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
Developing the Technologies and Infrastructure for CCS
August 12-14, 2014

Acknowledgements

- Co-PI: Eric Darve
- Post Doc: Amalia Kokkinaki
- Research Assistants: Judith Li, Hojat Ghorbanidehno, Ruoxi Wang
- Former Research Assistant: Sivaram Ambikasaran
- Our LBNL Collaborators: Jens Birkholzer, Quanlin Zhou, Xiaoyi Liu, Keni Zhang
- Program Manager at DOE: Karen Kluger

Outline

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

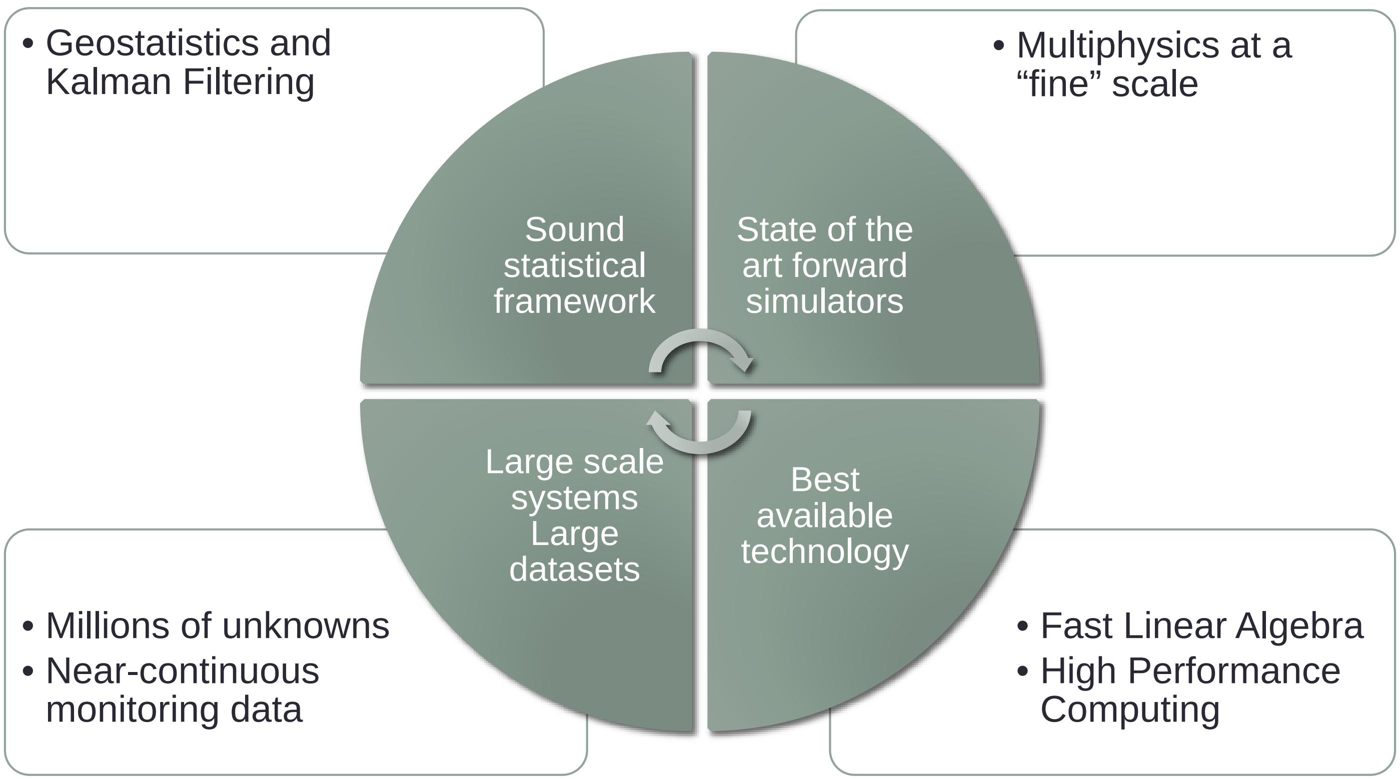
Current needs in CCS

Support decision making for best design and control of CO_2 injection and storage operations

- This involves:
  - *Process simulation of complex, large, multiphase systems.*
  - *Dynamic monitoring with instrumentation providing near-continuous, but noisy datasets.*
  - *Assimilation of data of multiple types.*
  - *Uncertainly quantification and risk assessment.*

Our objective

- **Develop, test, and apply advanced algorithms for high resolution estimation of subsurface properties and CO_2 transport and provide uncertainty estimates.**



