



Scalable Subsurface Inverse Modeling Using Big Environmental Data Sets

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Overview

With recent advances in sensor and computation technology, unprecedented large volumes of hydro-geophysical and geochemical data sets can be obtained to achieve high-resolution images of subsurface properties for more accurate and reliable subsurface flow and reactive transport prediction. However, massive data set inversion is challenging due to the cost of:

- 1) numerous simulation model runs to compute Jacobian matrix
- 2) large and dense matrix multiplications and storage

To tackle these challenges, the **Principal Component Geostatistical Approach** [1-3] has been proposed with following advantages:

- **Jacobian-free**: no need to compute/store full Jacobian matrix
- **forward model runs independent of the problem size**: often runs much smaller number of simulations in practice
- **linear scalability**: matrix computation/storage costs grow linearly with respect to the problem size
- **easy to implement**: linked with any “black-box” multi-physics simulation models **without invasive changes**
- **independent forward model executions in parallel**

Principal Component Geostatistical Approach

With \mathbf{m} unknowns, \mathbf{n}_{obs} measurements and forward model(s) \mathbf{h} , one needs to compute:

- Jacobian matrix \mathbf{J} , *i.e.*, sensitivity of the data to unknown parameters
- Jacobian products with the prior covariance $\mathbf{\Gamma}_{\text{prior}}$, *i.e.*, $\mathbf{J}\mathbf{\Gamma}_{\text{prior}}$ and $\mathbf{J}\mathbf{\Gamma}_{\text{prior}}\mathbf{J}^T$

For large-scale/joint inversions (large \mathbf{m} and \mathbf{n}_{obs}), one faces challenges

- time-consuming, invasive changes in multi-physics simulation code for efficient adjoint-state method implementation to evaluate Jacobian \mathbf{J}
- expensive Jacobian construction requiring \mathbf{n}_{obs} ($\geq \mathcal{O}(10^4)$) simulations
- prohibitive large dense matrix multiplication/storage for \mathbf{m} ($\geq \mathcal{O}(10^6)$)

In order to tackle these challenges, we developed PCGA that **avoids expensive Jacobian evaluation and its matrix products** (cross-covariance) by using a **fast truncated decomposition** [1] of the prior covariance

$$\mathbf{\Gamma}_{\text{prior}} \approx \mathbf{\Gamma}_{\kappa} = \sum_{i=1}^{\kappa} \zeta_i \zeta_i^T \quad \leftarrow \text{scales linearly (Cost } \mathcal{O}(m\kappa^2))$$

and **finite-difference approximation**:

$$\mathbf{J}\zeta_i \approx \frac{1}{\delta} [\mathbf{h}(\mathbf{s} + \delta\zeta_i) - \mathbf{h}(\mathbf{s})], \quad \mathbf{J}\mathbf{\Gamma}_{\text{prior}} \approx \sum_{i=1}^{\kappa} (\mathbf{J}\zeta_i) \zeta_i^T \quad \leftarrow \text{total } \kappa + 1 \text{ simulations!}$$

Thus, PCGA can achieve **a significant speed-up with reasonable accuracy**, using simulation outputs **without modifying multi-physics simulation code**.

Application to conductivity estimation in a sand box from a massive MRI dataset

Objective: reconstruct **99,072** $\log K$ of a laboratory-scale sand box from **5,777,408** tracer concentration measurements obtained from MRI [3].

