Inexpensive Monitoring and Uncertainty Assessment of CO_2 Plume Migration

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Developing the Technologies and Building the Infrastructure for CO_2 Storage

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Presentation Outline

- Motivation and relevance to Program
- Project goals
- Technical status
- Accomplishments
- Summary
- Future plans

Benefit to the Program

- Program goal being addressed:
  - Develop technologies to demonstrate that 99 percent of injected CO_2 remains in the injection zones
- Project benefits statement:
  - The project will implement a novel computational approach for monitoring the location of CO_2 during injection. The approach has two notable advantages: it is very inexpensive, and it quantifies the uncertainty in the plume location. It thus addresses the primary objective of DOE Carbon Sequestration Program, *viz*. technologies to cost-effectively store and monitor CO_2 in geologic formations. One significant potential benefit will be low-cost “early warning” of unanticipated plume movement.

Project Overview (1): Goals and Objectives

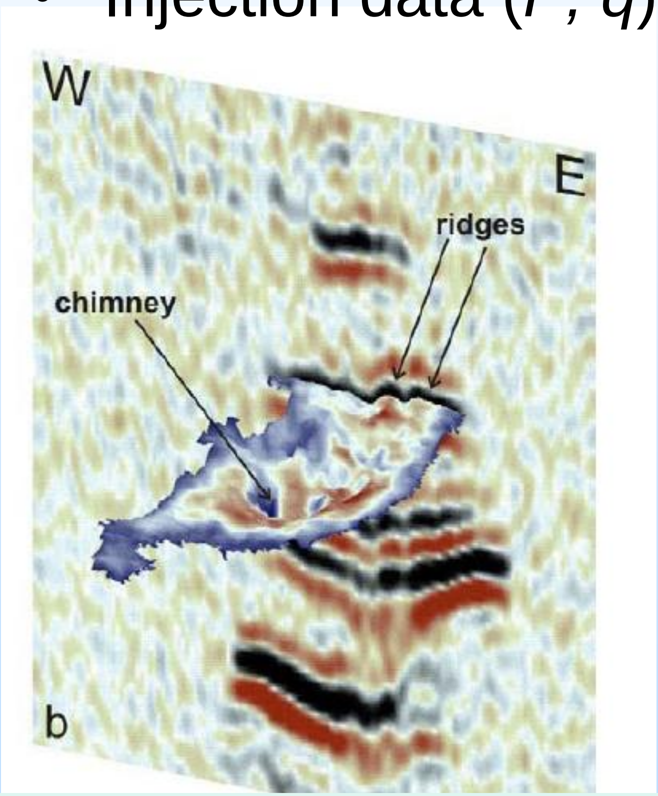
- Overall objective: software for monitoring location of CO_2 plume during injection
- Project goals
  - novel technique for probabilistic assessment of plume migration based on a Bayesian approach for geological model selection using **injection data** and, when available, other information;
  - modular software that can be readily integrated with existing flow simulators,
  - demonstrate the approach on field datasets.
- Relevance to program goal
  - Enable low-cost "early warning" plume monitoring
  - Is CO_2 remaining in planned containment area?