Project overview 1/2

Advance Methodologies

- **Static inversion → Geostatistical inversion → Characterization**

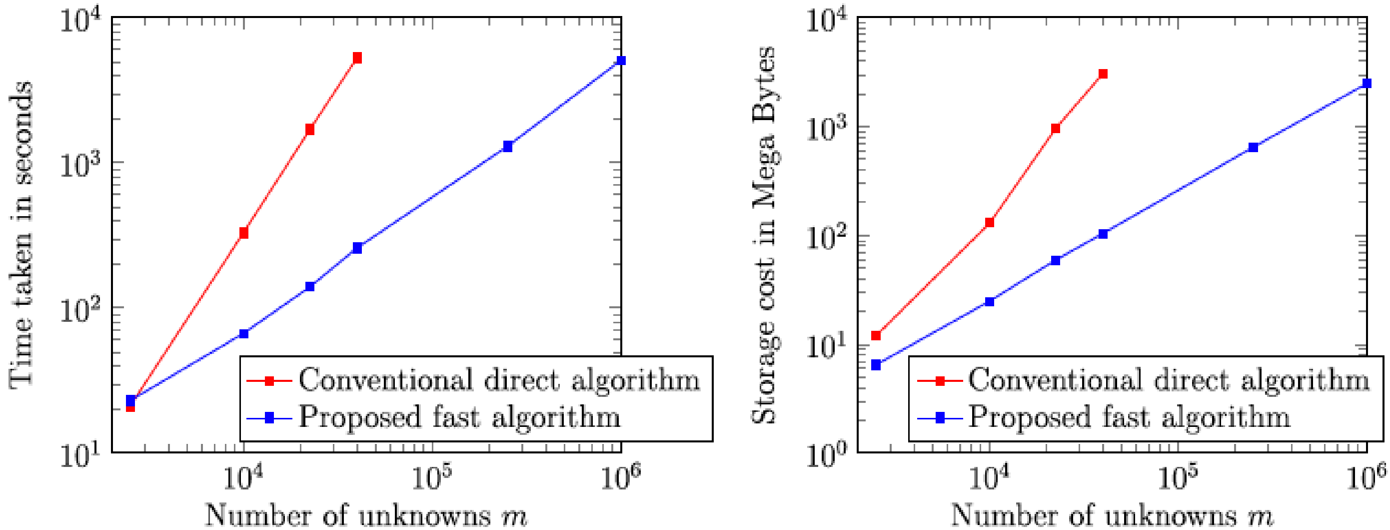
- **Dynamic inversion → Kalman Filter → Real-time CO_2 monitoring**

Project overview 2/2

- **Evaluate developed methods for realistic CCS examples**
  - Synthetic cases
    - Three-dimensional, heterogeneous, real-sized domains
  - Real cases
    - Frio-I pilot test and In Salah site

