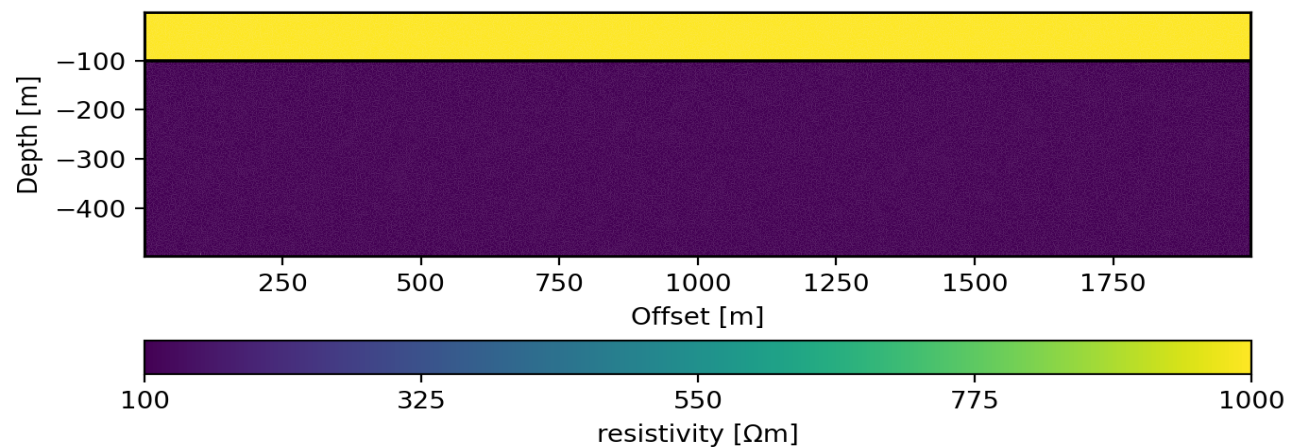


Over-regularized model

Lambda = 100000, Data misfit (χ^2) = 247.68



True Model



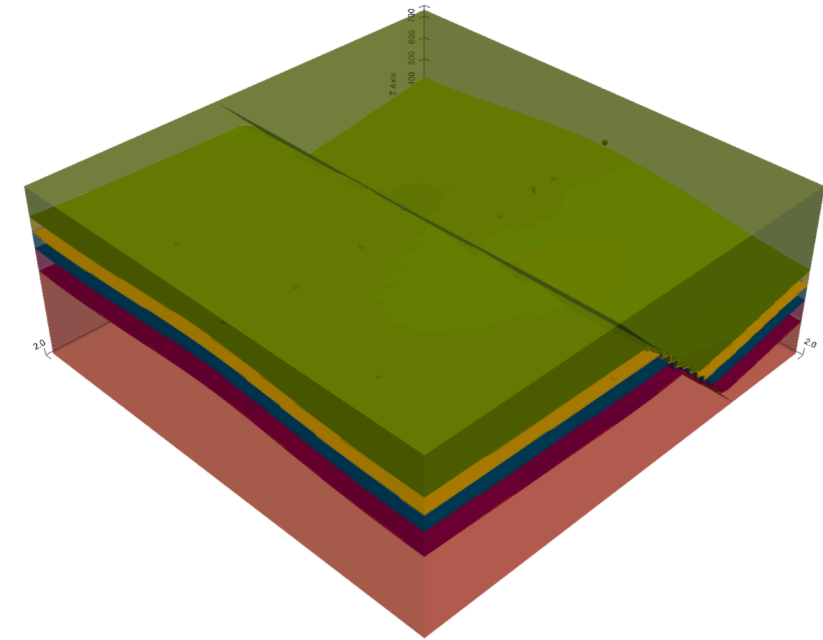
Implicit Geological Models

To mitigate the problem of oversmoothing, and also reduce the model dimensionality, implicit geological models can be leveraged. They are based on the construction of an interpolator function that is constructed based on the input points. The scalar field approach that is leveraged here generally takes two types of input data: Interface points, which define the location of an interface between geological units, and orientations, which define the dip and strike of a geological structure at a given point.

