FE0009260: Advanced joint inversion of large data sets for characterization and real-time monitoring of CO_2 storage systems

Enhancing storage performance and reducing failure risks under uncertainties

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U.S. Department of Energy

National Energy Technology Laboratory

Carbon Storage R&D Project Review Meeting

Transforming Technology through Integration and Collaboration

August 18-20, 2015

Presentation Outline

- Role in the program
- Objectives
- Contributions to date
- Ongoing work
- Road ahead

Benefit to the Program

- Program goals being addressed:
  - Develop and validate methods for detecting and **monitoring** CO_2 to ensure permanence and containment efficiency.
  - Develop **Software** and Best Practice Manuals for site characterization, site management and risk analysis.

- **Project benefits:** Support decision making for best design and control of CO_2 injection and storage operations, by developing **faster and more reliable data utilization algorithms**.

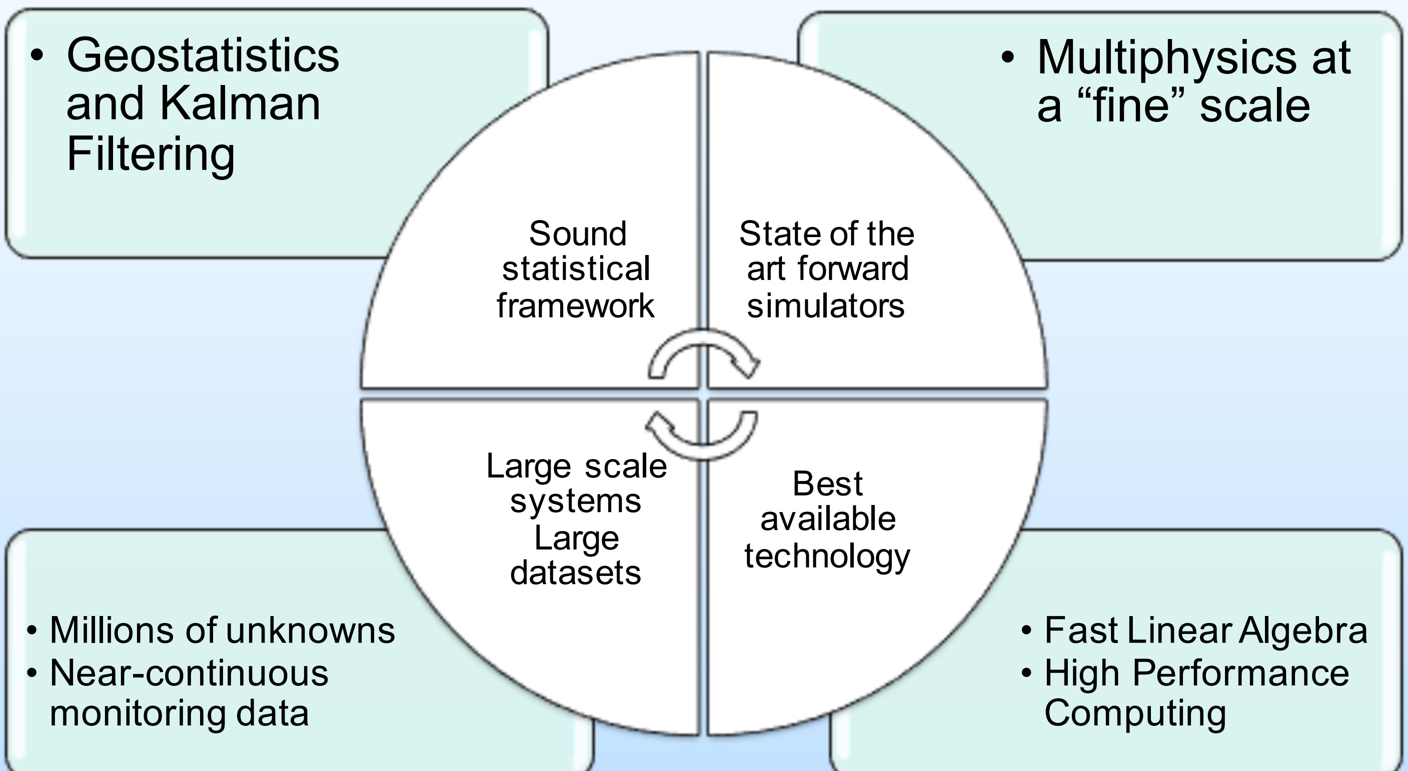
Project Overview: Goals and Objectives

Develop methods

- For **characterization and monitoring** of injected CO_2:
  - Using data with significant noise
  - Using jointly multiple data types
- To **quantify uncertainty and risk**
- That can handle LARGE systems ($>10^6$ unknowns)

Project Overview:
Goals and Objectives

Develop, test, and apply advanced algorithms for estimation of subsurface properties and CO_2 transport for large scale systems with uncertainty estimates.



Technical Status

- **Method development**
  - Fast characterization and dynamic inversion by geostatistical and Kalman Filter methods
- **Testing with synthetic and real data**
  - Large scale, three dimensional heterogeneous
  - Frio-I site, In Salah site
- **Software & best-practice manual development**
  - FKF-TOUGH
  - DAsoftware