Static inversion using *H* matrices

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

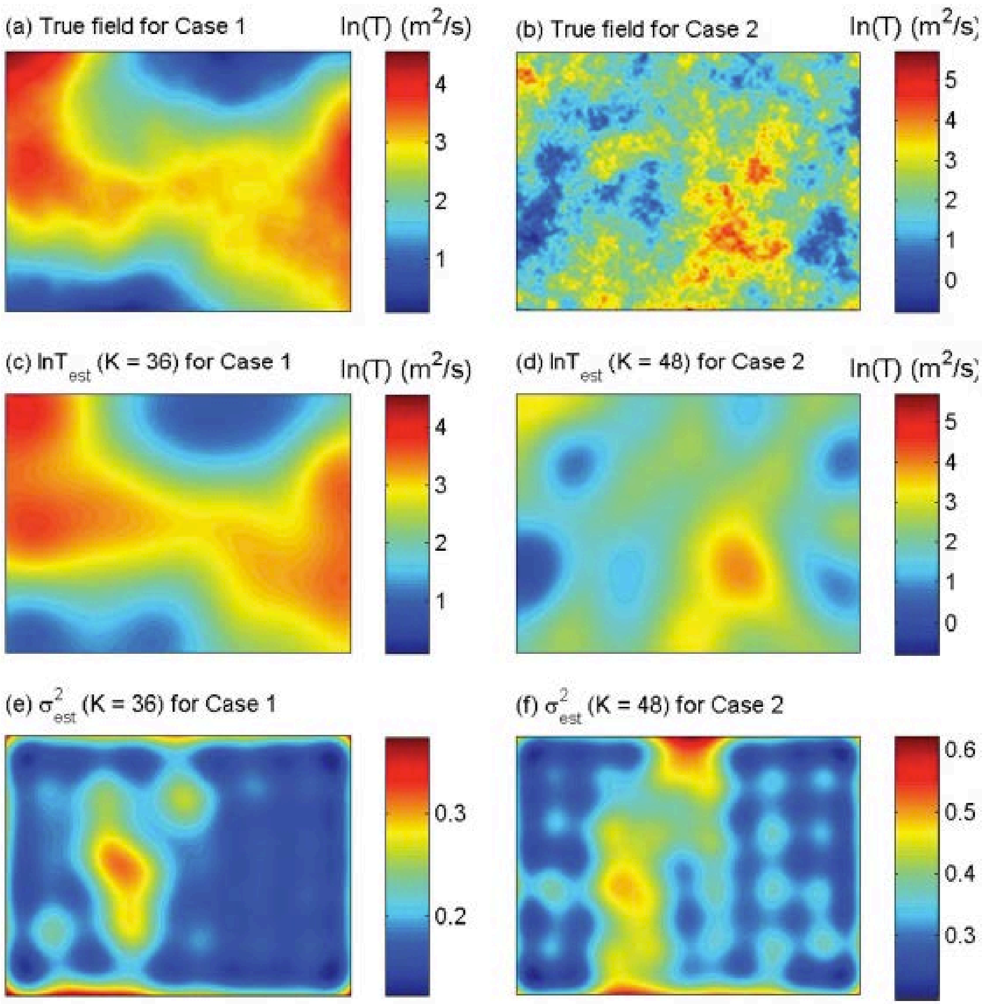


- Hierarchical matrices: data-sparse approximations of non-sparse matrices.
- Harnessing the hierarchical structure of matrices used to describe geospatial correlation, we can dramatically reduce the cost of matrix operations.

Static inversion

Principal Component Geostatistical Approach

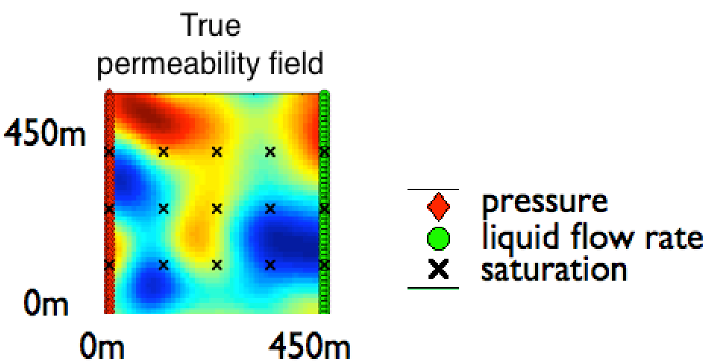
- Hydraulic tomography application to large-scale system: 750 m x 1000 m, 3×10^6 unknowns
- < 50 terms needed!
- Inversion completed in less than two hours, with a storage cost of roughly 1.5 GB



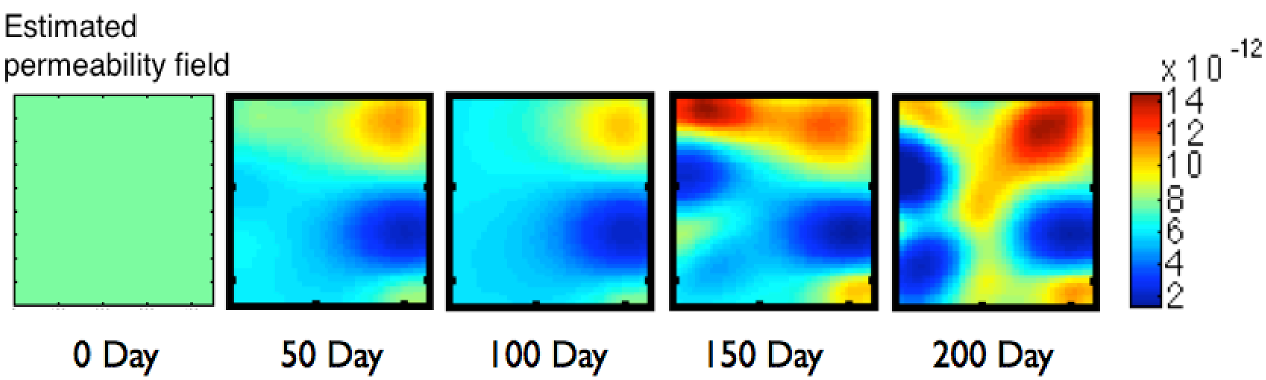
Lee, J. and Kitanidis, P. K. 2014, Water Resour. Res. 50

Dynamic monitoring - CSKF

- Compressed State Kalman Filter



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



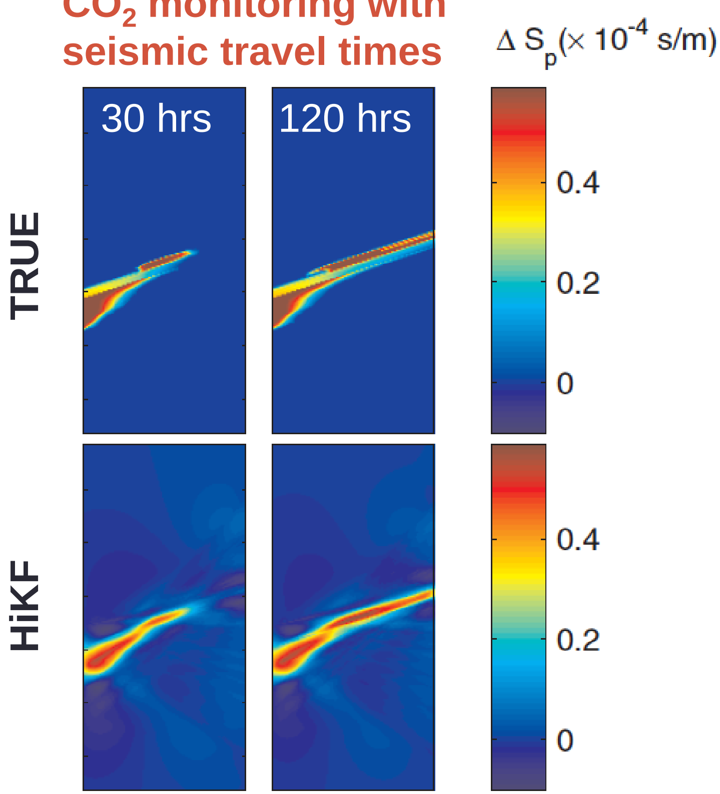
Joint estimation of permeability and CO_2 saturation using measurements of CO_2, pressure, and water production rates.