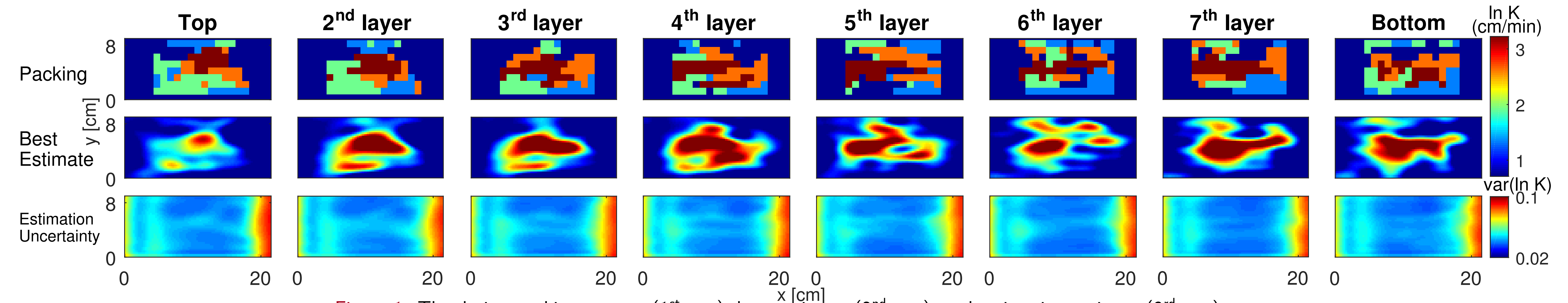


Figure 1: The design packing pattern (1st row), best estimate (2nd row), and estimation variance (3rd row).

Experimental & Numerical Setup

The entire flowcell has dimensions of $21.5 \times 9 \times 8.5$ cm, and is packed with 1 cm cubes of five different sand types [4]:

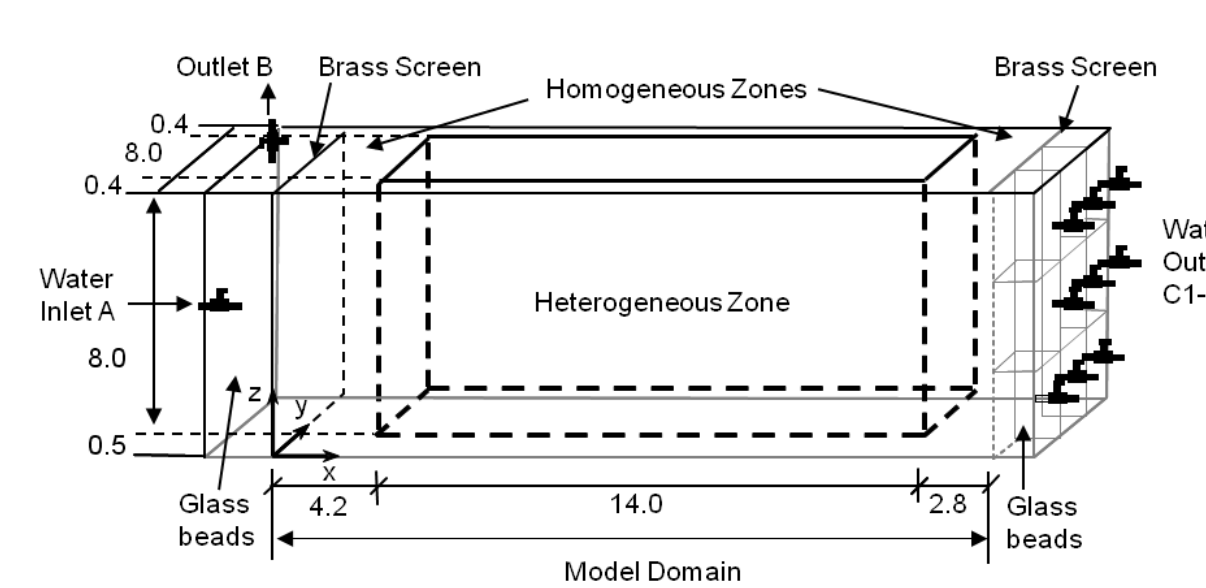


Figure 2: Illustration of 3-D flowcell

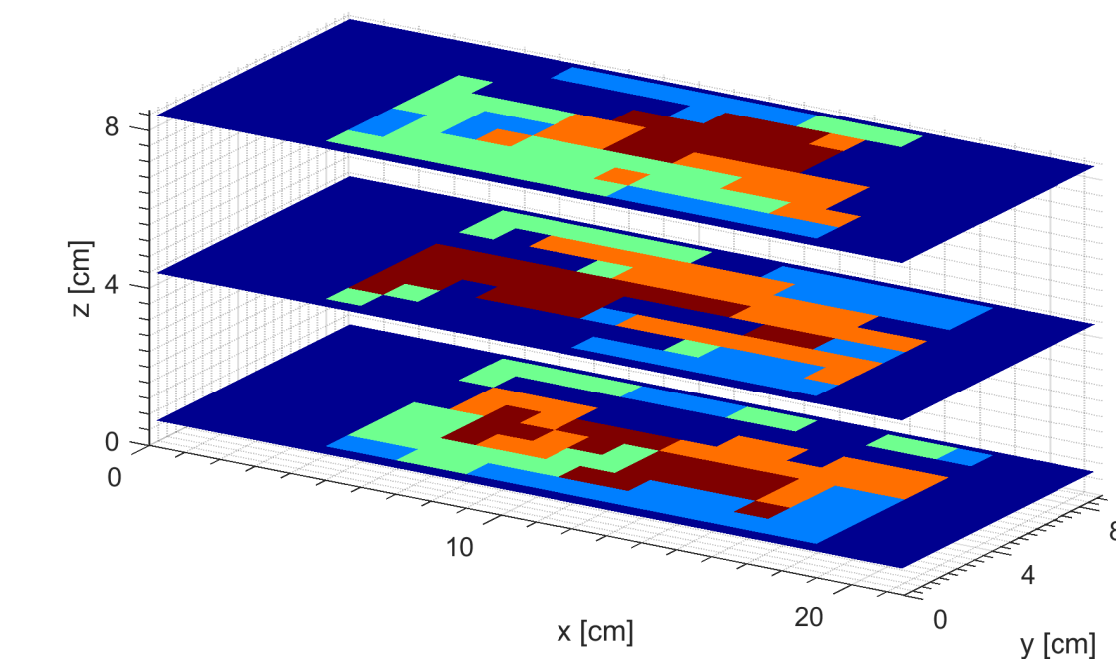


Figure 3: Sand packing in 3 layers (out of 8)

- Sand distribution was created using SISIM in GSLIB to construct a heterogeneous K field for the central portion ($14 \times 8 \times 8$ cm³).
- Constant water flow rate with a uniform tracer concentration
- ~ 6 million transient tracer concentrations were imaged using MRI at a resolution of 0.25^3 cm³ at a regular interval time over the central region.
- A uniform grid spacing of 0.25 cm used for MODFLOW and MT3DMS.
- Forward simulations and inversions executed on a 36 core workstation.
- Using the zero-th temporal moment, 5,777,408 data records were reduced to 51,584 mean travel time records for the inversion.