Project Overview (2): Goals and Objectives

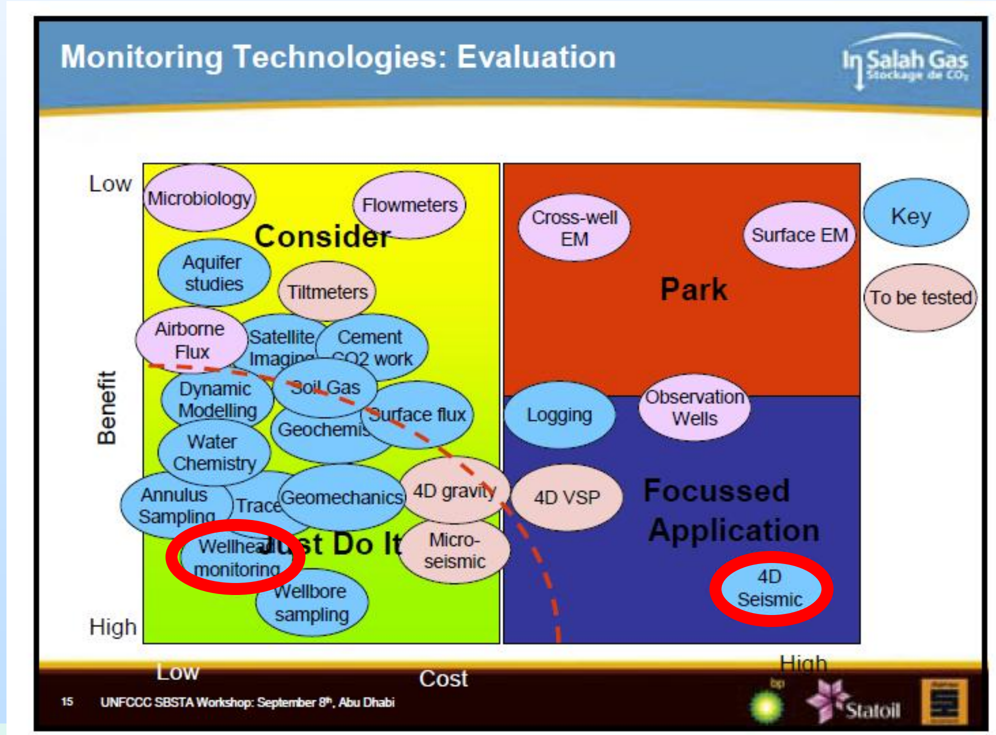
- Project goals
  - novel technique for probabilistic assessment of plume migration based on a Bayesian approach for geological model selection using **injection data** and, when available, other information;
  - modular software that can be readily integrated with existing flow simulators,
  - demonstrate the approach on field datasets.
- Success criteria
  - **Decision Point 1: Q3 Y1.** *What are the limits of applicability of the proposed approach for inferring plume location from injection data alone?*
  - **Decision Point 2: End Phase 1 (Q2 Y2).** *Can we efficiently apply the new technique developed in this research to infer plume location and its uncertainty?*
  - **Decision Point 3: End Phase 2 (Q1 Y3).** *Can we deploy the modular software such that it could be integrated with existing tools and frameworks for risk assessment?*

Technical Status: Motivation

- Monitoring plume migration critical for geologic sequestration
- Seismic surveys expensive
- Injection data (*P, q*) cheap



Chadwick et al., 4D seismic imaging of an injected CO2 plume at the Sleipner Field, central North Sea, 2004.



Wright, I. In Salah CO2 Storage Project: Monitoring Experience, 2011.

Technical status: Technology basis

- Pro-HMS history matching software
- Developed by PIs 2003-7 with NETL support
- Probabilistic approach
  - Honors geologic reality
  - Allows quantification of uncertainty – but in practice, assessment process is computationally expensive because of grid node-by-node perturbation

Technical Status: Scientific Basis

- Injection data (pressure, rate) inexpensive, available in every sequestration project
- Premise: gross geologic features that affect plume movement also affect injection data

Proof-of-concept:
simulated injection well pressure with and without high-permeability streaks