Dynamic monitoring - HiKF

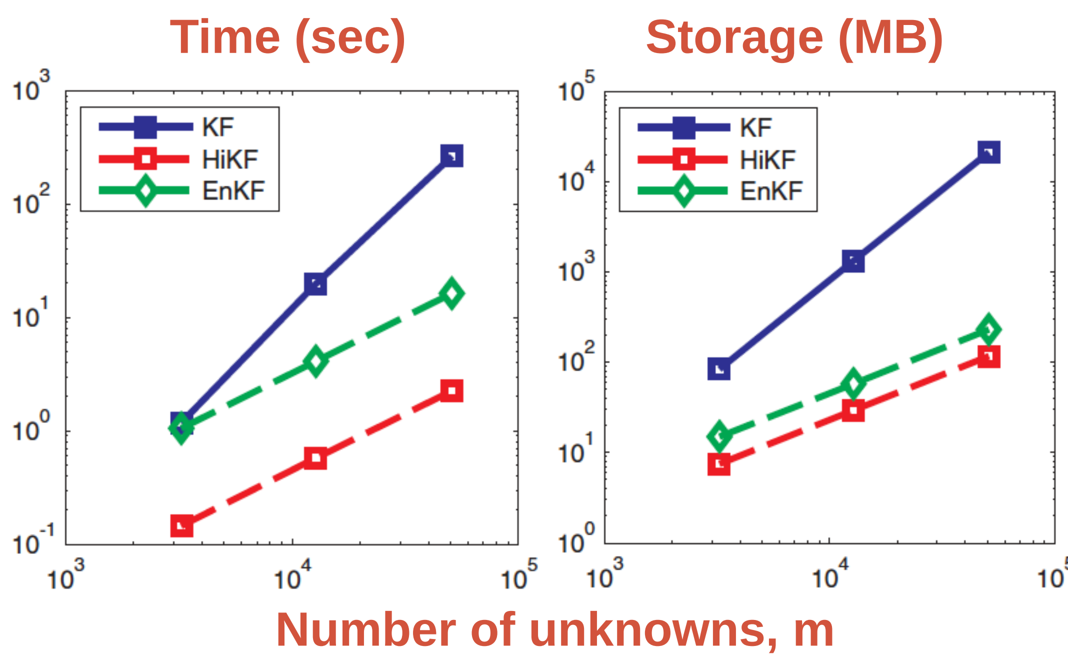
Li, J. Y., S. Ambikasaran, E. F. Darve, and P. K. Kitanidis, 2014 Water Resour. Res., 50