Basing an inversion around implicit geomodels yields the benefit that distinct boundaries between geological bodies are inherently incorporated into the model. Furthermore, the model dimensionality can be reduced significantly, since very few interface points are needed to define one surface. For more information on this, [this](#) paper (de la Varga et al, 2019) provides an in-depth explanation of GemPy, the open-source Python package that is used in the present approach.

Implicit Geological Models

- Current ,state of the art' for the creation of 3D geological models
- Global interpolator constructs continuous, monotonous scalar fields that determine the position of geological interfaces
- Input data:
 - Interface points (contact between geological units)
 - Orientations of geological bodies (dip and strike)
- Surface geometries derived from scalar field(s)
 - Few input parameters define relatively complex models
 - Co-Kriging algorithm ensures realistic interface geometries
- Combinations of different scalar fields can be used to model unconformities and faults

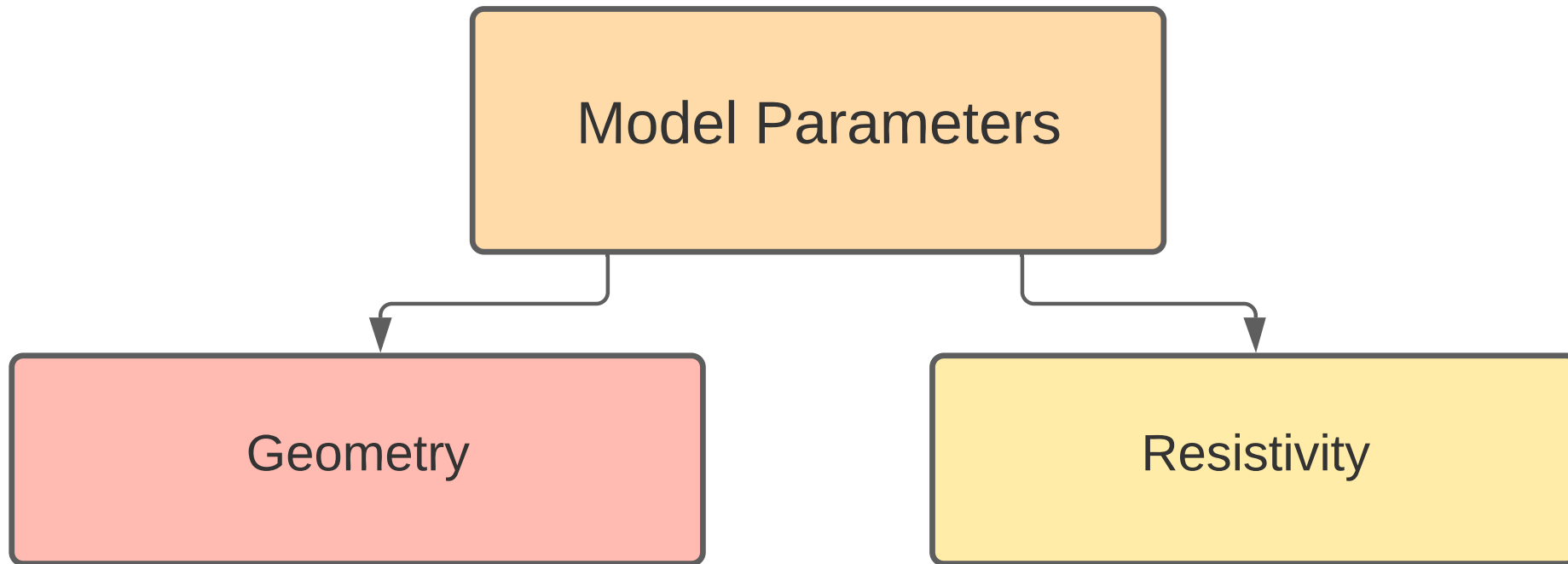


Geometric Inversion

The implicit geomodel approach can be used within a geophysical inverse framework. Each geological unit in the geomodel can be assigned a resistivity (or any other physical quantity for that matter) in order to solve the forward problem.

