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Geophysics

Building Flow and Transport Models with Electrical Resistivity Tomography Data

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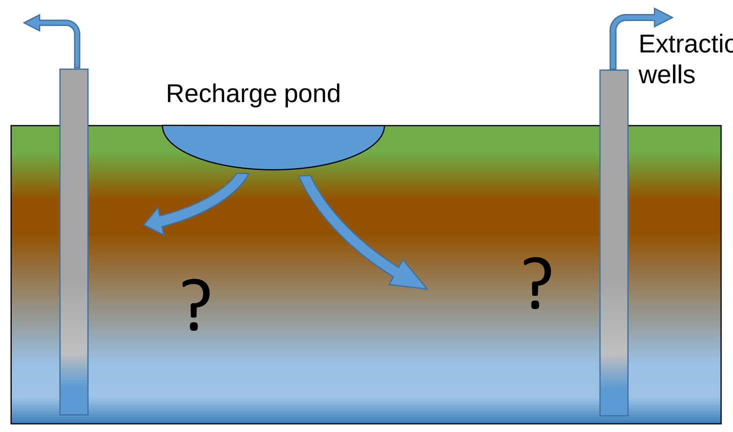
Introduction

Aquifer recharge and recovery (ARR) is the critical zone process of enhancing natural groundwater resources and recovering water for later use by constructing engineered conveyances—in our case by recharge ponds. Subsurface lithological heterogeneity can impair attempts at estimating **where** and **how quickly** water flows through the critical zone.

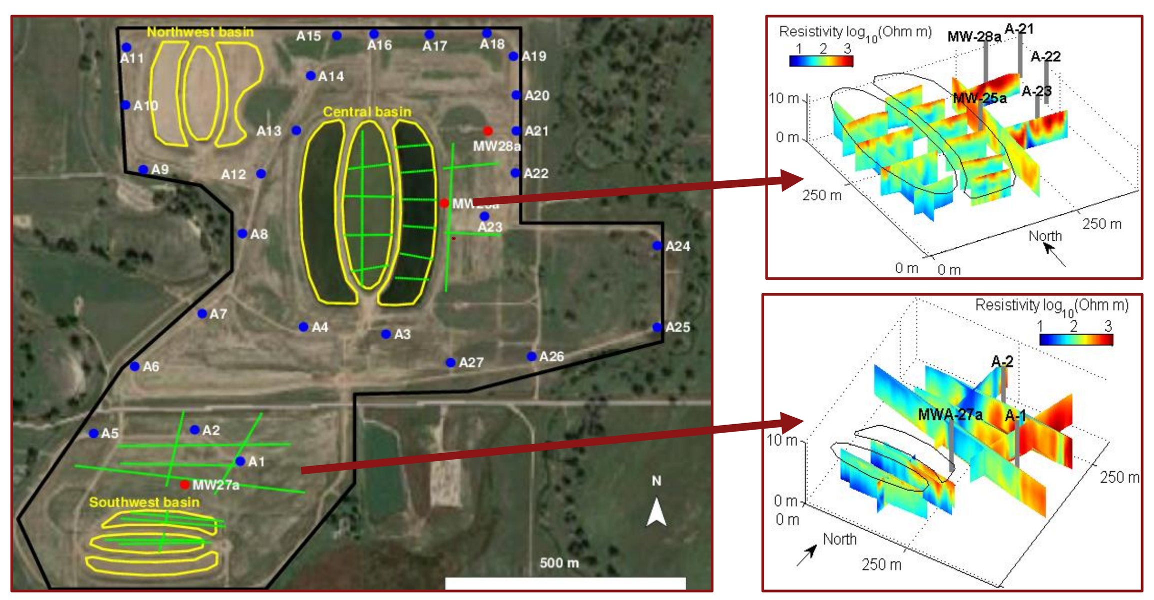
Here, we employ two separate methods for transforming geophysical data not collocated with borehole information into lithological data at an ARR site. We then use geostatistical simulations to build an ensemble of lithology models, and run numerical flow simulations to compare with field observations.