- Hierarchical Kalman Filter for quasi-continuous data assimilation

CO_2 monitoring with seismic travel times



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

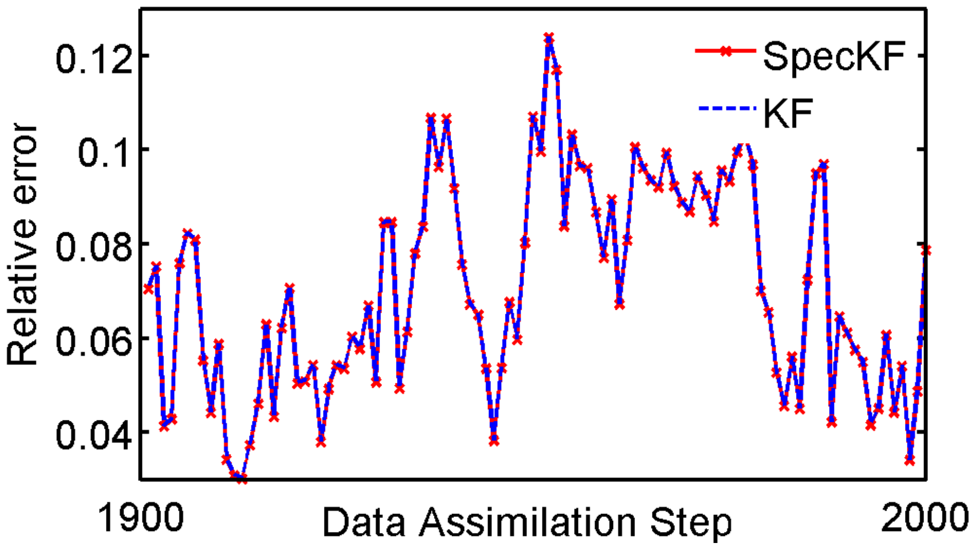


Dynamic monitoring – Spec KF

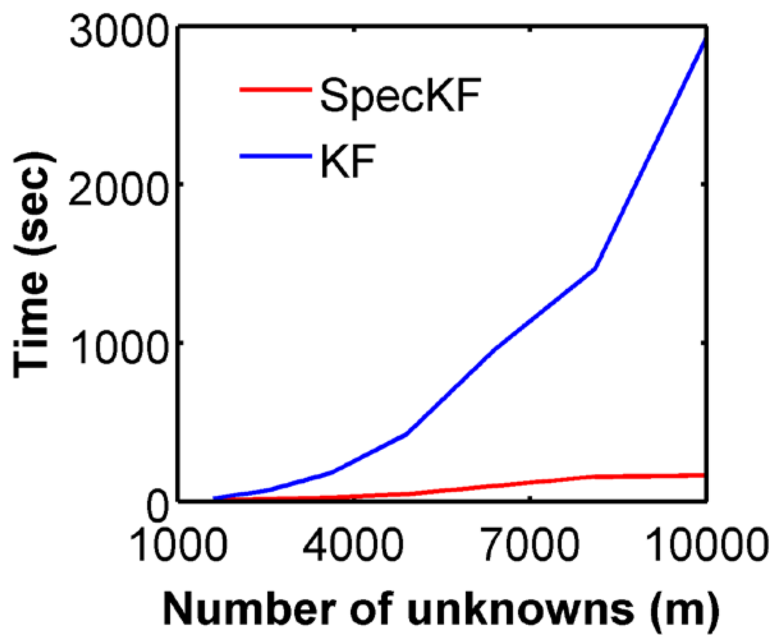
- Spectral Kalman Filter → A Kalman Filter with better convergence than EnsKF, combining:
  - Low-rank representation of covariance matrices (hierarchical)
  - Matrix-free calculation for non-linear problems (*i.e.*, no explicit calculation of Jacobian)
  - Avoid constructing and updating the full covariance matrix
  - Works best for high-frequency data
  - Can handle less smooth functions.

Dynamic monitoring – Spec KF

- Negligible difference from (full) Kalman Filter in estimation



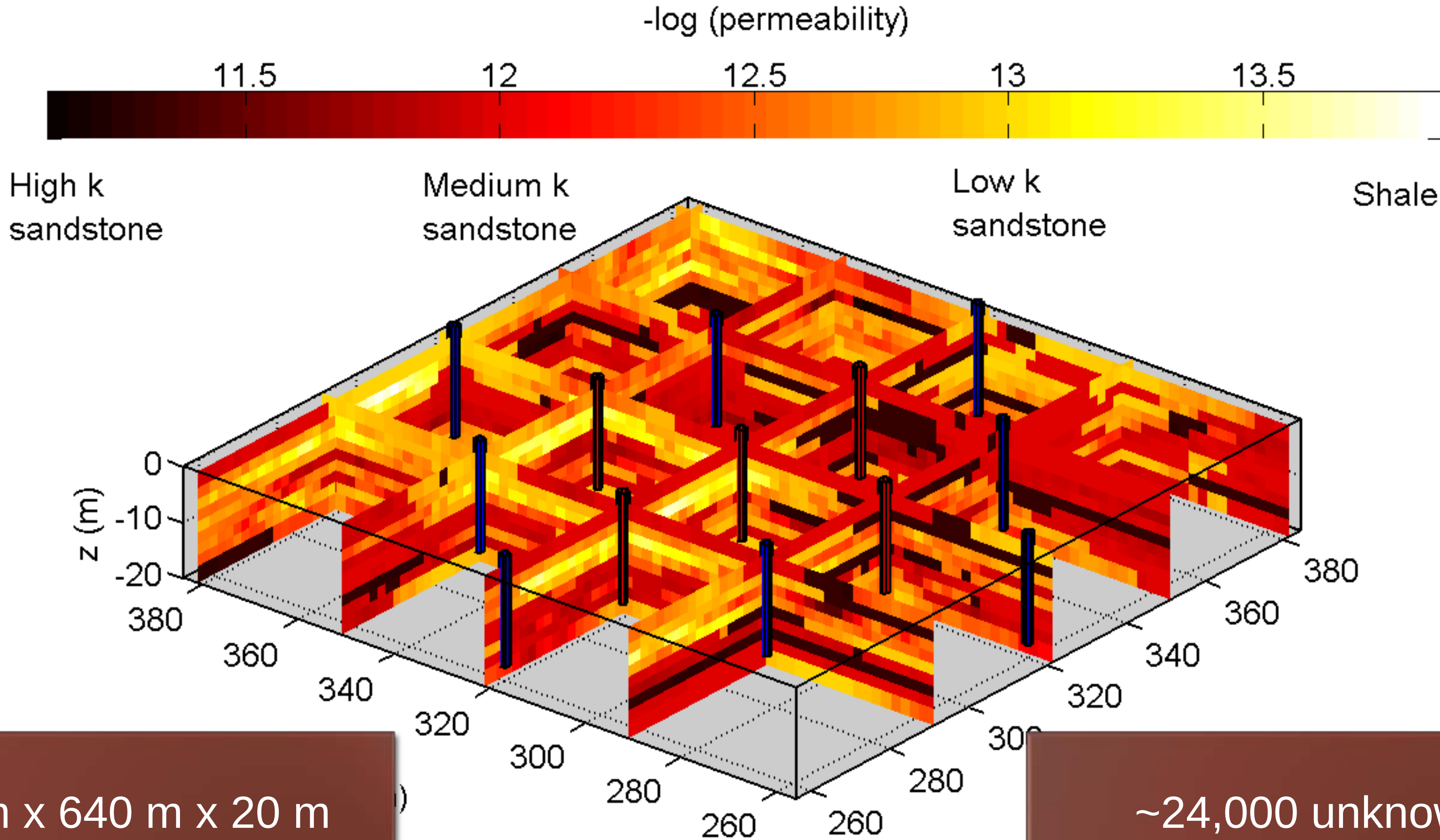
- Computation time of Spec KF increases slowly with problem size