Assumptions

- Subsurface is discretized along well-localized interfaces
- Units show intrinsically similar physical properties
- Physical properties within any unit are heterogeneously distributed



Since the implicit geomodel is used as the inversion's centerpiece, we end up with two fundamentally different groups of model parameters: Those defining the geometry and those that define the resistivity distribution within each geological body

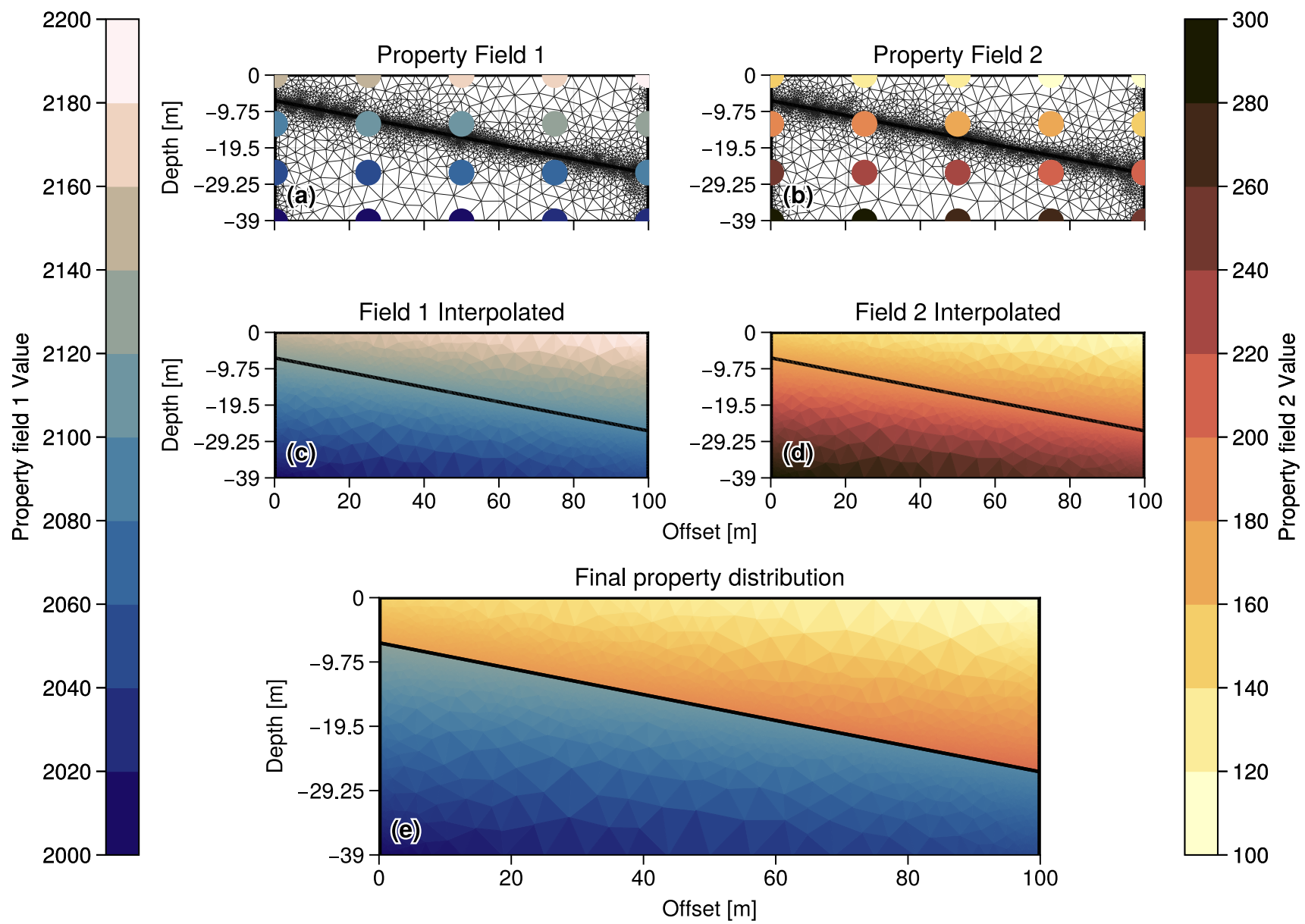
Property field approach

The following slide schematically explains the ,property field' approach that is used to assign resistivity values to each geological body in the 2D cross-section. This is necessary to solve the geoelectric forward problem.