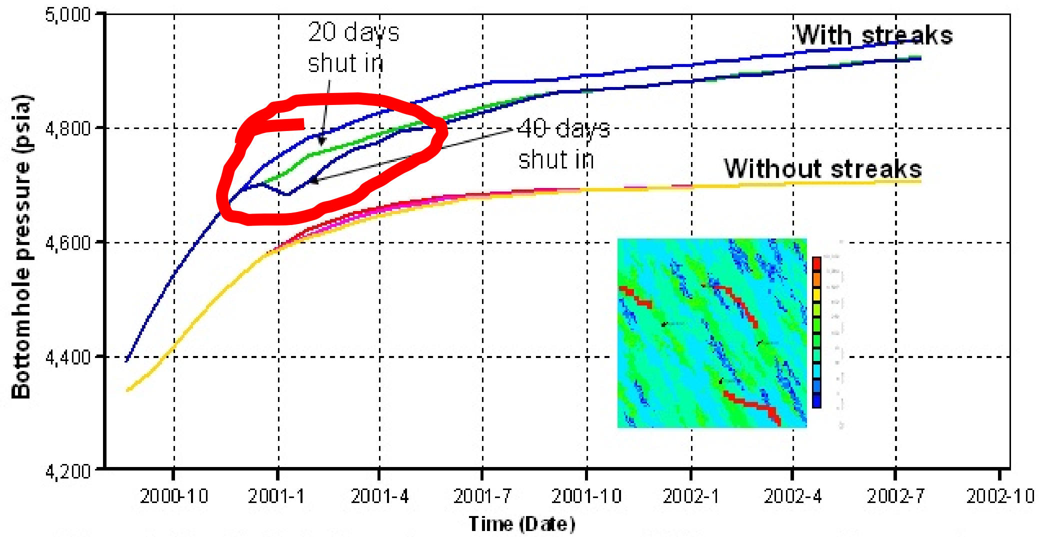


Figure 1. Simulated injection well pressures show sensitivity to presence of large-scale heterogeneities (in this case, streaks of large permeability (red regions in inset). When no streaks are present, shutting in one of the three injection wells has minimal effect on the pressure in the other injection wells. But when the streaks are present, the same shut-in produces a clear signal (Mantilla et al., 2008).

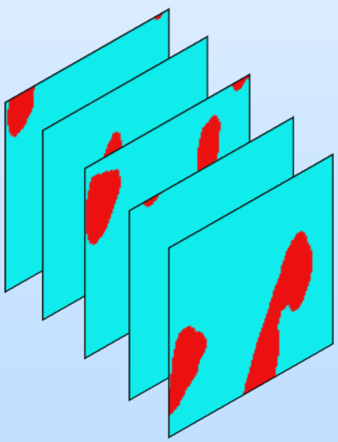
Essential Concept for This Project

Using Model Selection to Depict Uncertainty After History-Matching

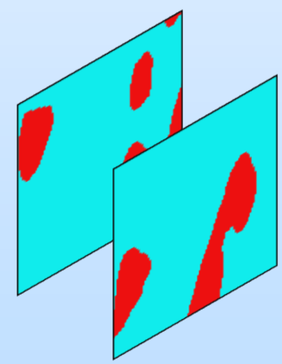
Uncertainty:
Geological properties, fluid properties, petrophysical properties

~~**Conventional history matching:**
Single model fit to available production data~~