Synthetic Cases

The mathematical methods we have developed allow us to handle realistic synthetic cases, with high heterogeneity and diverse and numerous observations.

Applications



640 m x 640 m x 20 m synthetic domain

~24,000 unknown permeabilities

Application to real sites

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

- **Fast algorithms cannot make up for the lack of information in the data; but they are necessary if we want to improve our rough prior models and operation design, as new data become available in real time.**

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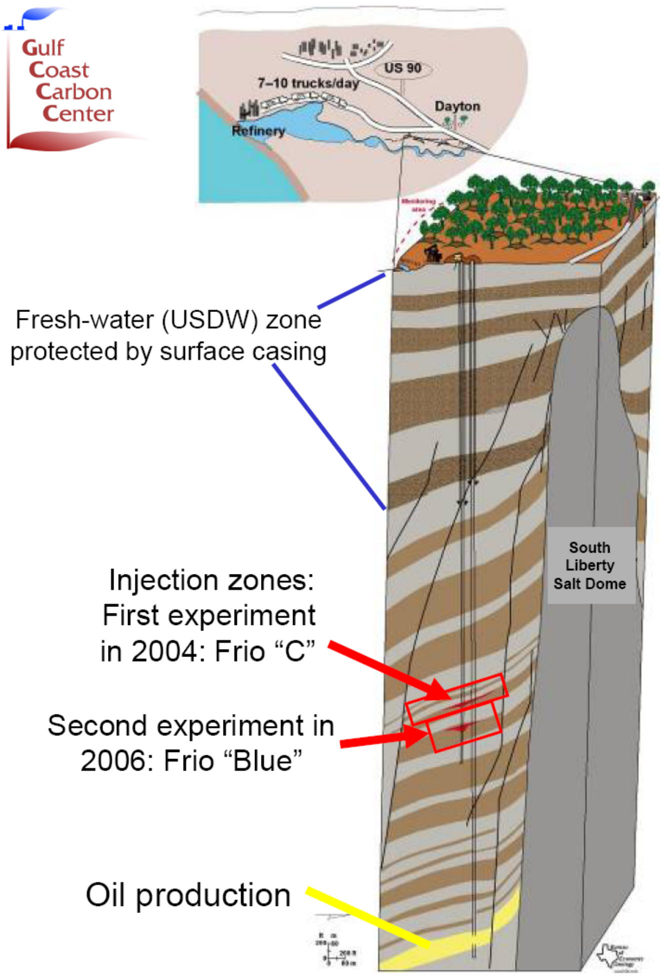
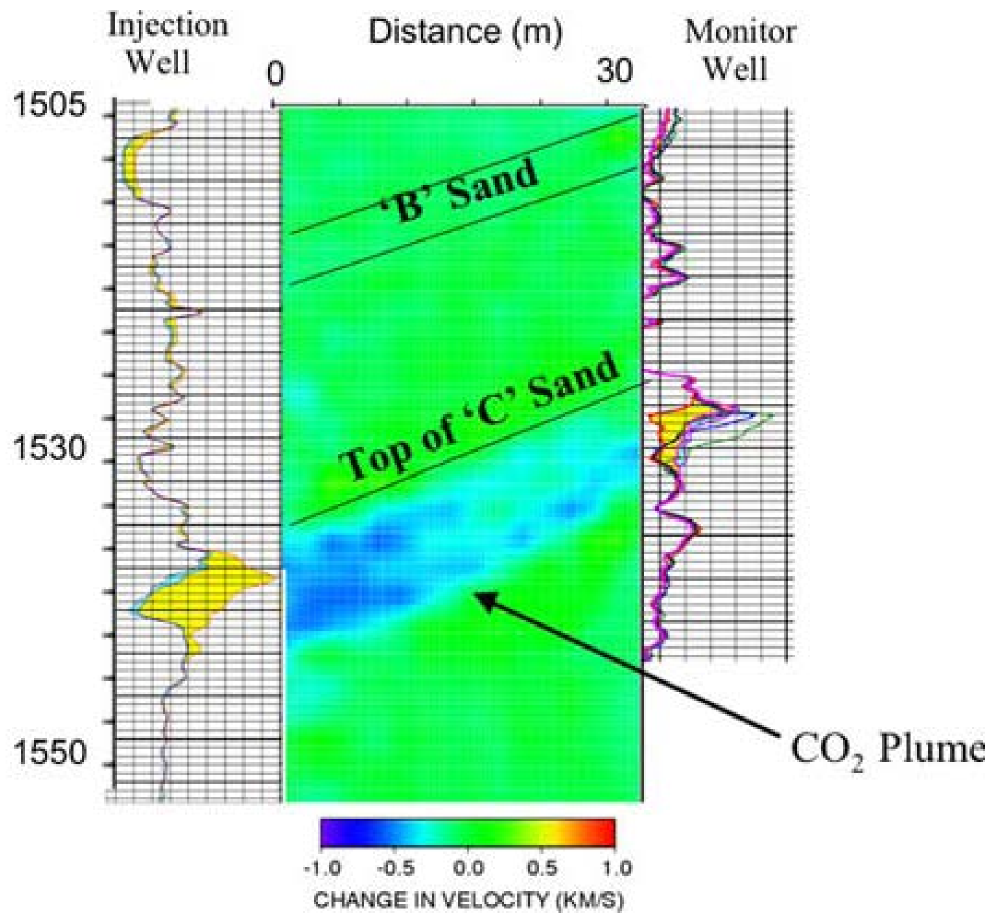
Frio – I site