Each geological unit is assigned one separate and unique rectangular grid, also termed ,property field'. Each grid node holds one resistivity value, and each grid spans the entire model domain. The grid nodes are plotted as circles on top of a finite element mesh in the next slides' figures (a) and (b).

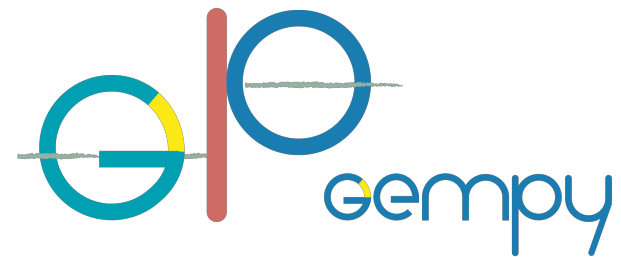
The cells of the finite-element mesh are then assigned resistivity values by linearly interpolating the node values. To assemble the final resistivity distribution that is used to calculate the forward response, the subsurface interfaces act as mapping operators as is shown in the next figure.

This approach reduces the number of model parameters that are inverted for, because the number of nodes in each property field will usually lie well below the number of cells employed in a mesh. This allows the imaging of smoothly distributed heterogeneities within geological layers.



Inversion Routine

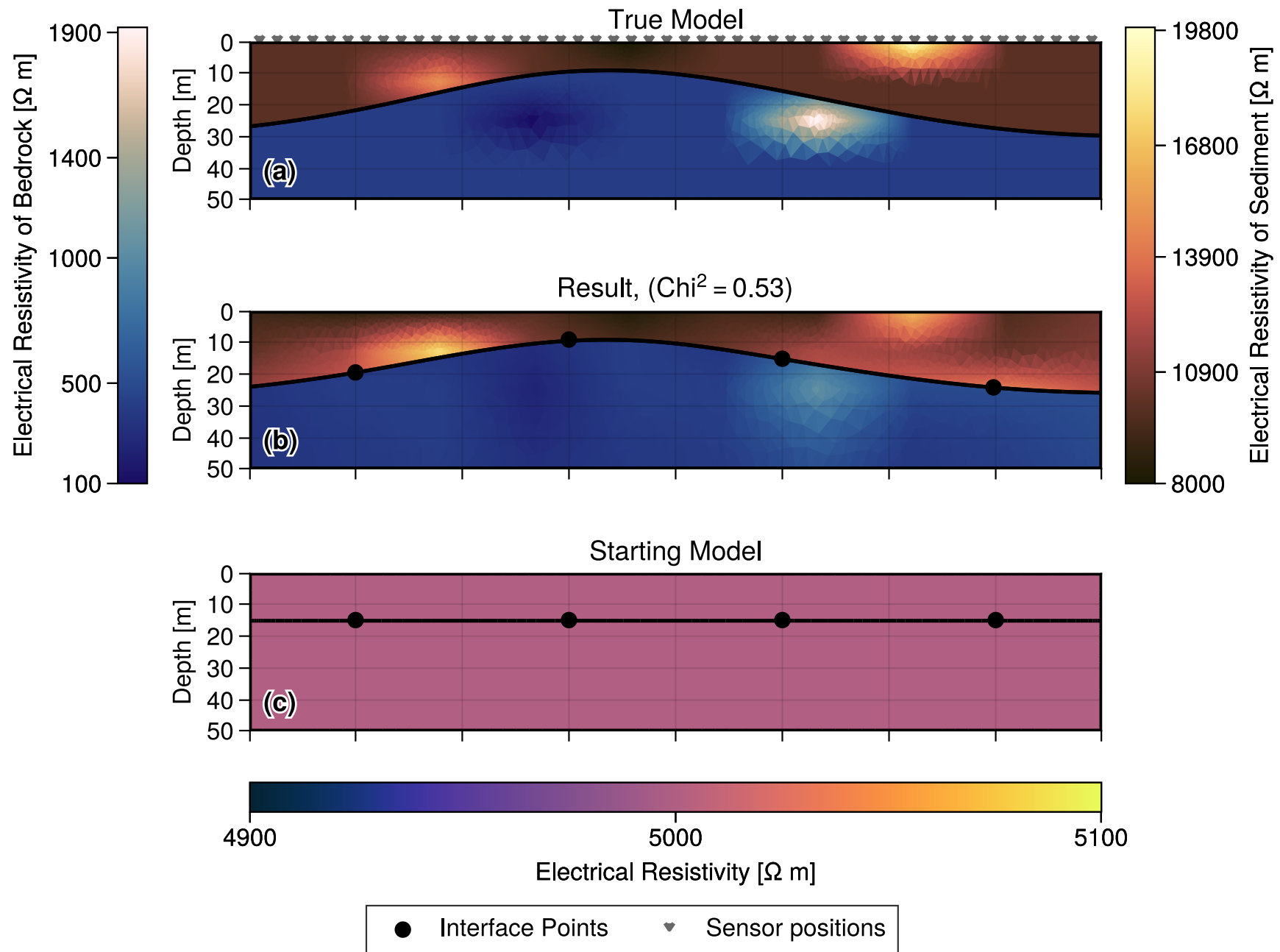
- Datasets: Synthetic dipole-dipole ERT data
- Model parameters:
 - Interface points' X- & Z-components
 - Property fields (logarithm of electrical resistivity at pilot points)
- Orientation measurements implemented as constant constraints
- Independent regularization of X-, Z-coordinates, and each property field
- 2D FE-based forward calculations of the geoelectric forward-problem
- Deterministic Gauss-Newton optimization
- Implementation with open-source Python packages
 - GemPy for implicit geological modeling
 - pyGIMLI for meshing, optimization and forward calculations