Probabilistic history matching:
Multiple history-matched models



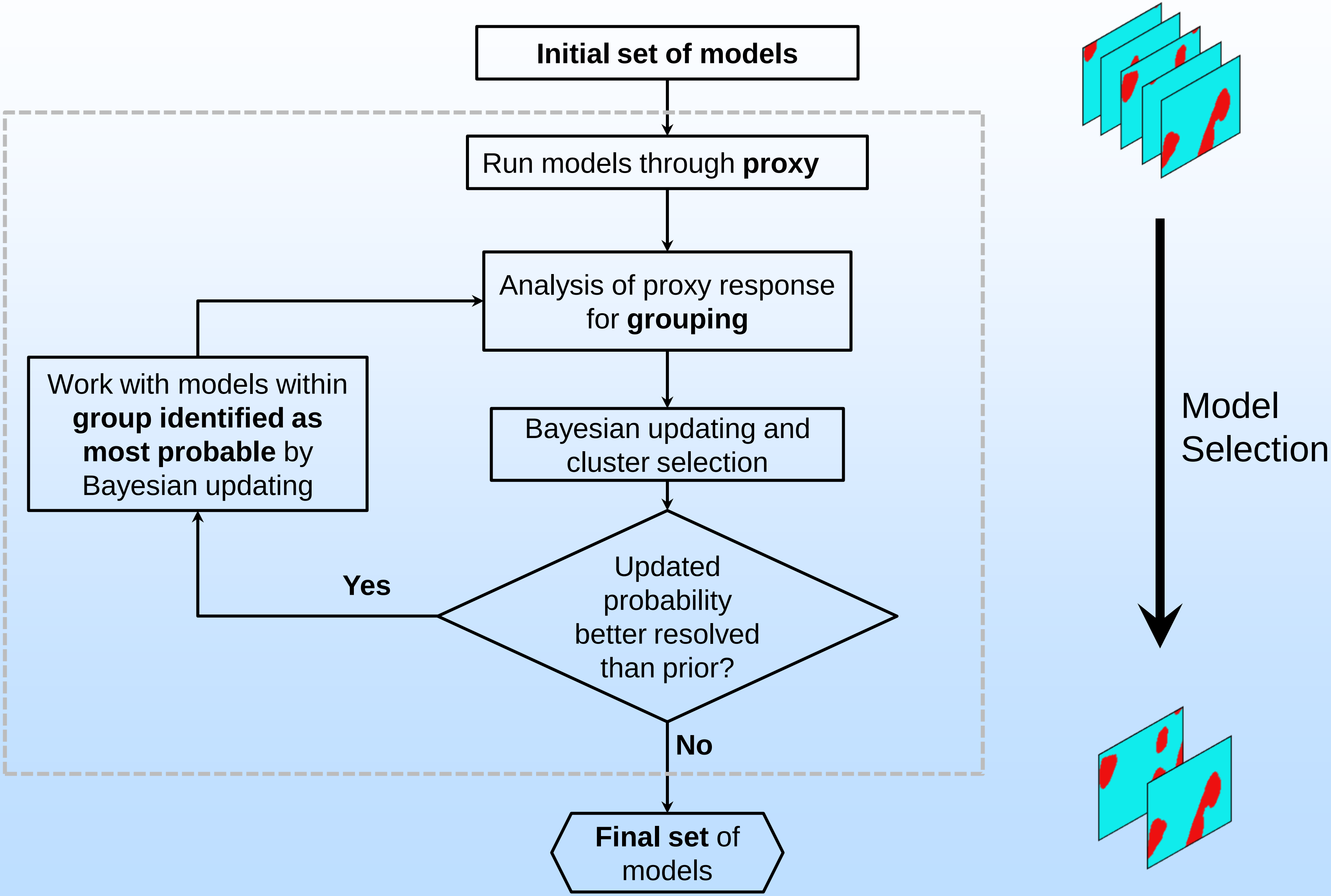
Model selection, conditioned to field data