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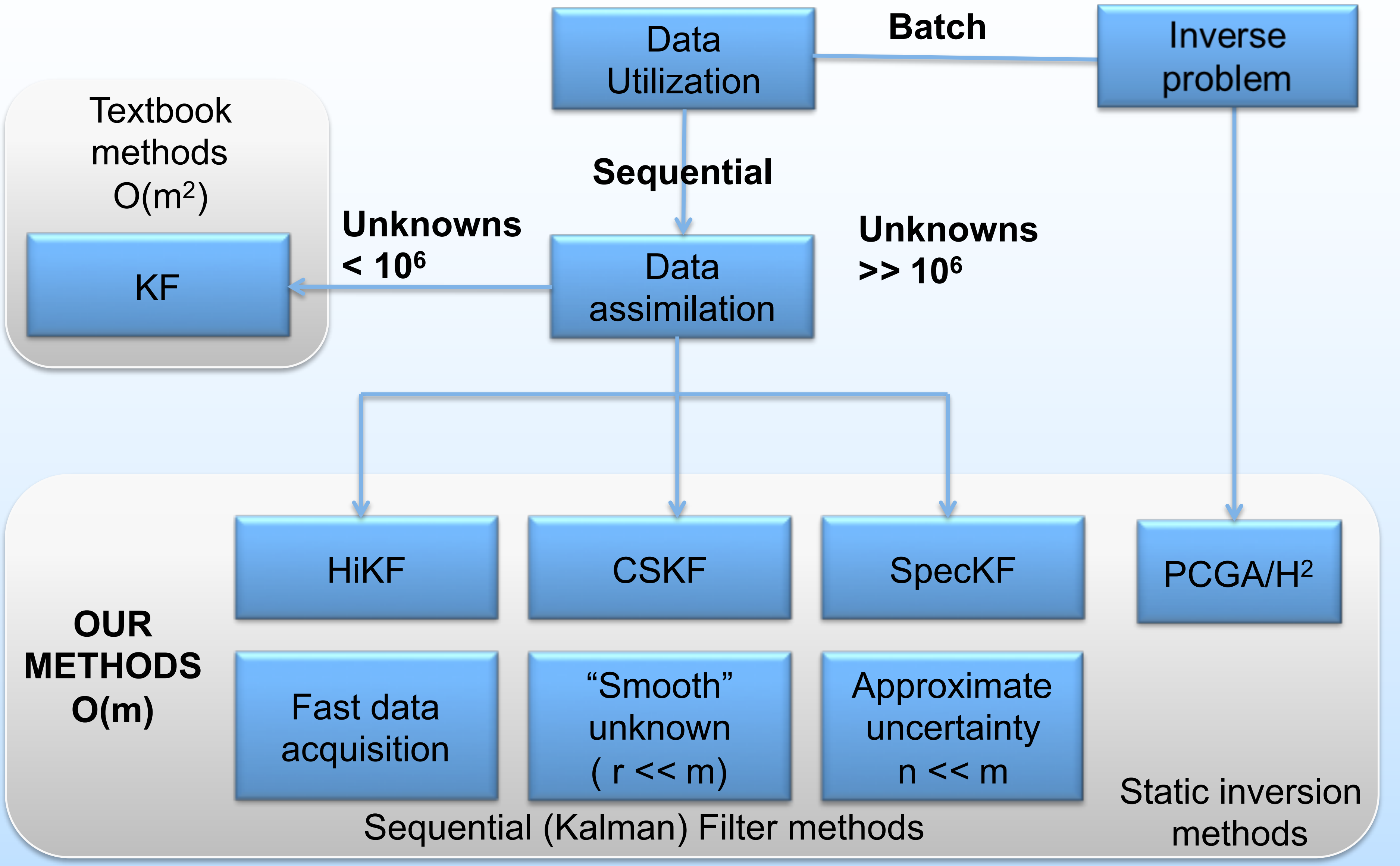
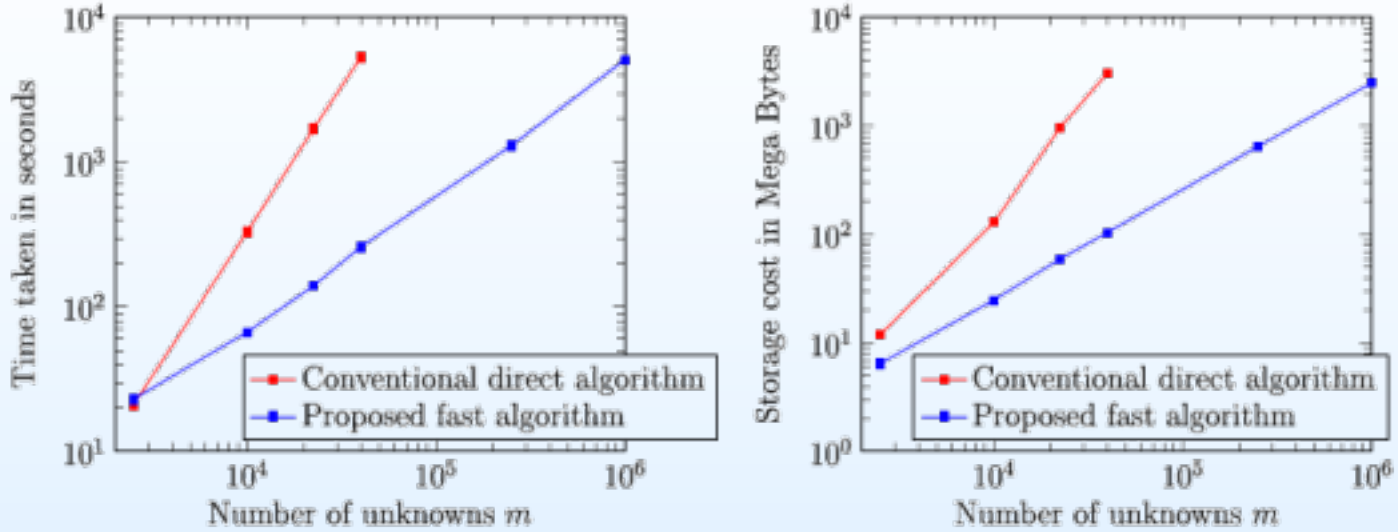


Scaling

S. Ambikasaran, J. Y. Li, P. K. Kitanidis and E. F. Darve, 2013 J. Comp. Geosc. 17:913–927

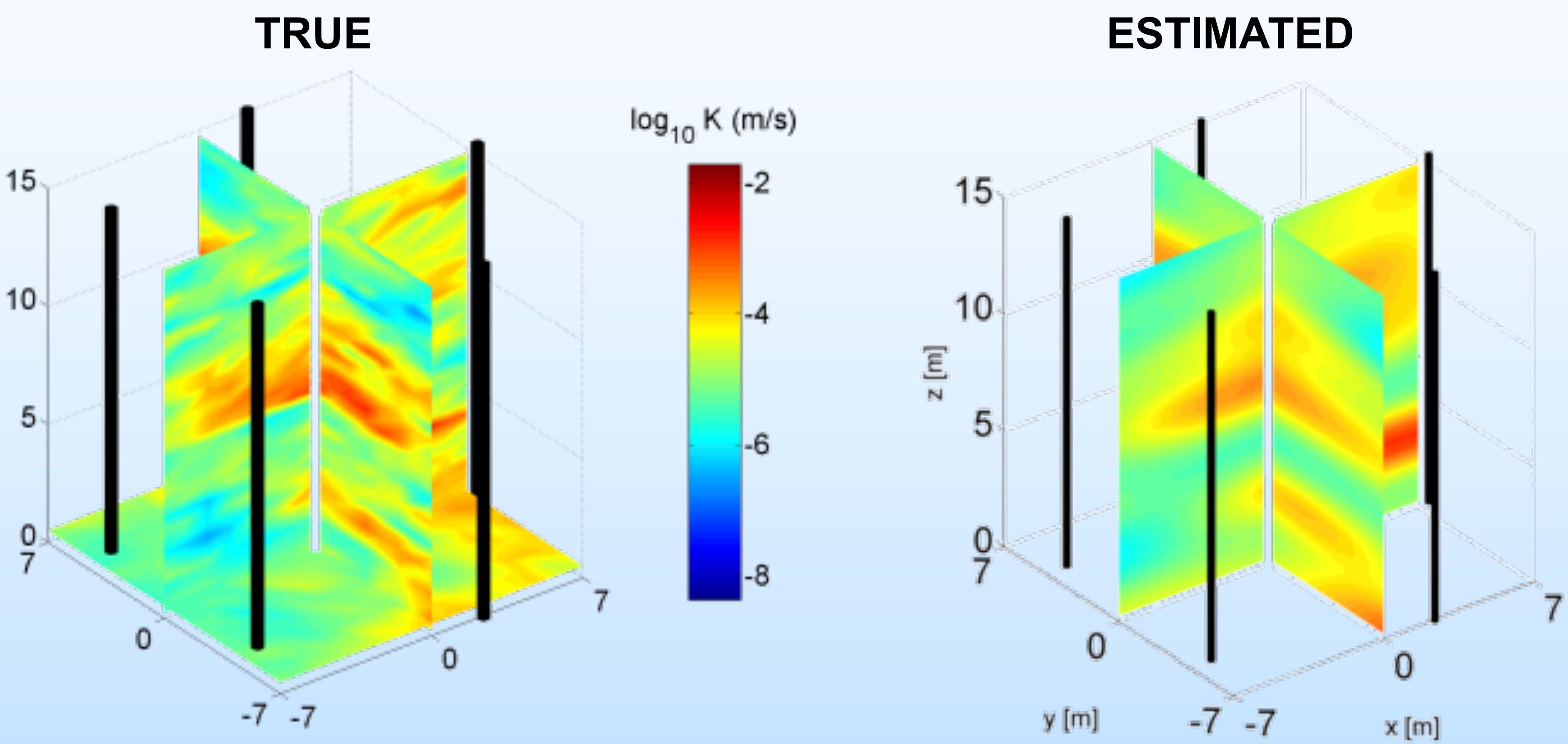


- Harnessing the hierarchical structure of matrices used to describe geospatial correlation, we can dramatically reduce the cost of matrix operations