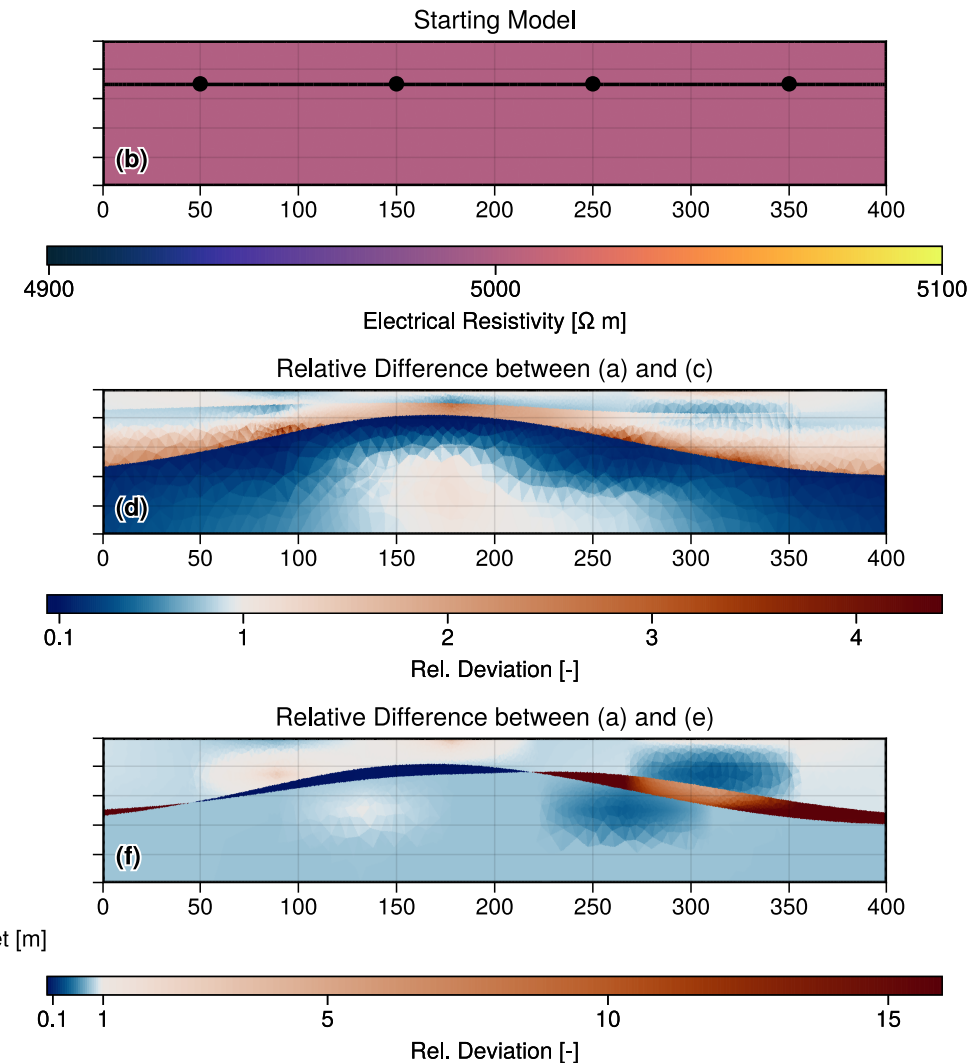