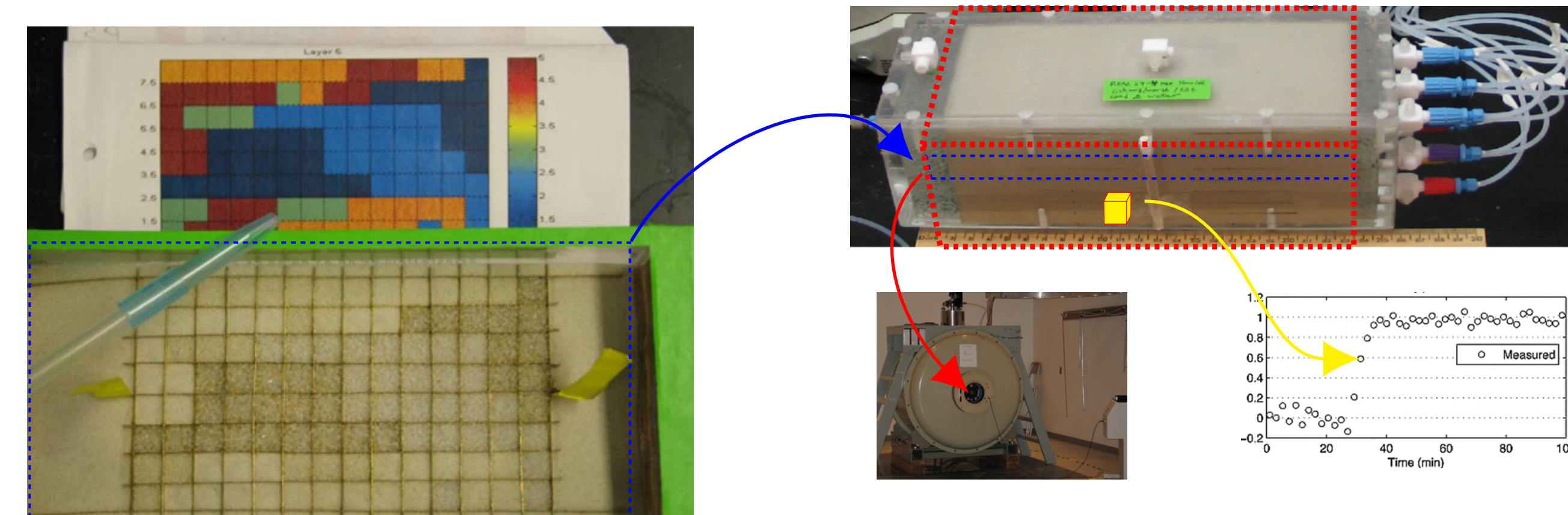


Figure 4: Packing with a brass divider with 1cm³ openings (left), flowcell (upper right), MRI magnet (lower left) and normalized signal intensity at a voxel (lower right).

Results

- A total of **1,952** MODFLOW-MT3DMS simulation runs in **5 hours**.
- $\kappa = 500$ forward simulations for each iteration were enough to approximate a full inverse solution, which would require 51,584 runs.

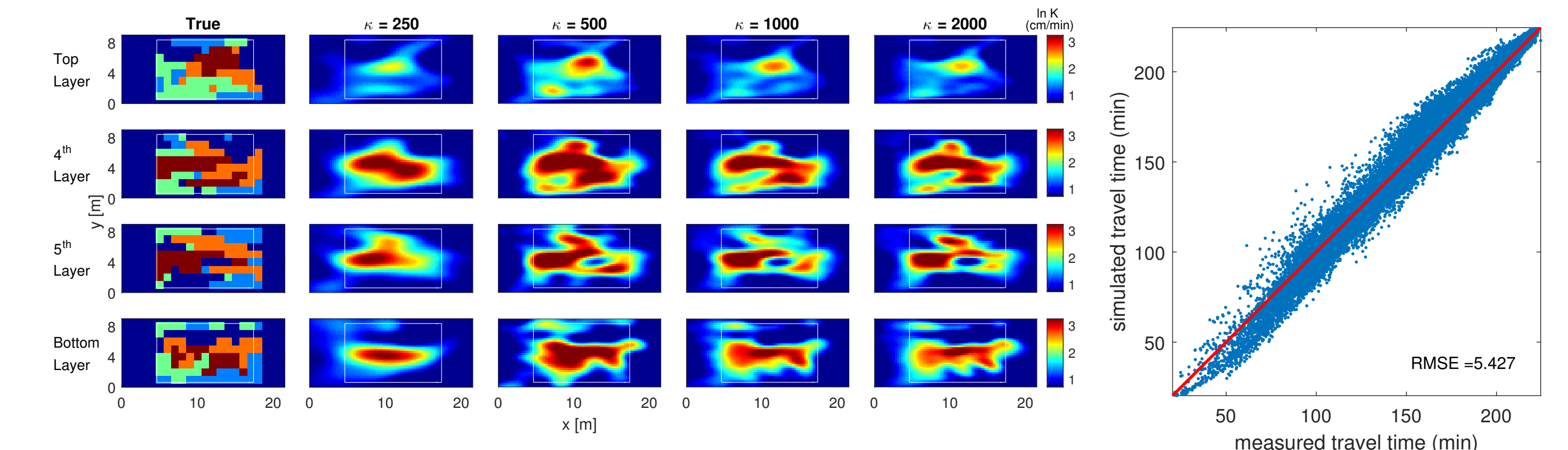


Figure 5: The best estimate with different κ values (left); data fitting with $\kappa = 500$ (right).

Conclusion

- PCGA performed a data-intensive inversion efficiently.
- Key patterns of the original sand packing design were identified.

References

- [1] Lee and Kitanidis, 2014
- [2] Kitanidis and Lee, 2014
- [3] Lee *et al.*, Scalable inverse modeling of huge datasets, *in review*
- [4] Yoon *et al.*, *WRR*, 2008

Acknowledgment

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