Principal Component Geostatistical Approach (PCGA)

Lee, J. and Kitanidis, P. K. 2014, Water Resour. Res. 50

- 300,000 unknowns, 2500 HT data, 16 hours

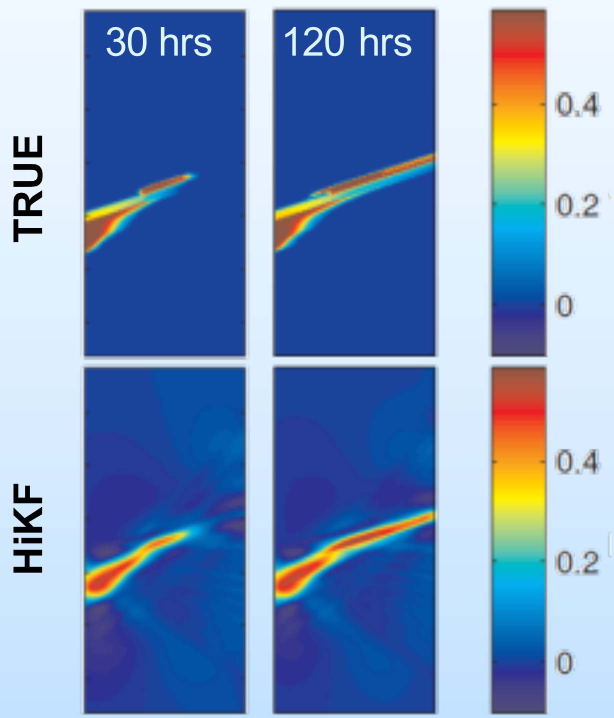


Hierarchical Kalman Filter (HiKF)

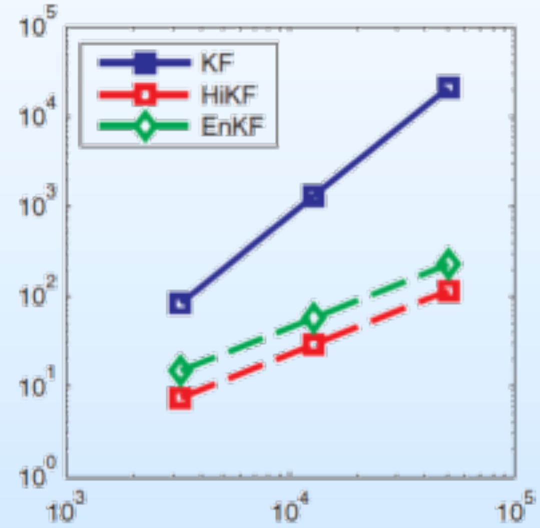
Li, J. Y., S. Ambikasaran, E. F. Darve, and P. K. Kitanidis, 2014 Water Resour. Res., 50

- Hierarchical Kalman Filter for quasi-continuous data assimilation

CO_2 monitoring with seismic travel times



Storage (MB)



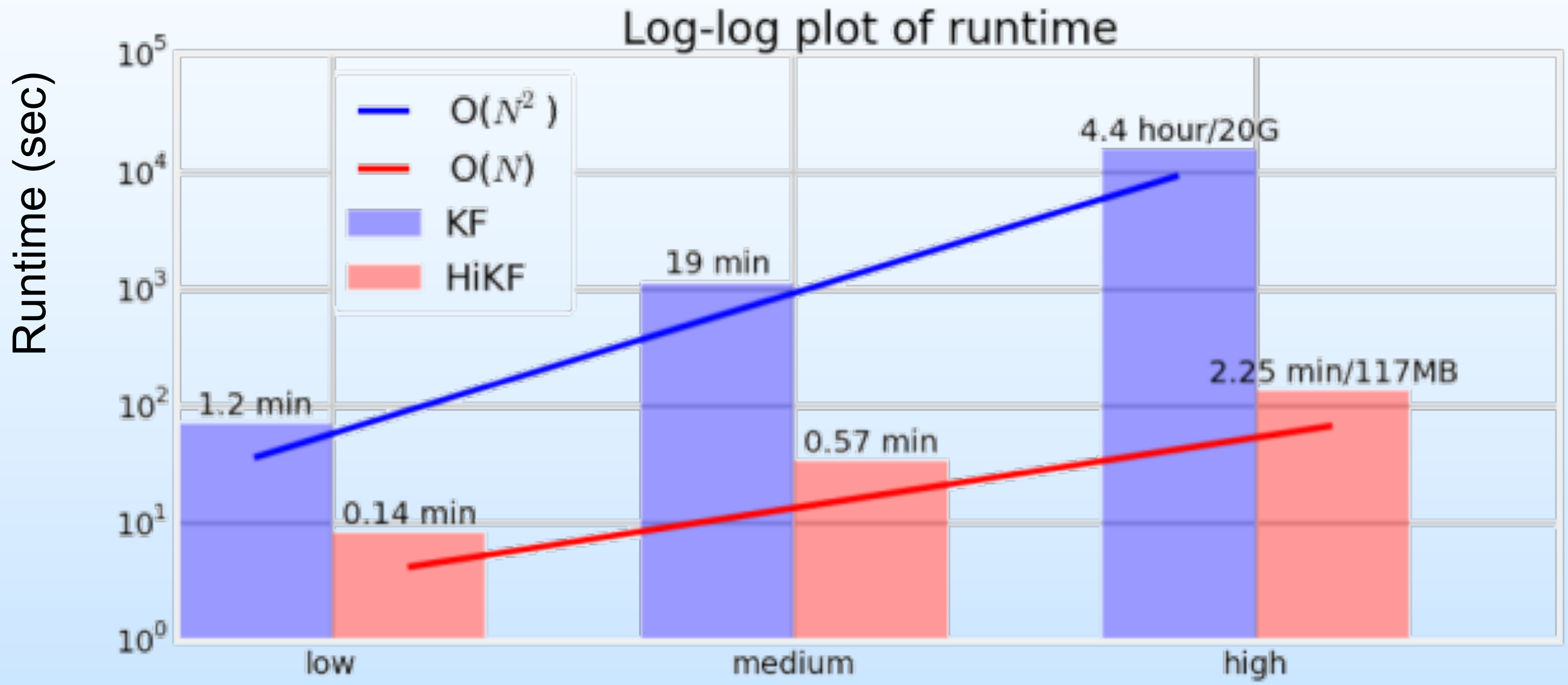
Number of unknowns, m

Hierarchical Kalman Filter (HiKF)

Li, J. Y., S. Ambikasaran, E. F. Darve, and P. K. Kitanidis, 2014 Water Resour. Res., 50