Figure 1: Aquifer recharge and recovery



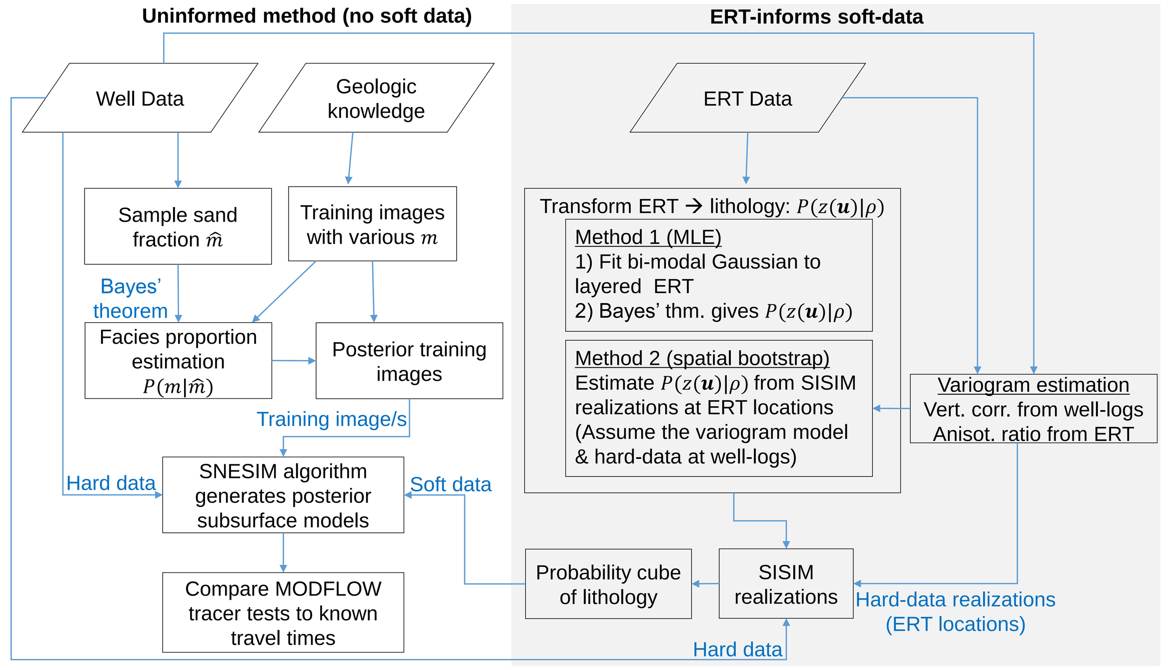
Field Site

- Near Aurora, CO
- Geomorphological setting: unconsolidated fluvial sediments, with many thin clay fingers.
- 26 recovery wells (blue) around the perimeter, 75-170m apart.
- 25 electrical resistivity tomography (ERT) profiles were collected in and near the central and southwestern recharge basins.
- ERT measurements are not collocated with the wells in the area



Workflow

A large amount of uncertainty exists when assigning values to subsurface flow properties. We quantify this uncertainty in a Bayesian framework:



Modeling lithology

1. Resistivity-lithology transform

Because we are interested in preferential flow paths in the fluvial depositional setting, we use a binary hydro-facies categorization of high and low hydraulic conductivity (referred to simply as sand and clay).

Two separate methods were used to define a probabilistic transfer function, mapping resistivity to hydro-facies at the site:

1. Fitting a bimodal lognormal distribution to the inverted ERT data itself, using a maximum likelihood estimator.

2. Using a spatial bootstrap to simulate facies in the region, and then sampling the simulated facies at locations coinciding with ERT data.