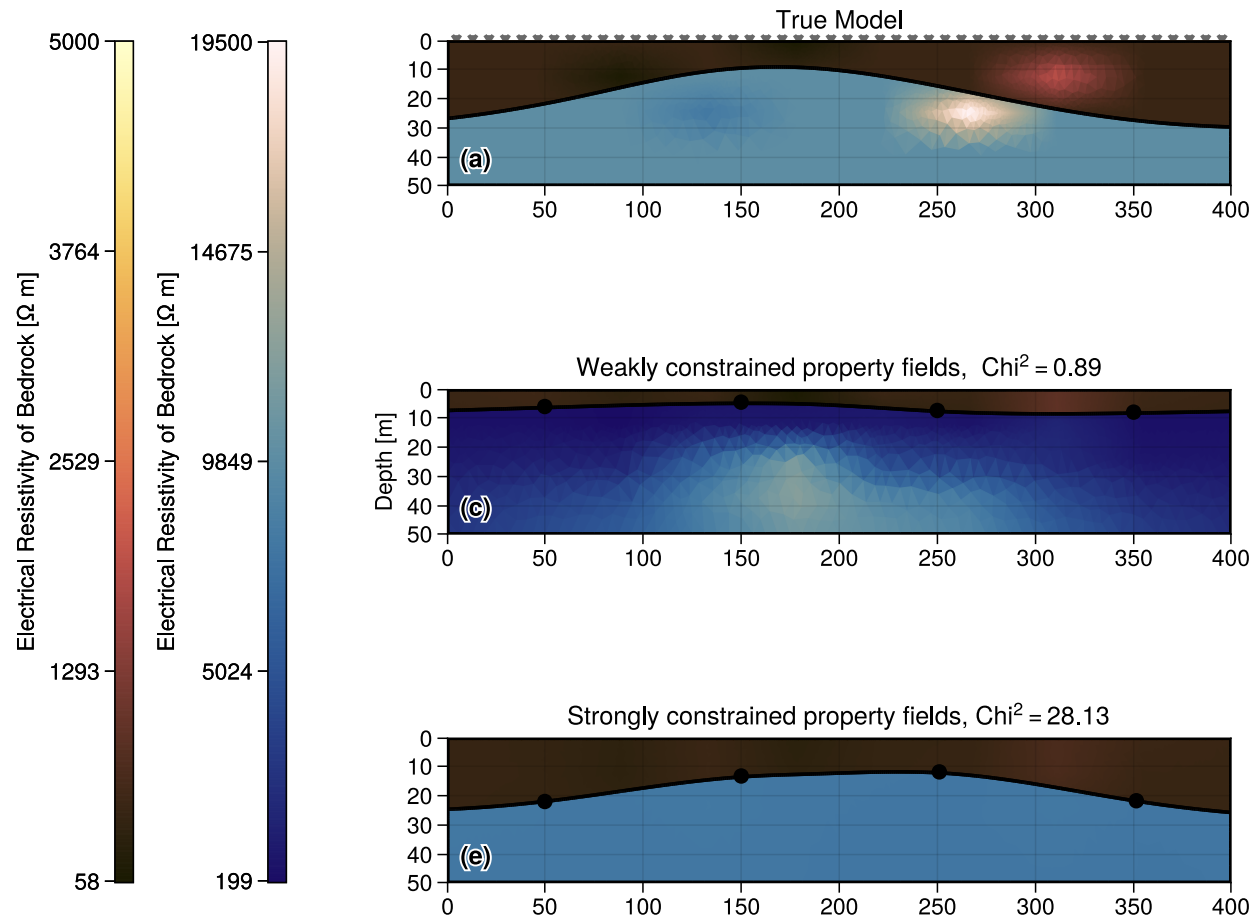