- Reduction of computation cost from $O(m^2)$ to $O(m)$

m: # unknowns



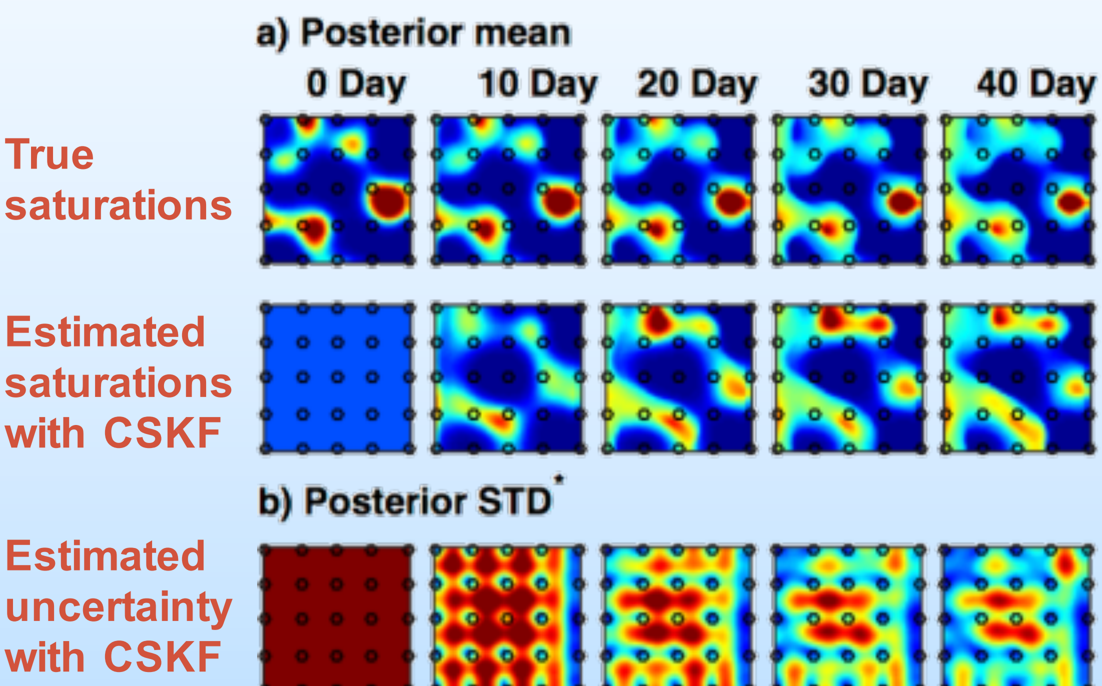
Resolution / Number of unknowns, m

Compressed State Kalman Filter (CSKF)

Kitanidis, P. K., 2014. Compressed State Kalman Filter for large systems
Li et al., The non-linear compressed state Kalman Filter for efficient large-scale reservoir monitoring

- Factorization of the covariance matrix using a fixed basis leads to smaller matrices and faster computations, with minimal loss of accuracy of the inversion algorithm.

CO_2 monitoring example



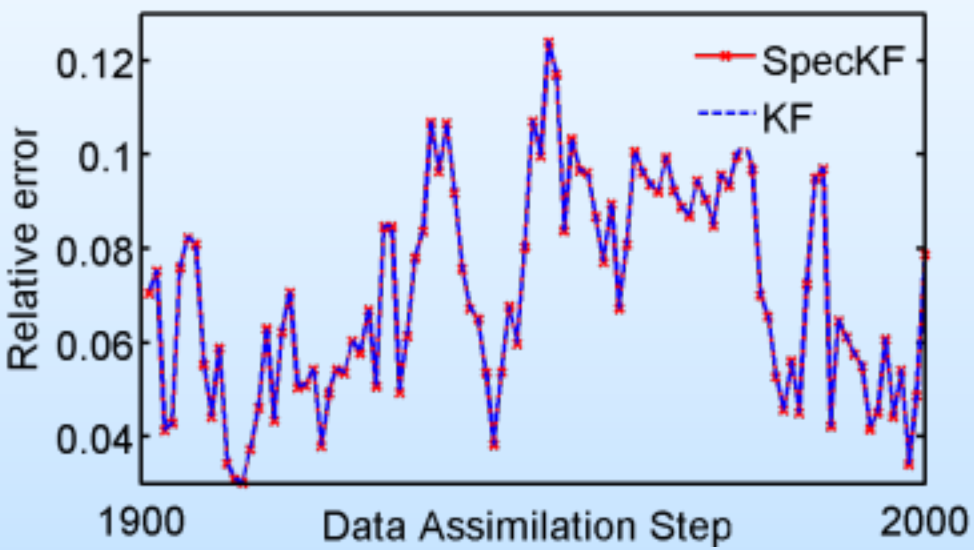
- Variants of the method to handle nonlinear problems and parameter estimation:
  - Iterative CSKF
  - Smoothing based CSKF

Spectral Kalman Filter (SpecKF)

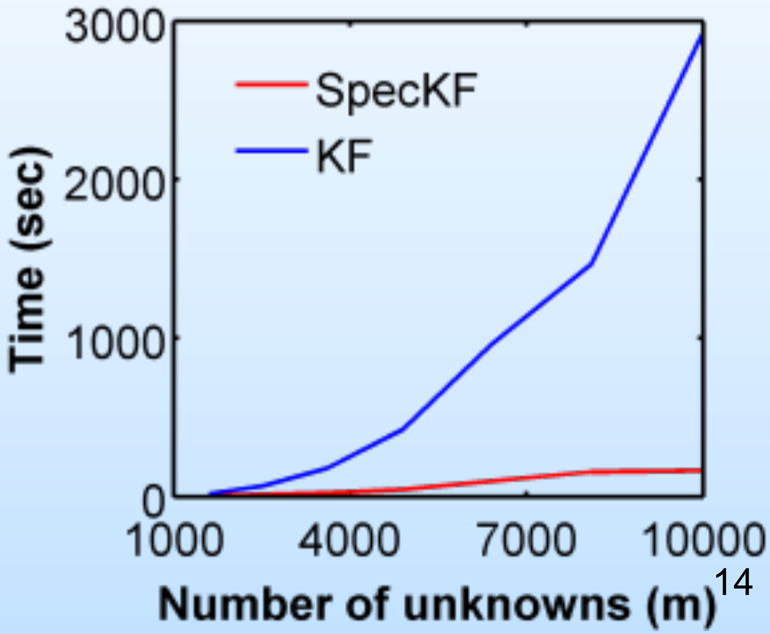
Ghorbanidehno, H., et al., 2015. Real time data assimilation for large-scale systems: the Spectral Kalman Filter.

- Constructing and updating the full covariance matrices is avoided by an approximation of the forward model operator.