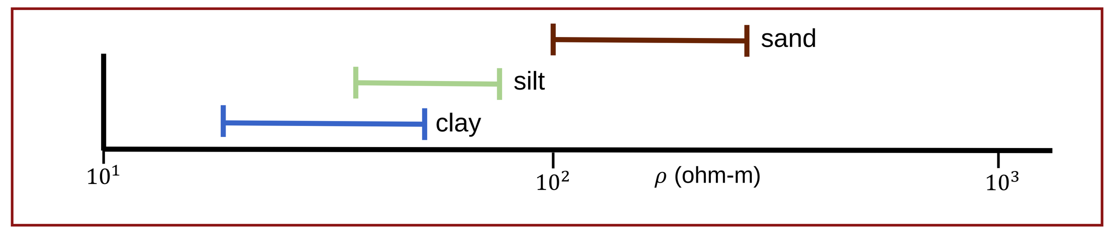
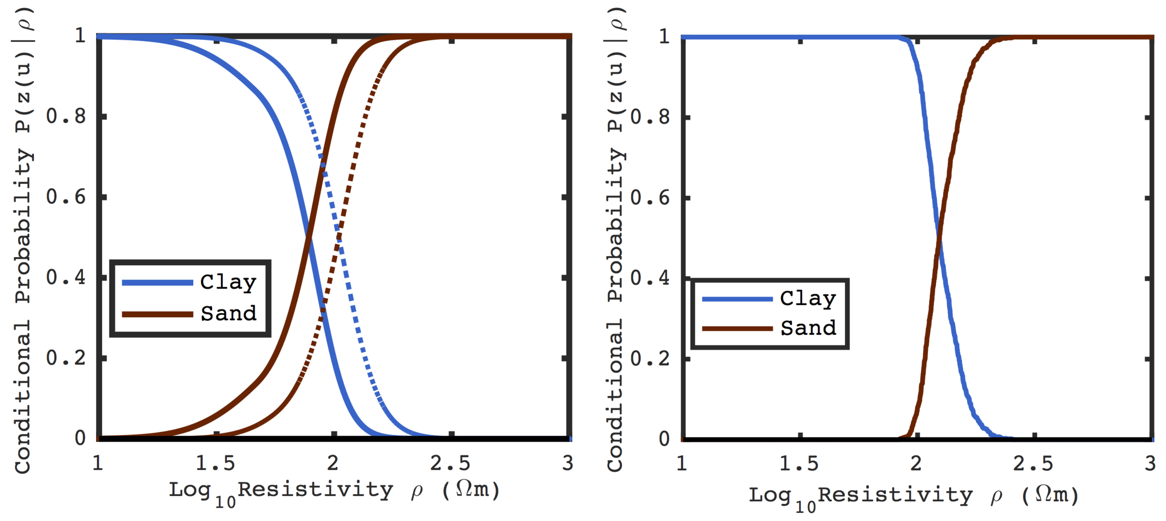


Figure 3: Field measurements of resistivity from the ARR site (after Parsekian et al., 2014)

Figure 4: Resistivity-lithology transfer function defined by: **a)** fitting ERT data (method 1). Dashed lines indicate the resistivity-lithology transform in the unsaturated zone; and **b)** using a spatial bootstrap (method 2).



2. Simulating lithology

Two ensembles of lithology grids were simulated using the multiple point statistical algorithm SNESIM.

One ensemble was simulated for each of the resistivity-lithology transforms described above, using a fluvial training image.

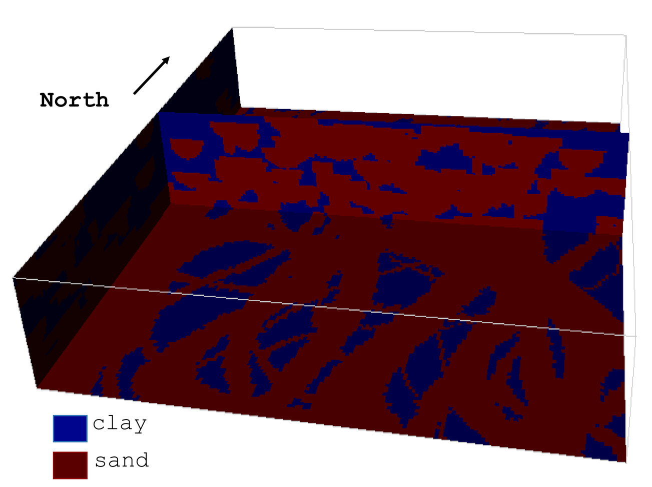


Figure 5: Cutaway of an example training image used in lithology simulations. The channels of various dimensions run generally N-S