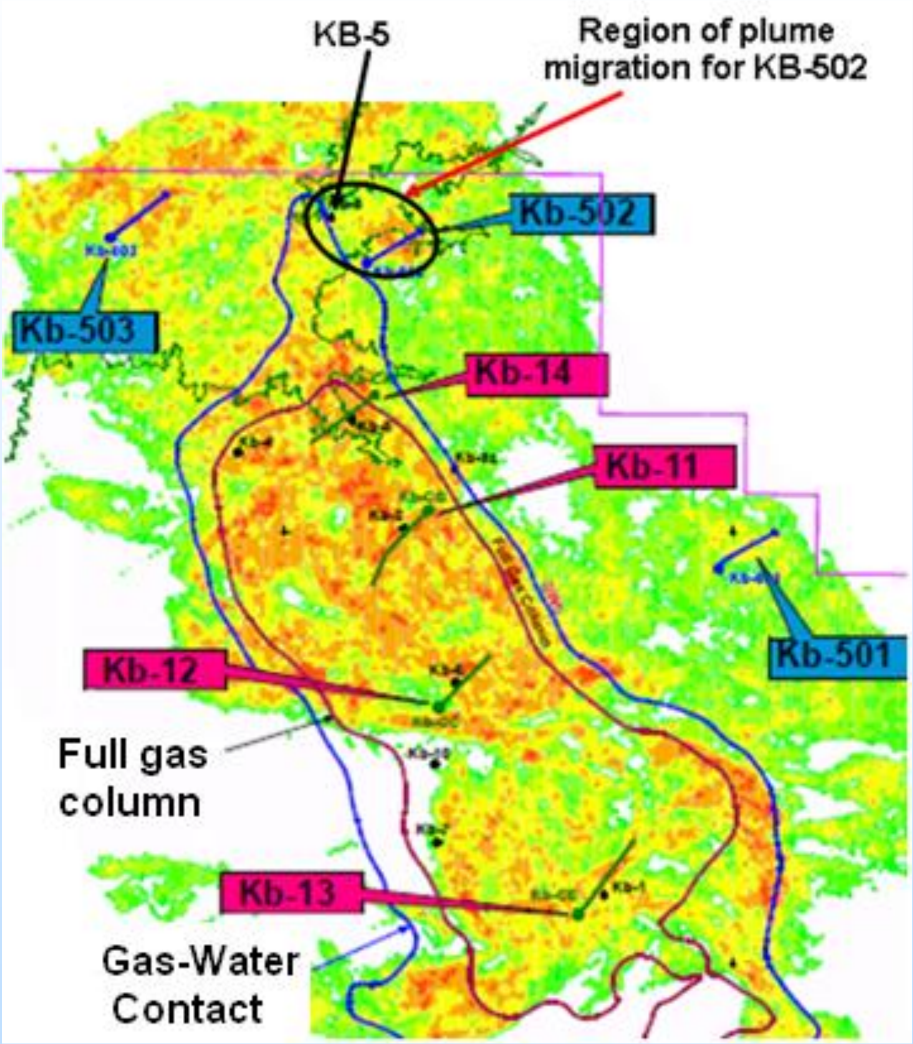
Initial models
Prior uncertainty

Final models
Posterior uncertainty

Algorithm for Model Selection



Example Application of Model Selection Preferential CO_2 Migration at Krechba



Qualitative map of porosity distribution in Krechba*

*Ian Wright, "The In Salah gas CO_2 storage project," IPTC 11326, 2008

Step 1: Initial Model Set Reflects Prior Uncertainty

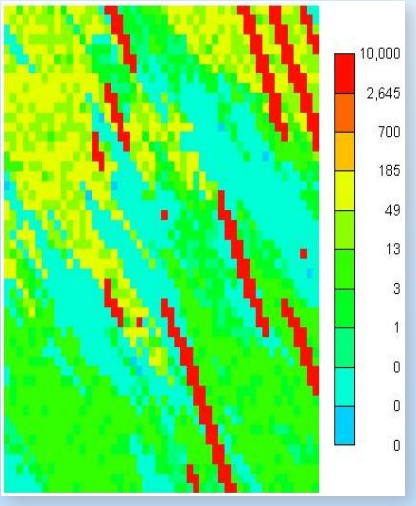
Sources of uncertainty:

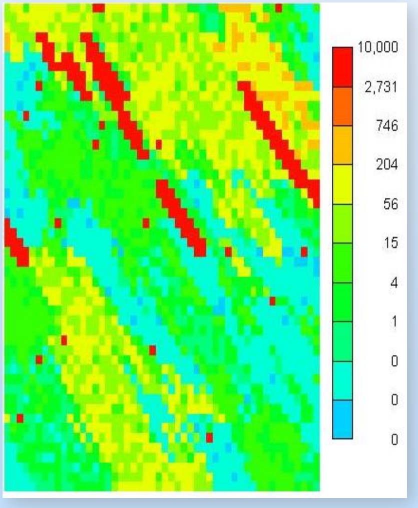
• Depositional environments

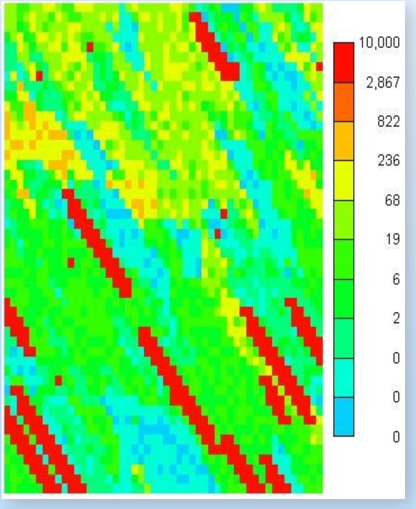
• Aquifer architecture

→ Distribution of heterogeneity features

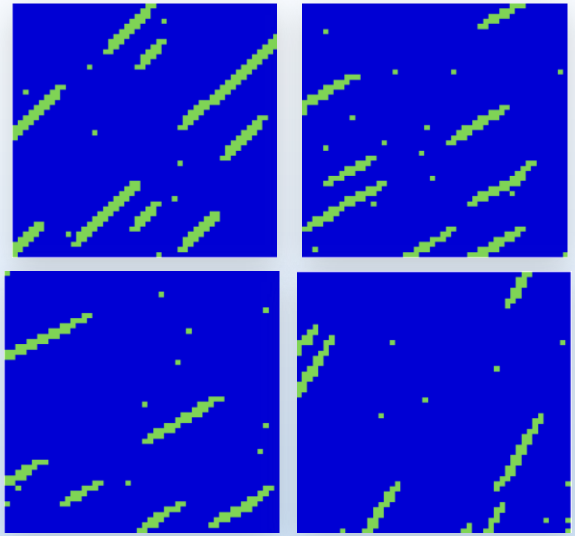
NW-SE natural fractures







Step 2: Classify models on basis of flow response



Initial set of models

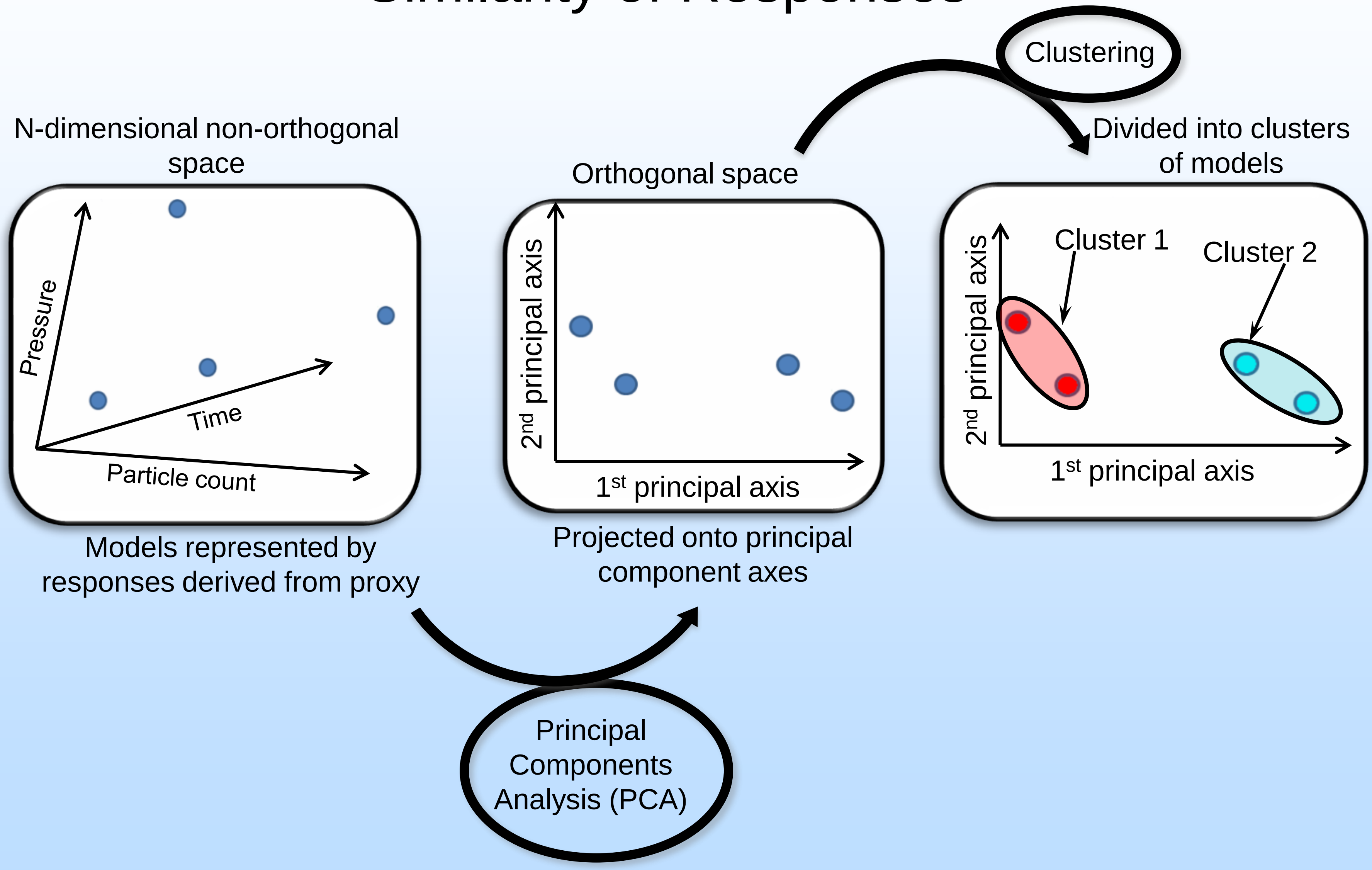
FULL-PHYSICS NUMERICAL SIMULATOR

Computationally expensive