- Negligible difference from (full) Kalman Filter in estimation



- Computation time of SpecKF increases slowly with problem size



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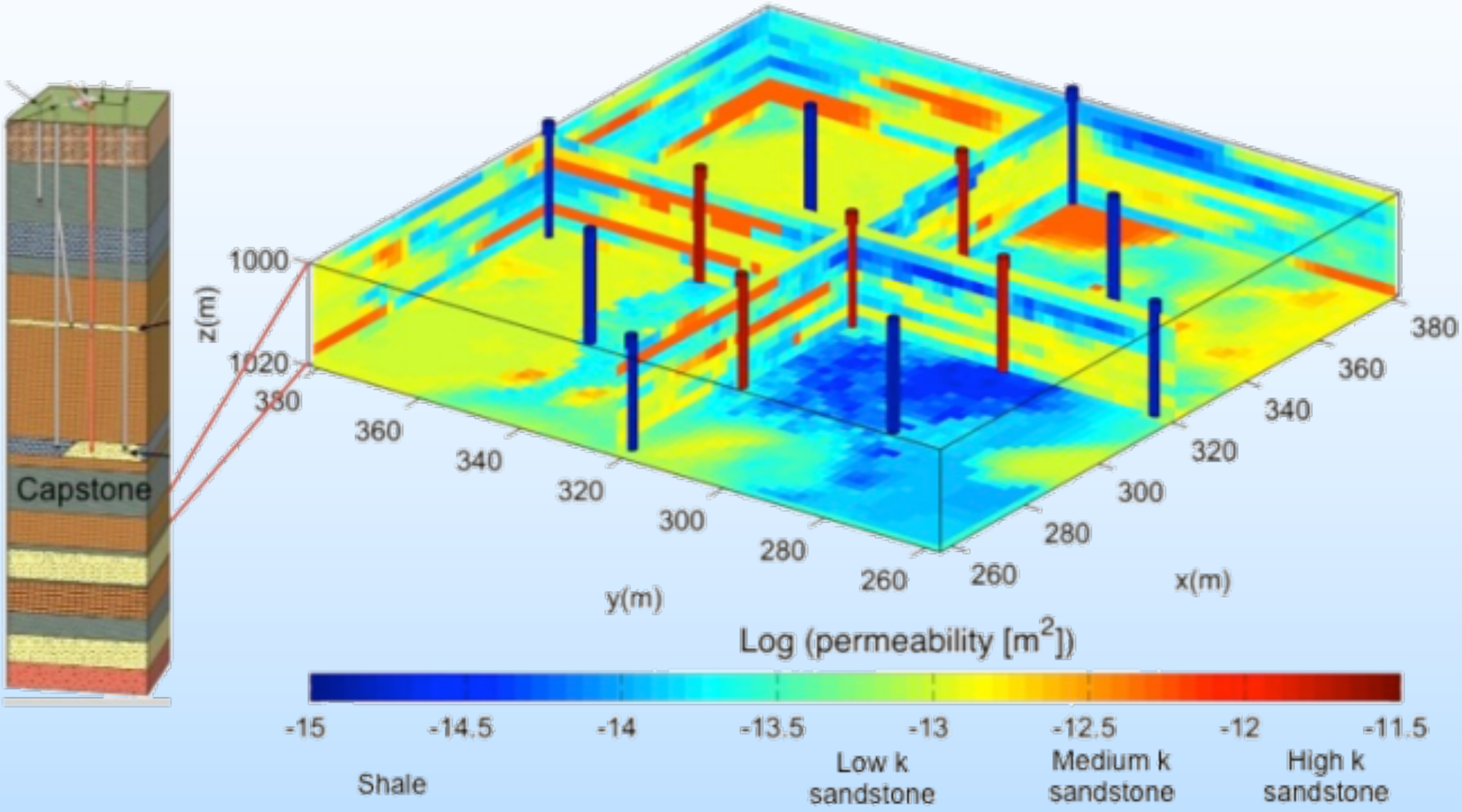
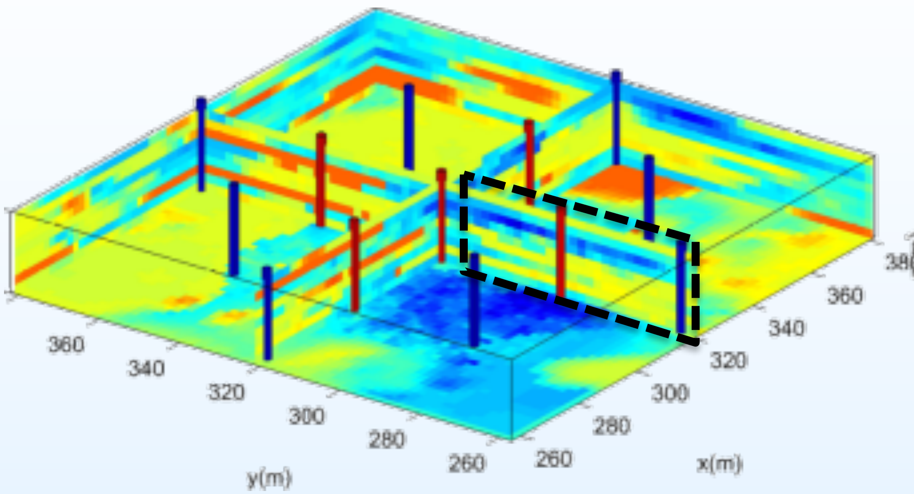
Synthetic domain

Objective: Use various types of field data to characterize a strongly heterogeneous domain

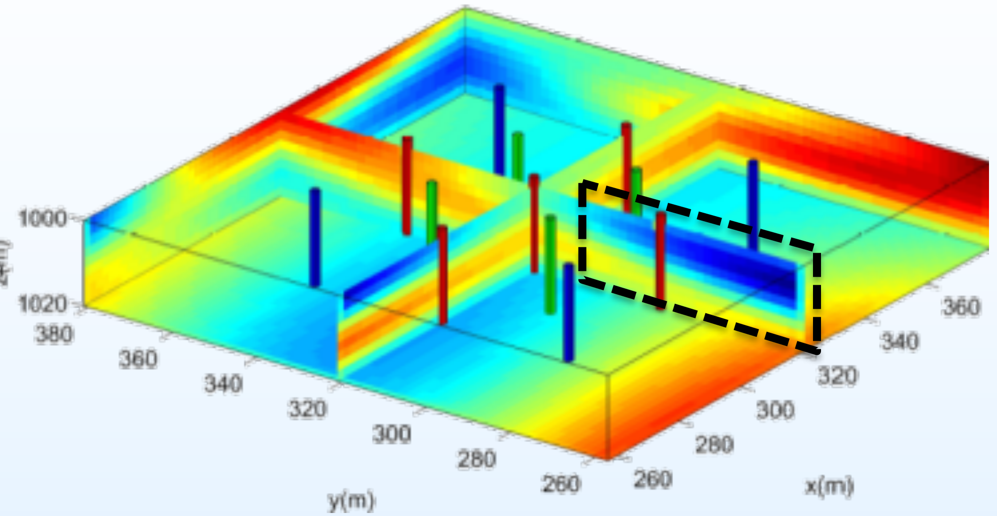


CSKF: Pumping data

True log-permeabilities



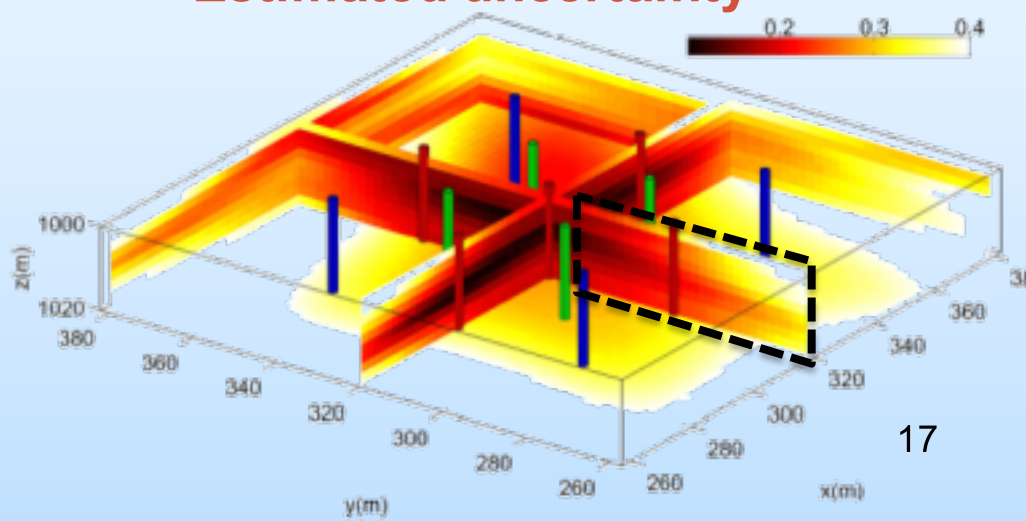
Estimated log-permeabilities



- 24040 unknowns
- 80 measurements
  (pressure and permeability)