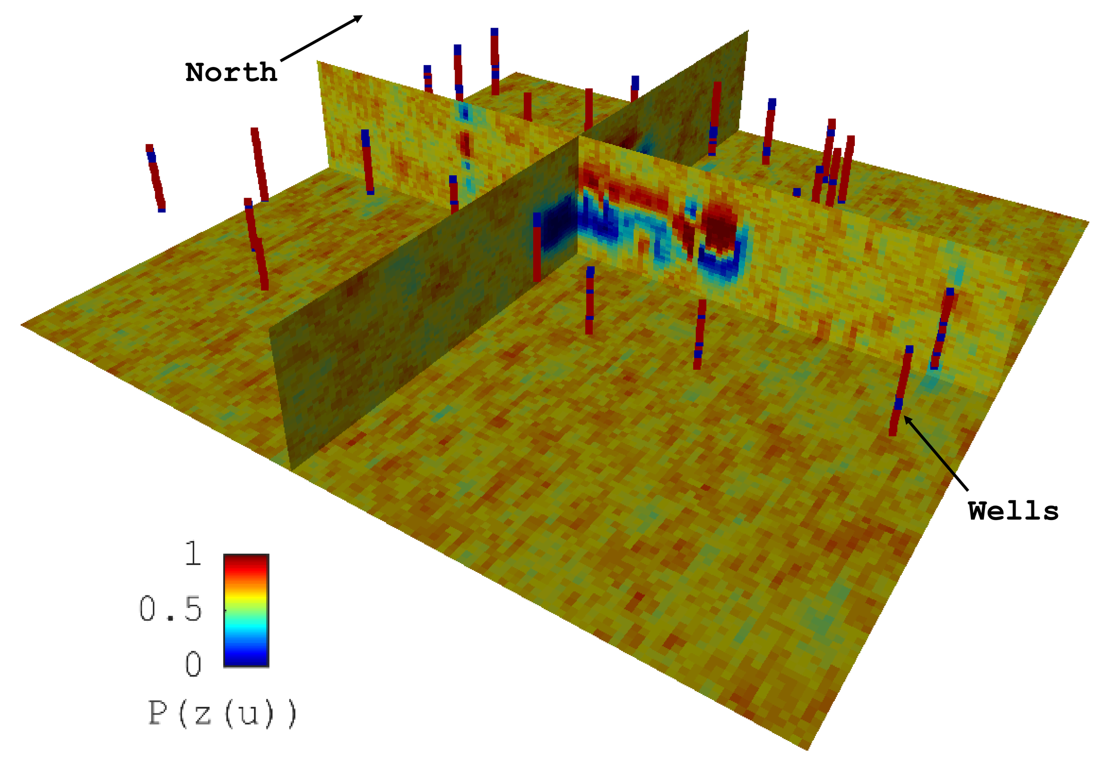


Figure 6: Cutaway of the soft data probability cube, which integrates the information from wells and ERT to assign a probability of sand $P(z(\mathbf{u}))$ at each voxel

Discussion

- **Incorporating geophysical information into flow models refines the precision and accuracy of flow models at the ARR site.**
- Choice of the rock-physics transform has an effect on the on the variance of simulated breakthroughs.
- Simulated tracer breakthroughs never perfectly overlap the field observed values.
    - This is likely because flow parameters (e.g. hydraulic conductivity, porosity) were fixed values for each facies.
    - By using a probability perturbation method, a more plausible set of hydraulic parameter could be found.
- The transformation methods described here can be applied to many different geophysical methods.