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.

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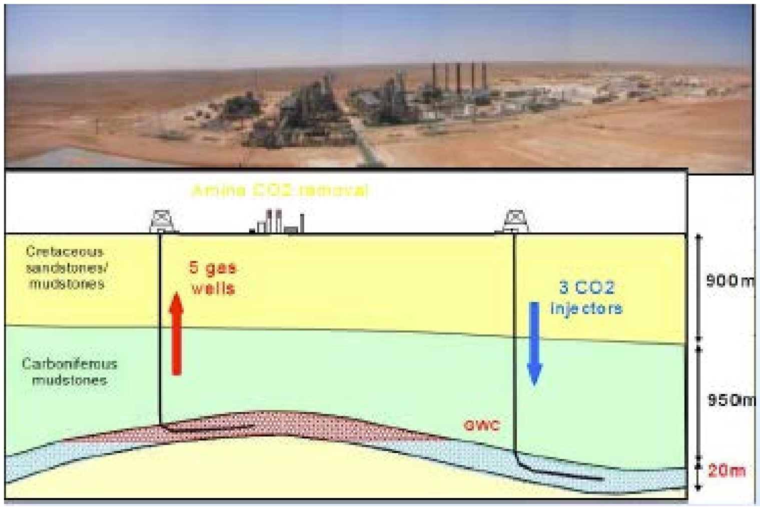
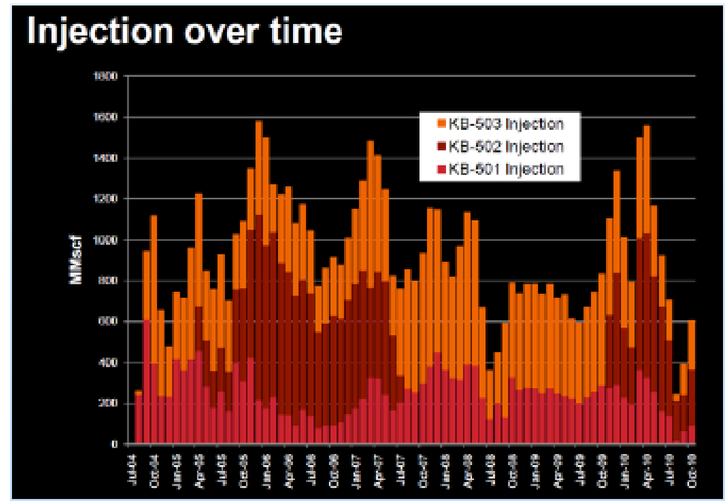
In Salah site