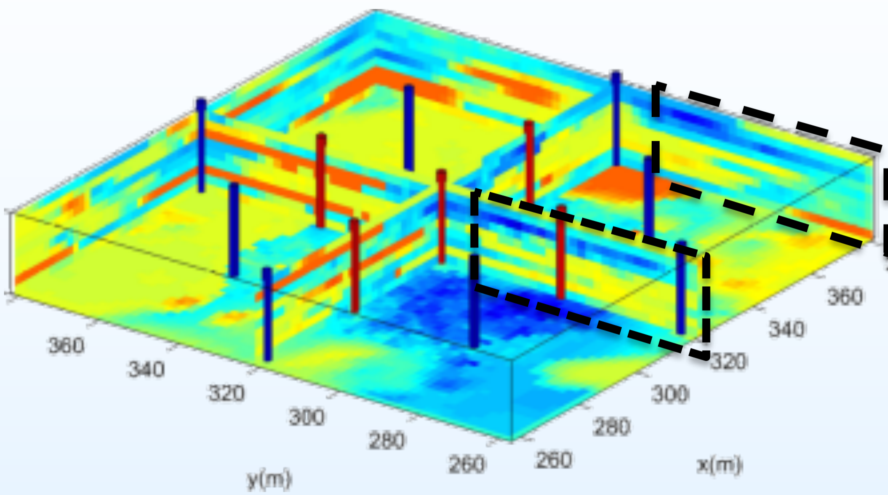
- Covariance compression using just 25 bases
- Estimation at ~1/1000 of the cost of the full method!

Estimated uncertainty

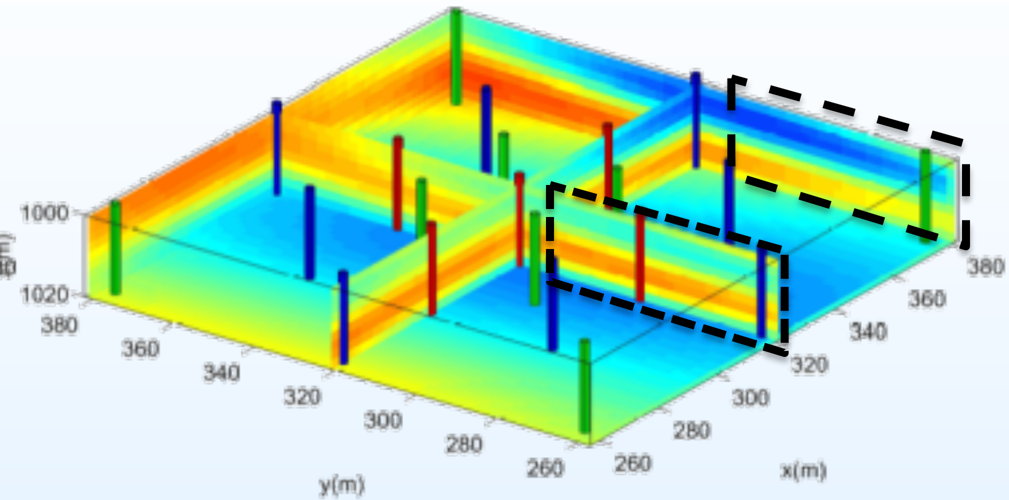


CSKF: Pumping and thermal tracer data

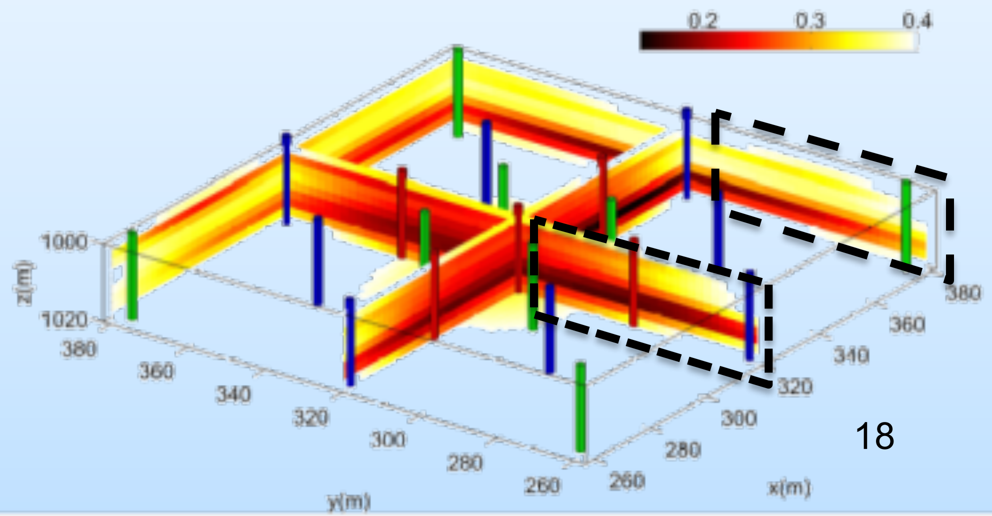
True log-permeabilities



Estimated log-permeabilities



Estimated uncertainty



- 24040 unknowns
- 160 measurements
  (pressure, temperature and permeability)
- With reduced computational cost, we can now explore the value of collecting additional datasets.