References

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Modeling flow

- Hydraulic parameters assigned to sand and clay
- Boundary values set to approximate tracer test at the Aurora ARR site
- Tracer infiltrated through recharge basins for one day, then only water
- 14 wells extracting water to maintain volume
- Concentrations recorded at monitoring wells
- Flow modeled with FloPy—a Python package for MODFLOW

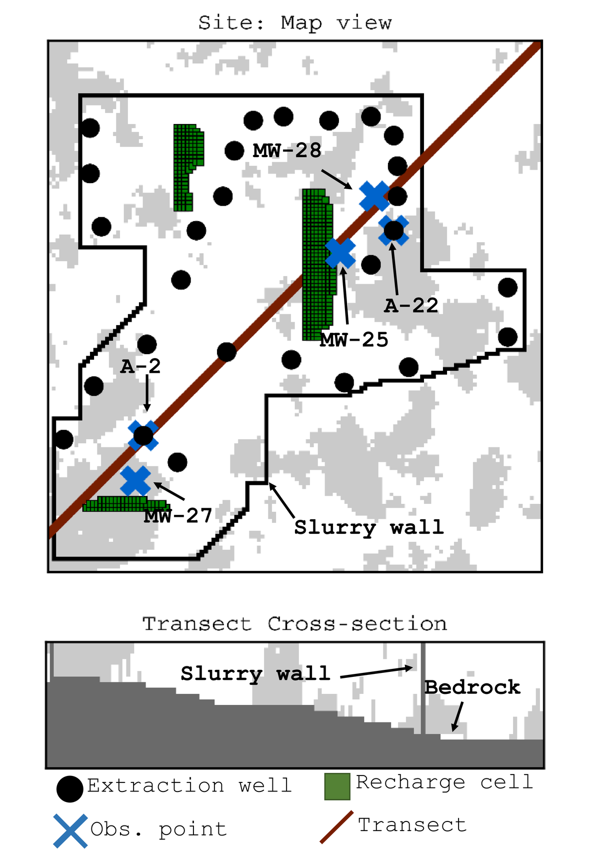

Figure 7: Site map of an example simulated flow grid. White background represents the sand facies, while light grey represents the clay facies