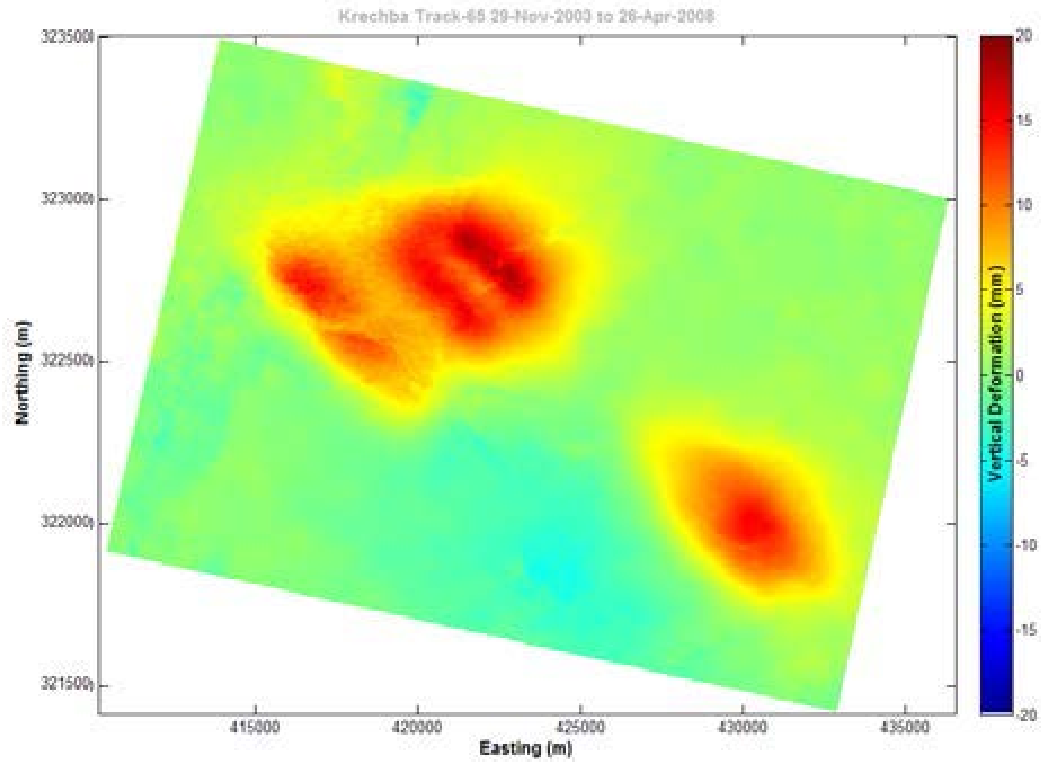




- Fewer data yet even larger scale:
  - 27 km x 43 km, 3 horizontal wells
- Even more complex physical problem
  - Fractured storage system
- Challenging the limits of forward and inverse modeling

In Salah site

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



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:
  - Computational efficiency and accuracy validated using synthetic examples.
  - Currently being tested on real-sized domains with synthetic and real data.

- 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.

Approach

- Develop inversion methods that utilize fast linear algebra tools
  - Take advantage of structure and properties of the problem
  - Compute only what is needed
  - Compute at as high accuracy as needed
- Utilize modern computational environments (parallel computing)
- Can be used as black-boxes without specialized knowledge

- By doing that, we can :
  - Process large datasets in real time with modest computer resources
  - Provide estimates and their uncertainties to inform decision making

Appendix

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

Organizational 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

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Project Team

At Stanford University:

- Sivaram Ambikasaran, PhD candidate in Computational and Mathematical Engineering (graduated in Aug 2013)
- 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

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Project Team

At Lawrence Berkeley National Laboratory:

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

Gantt Chart

DOE FY	2013				2014				2015			
Quarter	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
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												
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												F_2

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

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  - 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/.

Bibliography

Peer-reviewed publications

1. S. Ambikasaran, J. Y. Li, P. K. Kitanidis and E. F. Darve, 2013 Large-scale stochastic linear inversion using hierarchical matrices, Journal of Computational Geosciences. 17:913–927, DOI 10.1007/s10596-013-9364-0
2. Ambikasaran, S., E. F. Darve, 2013 An O(N log N) fast direct solver for hierarchical semi-separable matrices, Journal of Scientific Computing. 57:477–501, DOI 10.1007/s10915-013-9714-z
3. Li, J. Y., S. Ambikasaran, E. F. Darve, and P. K. Kitanidis, 2014 A Kalman filter powered by H^2 matrices for quasi-continuous data assimilation problems, Water Resour. Res., 50, doi:10.1002/2013WR014607
4. Liu, X., Q. Zhou, P.K. Kitanidis, J.T. Birkholzer, 2014. Fast iterative implementation of large-scale nonlinear geostatistical inverse modeling, Water Resour. Res., 50, 198–207, doi:10.1002/2012WR013241.
5. Kitanidis, P. K., and J. Lee, 2014, Principal Component Geostatistical Approach for Large-Dimensional Inverse Problems, *Water Resour. Res.*, accepted for publication.
6. Aminfar, A., S. Ambikasaran, and E. Darve, A Fast Block Low-Rank Dense Solver with Applications to Finite-Element Matrices, SIAM Journal of Scientific Computing, submitted and under review.
7. Wong, J., E. Kuhl, E. Darve, A New Sparse Matrix Vector Multiplication GPU Algorithm Designed for Finite Element Problems, International Journal for Numerical Methods in Engineering, was reviewed and is now under revision.
8. Kitanidis, P. K., Compressed State Kalman Filter for Large Systems, submitted and is under review.