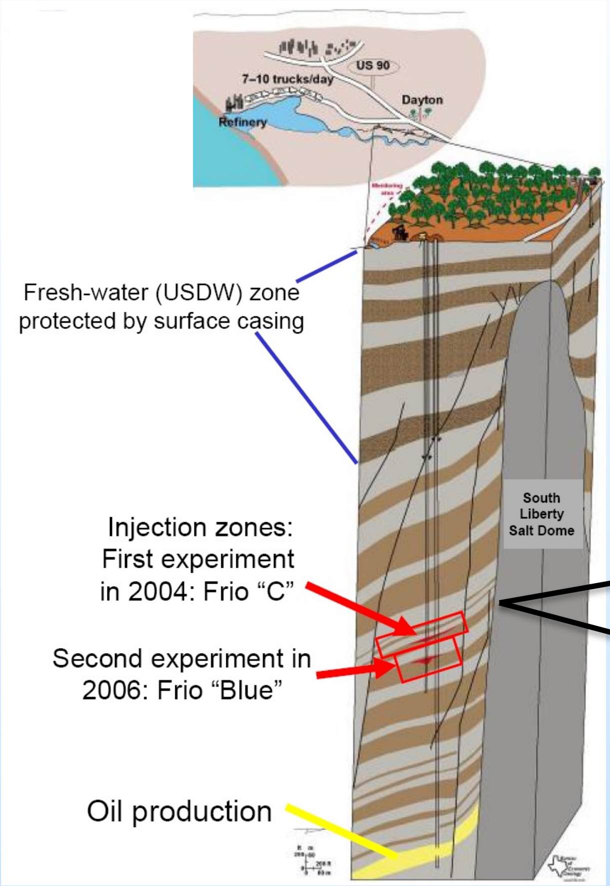
Application to real datasets

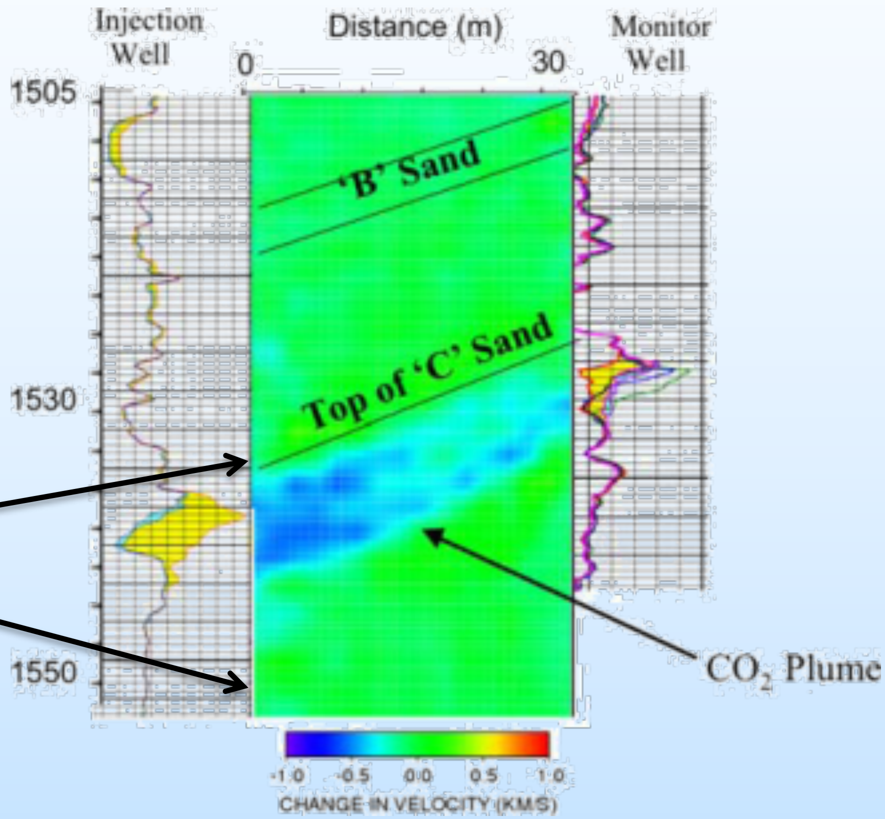
- **Data assimilation algorithms make up for lack of knowledge of processes and properties by continuously updating and correcting our prior models with data as they become available.**

- Many challenges:
  - Diverse and sparse datasets
  - Poor prior knowledge
  - Even larger number of unknowns
  - Forward model simulation challenges
  - Tendency to oversimplify and undersimulate

Application to real datasets

- Frio-I site





Frio-I site

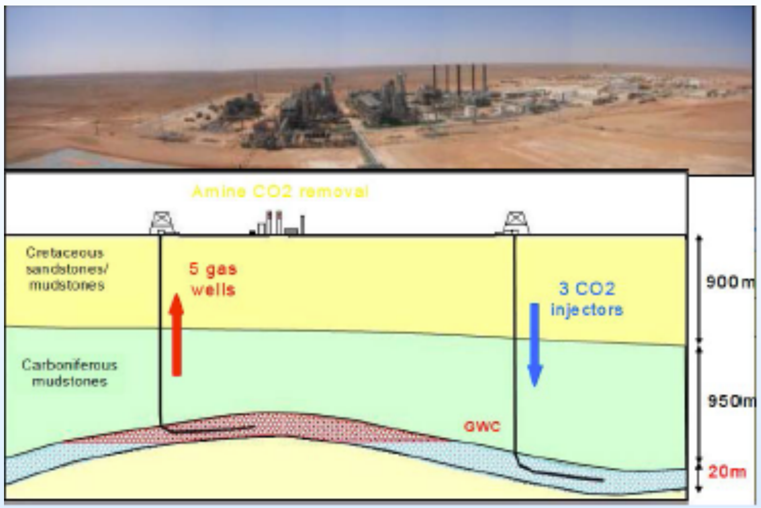
Two-well setup: injection and pumping well
Datasets

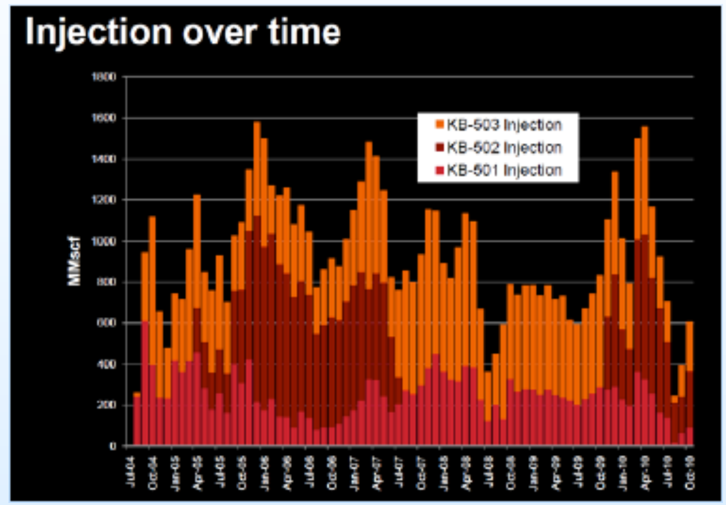
Prior to CO2 injection	During CO2 injection
Pumping tests	CO2 saturation vertical profiles
Thermal tracer tests	Temperature vertical profiles
Conservative tracer tests	Pressure

- Quantitative geophysical data indicate two major preferential pathways that CO_2 followed upon injection.
  - One objective: confirm preferential flow pathways and refine prior geological model.

In Salah site

To use high resolution InSAR data for surface deformation to calibrate geomechanical model and identify heterogeneity.





- Fewer data, larger scale:
  - 27 km x 43 km, 3 horizontal wells
- Complex physical problem
  - Fractured storage system
- Challenging the limits of forward and inverse modeling

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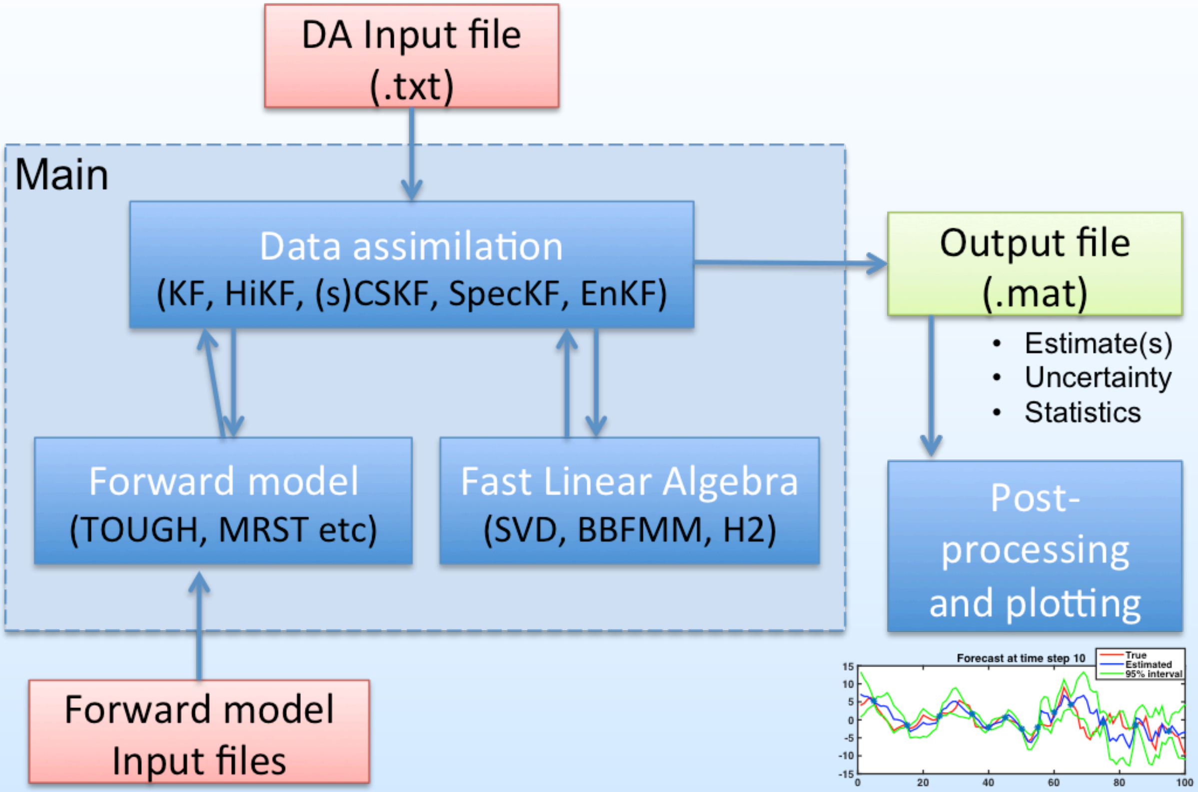
Software development