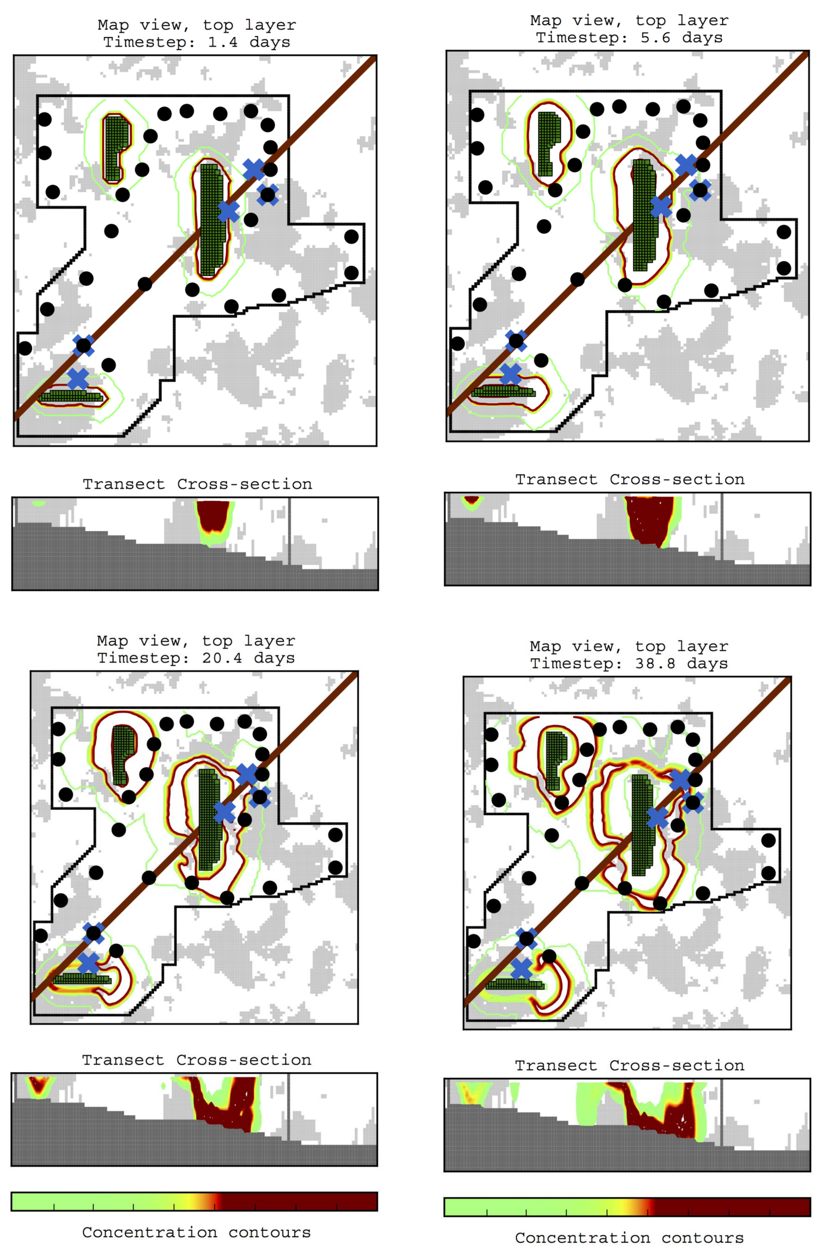

Figure 8: Tracer concentration contour map of a simulated flow grid, at **a)** 1.4 days after beginning tracer recharge, **b)** 5.6 days **c)** 20.4 days **d)** 38.8 days.

Results

Tracer breakthrough times at 5 monitoring wells were used to evaluate the accuracy of the simulated flow field.

We compare the breakthrough results obtained using the proposed methods to generate models with breakthrough results obtained using alternate, more standard methods to generate models:

1) assuming the subsurface is composed of a homogeneous sand, and
2) using SNESIM without incorporating additional information from ERT.

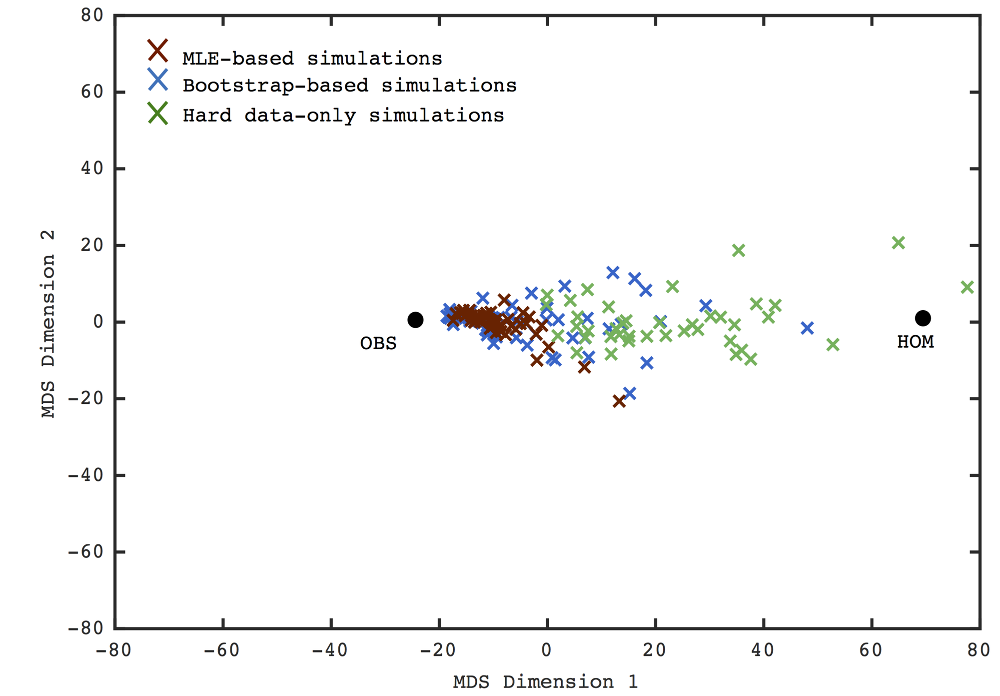

Figure 9: Multidimensional scaling plot showing difference in simulated breakthrough times, as compared to the field site observed values (**OBS**) and a homogenous sand model (**HOM**).

Acknowledgements

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