Some results

The following shows some significant results that were obtained using the method described above.

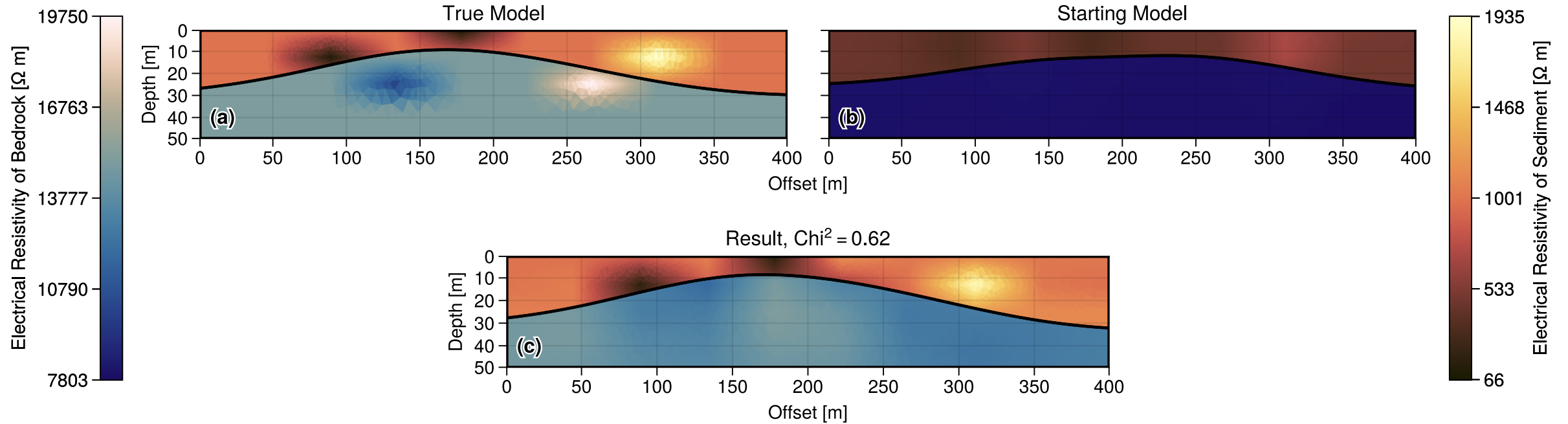
The data fit is described by the Chi^2 -measure. A value of 1 indicates that the data predicted with the given model explains the observed data exactly within its error bounds.





The smoothing constraints imposed on the property fields have a strong impact on the placement of a subsurface interface. Weak constraints tend to lead to results in which the interface is misplaced, but it's overall geometry is mimicked by the resistivity distribution

● Interface Points ▼ Sensor positions



A workflow that proves to be useful is the run of two subsequent inversions: One with strong smoothing constraints on the property fields and one with weak constraints, that uses the first inversion's result as a starting model. This figure was produced by using the model shown on the previous slide in panel (e) as a starting model. This time the smoothing constraints were much lower than in the first inversion, and the resulting model shows a vastly improved data fit, as well as better-placed interface and inter-layer heterogeneities.

Advantages

- Incorporation of complex a-priori information
- Flexible constraint options
- Low-dimensional models
- Achieves geological realism
- Well-suited for deductive workflows

Challenges

- Ambivalence in case of non-convergence
- Only smooth inter-layer heterogeneities are imageable
- Trade-off between data fit and heterogeneity imaging
- Multitude of constraint strategies

Sources and further reading

de la Varga, M., Schaaf, A., and Wellmann, F. (2019). “GemPy 1.0: open-source stochastic geological modeling and inversion”. In: *Geoscientific Model Development* 12.1, pp. 1–32.

Rücker, C., Günther, T., Wagner, F.M. (2017). “pyGIMLi: An open-source library for modelling and inversion in geophysics”. In: *Computers and Geosciences*, 109, 106-123.

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