- DAsoftware

  Educational/research data assimilation software package with all DA methods
- FKF-TOUGH

  TOUGH2 specific Kalman Filter package



Accomplishments to Date

1. Developed and tested multiple techniques for fast and reliable joint inversion of large datasets for CO2 monitoring and site characterization
2. Compared developed techniques with state-of-the-art alternatives and demonstrated similar or superior performance in terms of accuracy and cost.
3. Demonstrated suitability of developed approaches for realistic, large scale cases using synthetic datasets.
4. Started the development of user-friendly software package that will become available to the public for further use and extension.

Synergy Opportunities

Collaboration with projects in sensor technologies and geophysics will have a synergistic effect with this work. E.g.:

- Daley's (LBNL) advance monitoring technologies
- Delgado-Alonso's (Intelligent Optical Systems) CO2 minoring network
- Dobler's (Exelis) laser imaging, and
- Pashin's (Oklahoma SU) surface and airborn monitoring techology

Summary

- Faster data-assimilation algorithms make it possible to answer crucial questions about CCS design and operation.
- We have developed inversion algorithms that provide big computational speed-up and storage cost savings.
- Project products will include guidance documents and user-friendly inversion packages that can be used to optimize CO_2 injection design and operation at real sites.

Appendix

– These slides will not be discussed during the presentation, but are mandatory

Organization Chart

PI: Peter Kitanidis

Task 2: Stochastic Inversion Development
Task Lead: Peter Kitanidis[1]
Participants: Eric Darve[1], Judith Li[1], Hojat Ghorbanidehno[1], Amalia Kokkinaki[1]

Task 3: Efficient Algorithms and GPUs
Task Lead: Eric Darve[1]
Participant: Hojat Ghorbanidehno[1], Ruoxi Wang[1]

Task 1: Project Management and Planning
Task Lead: Peter Kitanidis[1]
Participants: Eric Darve[1] & Quanlin Zhou[2]

Tasks 4 & 5: Methodology Testing/ Application
Task Lead: Quanlin Zhou[2] & Peter Kitanidis[1]
Participants: Xiaoyi Liu[2], Judith Li[1], Amalia Kokkinaki[1], Jens Birkholzer[2]

[1]Stanford University, [2]Lawrence Berkeley National Laboratory

Project team

At Lawrence Berkeley National Laboratory:

- Jens Birkholzer, collaborates on mathematical modeling issues
- Quanlin Zhou, collaborates on mathematical modeling issues
- Keni Zhang, collaborates on high-performance computing and the use of TOUGH2 model (left in 2015)
- Xiaoyi Liu, collaborates on both forward modeling and inversion (left in May 2014)

Project team

At Stanford University:

- Peter K. Kitanidis
- Eric F. Darve
- Judith Li, PhD candidate in Civil and Environmental Engineering (CEE)
- Hojat Ghorbanidehno, PhD candidate in Mechanical Engineering (ME)
- Ruoxi Wang , PhD candidate in Computational and Mathematical Engineering (CME)
- Amalia Kokkinaki, post-doc in CEE
- Sivaram Ambikasaran, PhD Computational and Mathematical Engineering (graduated in Aug 2013)

Gantt Chart

DOE FY	2013				2014				2015				2016	
Quarter	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Jan 31
Task 1.0. Project Management/Planning														
Subtask 1.1: Project Management Plan	A													
Subtask 1.2:Project Planning and Reporting		B												
Task 2.0. Development of Stochastic Inversion Methods						D1								
Subtask 2.1. Development of Fast Bayesian Inverse Methods				C_1										
Subtask 2.2. Development of Efficient Joint Inversion Methods for Dynamic Monitoring														
Subtask 2.3. Fusion of Results from Separate Inversion of Multiple Different Data Sets														
Task 3.0. Development of Efficient Inversion Algorithms								D2						
Subtask 3.1. Algorithms for Solving Large Dense Linear Systems				C_2										
Subtask 3.2. High-Performance Implementation using GPUs														
Task 4.0. Testing of the Joint Inversion Methodology for a Synthetic Geologic Carbon Storage Example									E2					
Subtask 4.1. Generation of the "True" Fields of Porosity and Permeability of the Heterogeneous Storage Formation														
Subtask 4.2. Generation of the Simulated Data of Hydro-Tracer-Thermal Tests and CO2 Injection Test									E1					
Subtask 4.3. Joint Inversion of the Simulated Data									E2					
Task 5.0. Application of the Methodology to Test Sites														F3, F4
Subtask 5.1 Application to Test Site One														F1
Subtask 5.2 Application to Test Site Two														F2

Project Workplan/SOPO Project Tasks

- Task 1: Project Management and Planning
  - Subtask 1.1: Project Management Plan
  - Subtask 1.2: Project Planning and Reporting
- Task 2.0: Development of Stochastic Inversion Methods
  - Subtask 2.1: Development of Fast Bayesian Inverse Methods
  - Subtask 2.2: Development of Efficient Joint Inversion Methods for Dynamic Monitoring
  - Subtask 2.3: Fusion of Results from Separate Inversion of Multiple Different Data
- Task 3: Development of Efficient Inversion Algorithms
  - Subtask 3.1: Algorithms for Solving Large Dense Linear Systems (FDSPACK + Low Rank Approximations)
  - Subtask 3.2: High-Performance Implementation using GPUs in TOUGH+CO2

Project Workplan/SOPO Project Tasks

- Task 4.0: Testing of the Joint Inversion Methodology for a Synthetic Geologic Carbon Storage Example
  - Subtask 4.1: Generation of the “True” Fields of Porosity and Permeability of the Heterogeneous Storage Formation
  - Subtask 4.2: Generation of the Simulated Data of Hydro-Tracer-Thermal Tests and CO_2 Injection Test
    - Subtask 4.2.1: Creation of the Simulated Data for Hydro-Tracer-Thermal Tests Prior to CO_2 Injection
    - Subtask 4.2.2: Creation of the Simulated Data for CO_2 Injection Test
  - Subtask 4.3: Joint Inversion of the Simulated Data
- Task 5.0: Application of the Methodology to Test Sites
  - Subtask 5.1 – Application to Test Site One
  - Subtask 5.2 – Application to Test Site Two

Project Deliverables

1. Task 1.0 – Project Management Plan
2. Task 2.0 – Developed inversion algorithms and their demonstration cases, with the final joint inversion tool system, as documented in a quick-look report.
3. Task 3.0 – Developed fast large linear system solvers with different computational algorithms as documented in a quick-look report.
4. Task 4.0 – Test results of the joint inversion methodology for a synthetic Geologic Carbon Storage example as documented in a quick-look report.
5. Task 5.0 – Test results of application of the methodology to field test sites as documented in a quick-look report.
6. Task 5.0 – Validation of developed computational tools performance and cost as documented in quick-look report.
7. Project Data – Data generated as a result of this project shall be submitted to NETL for inclusion in the NETL Energy Data eXchange (EDX), https://edx.netl.doe.gov/.

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