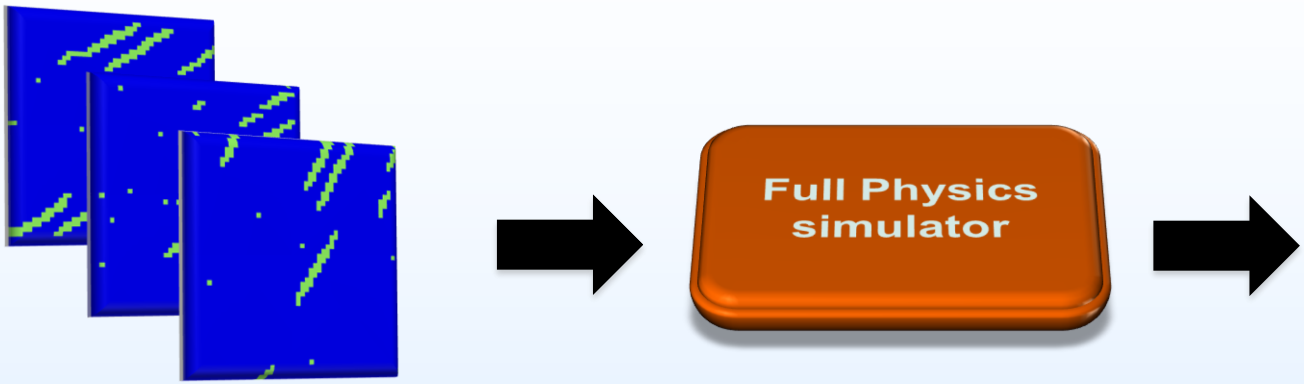
- **Alternative**: use short-run-time proxy, a program which approximates fluid movement in the aquifer

  → Particle Tracking

Step 3a: Principal Components Analysis and Clustering of Reservoir Models in Terms of Similarity of Responses



Step 3b: Bayesian Scheme for Picking a Cluster



Compare response with field observations and assign probability

Representative model for each cluster

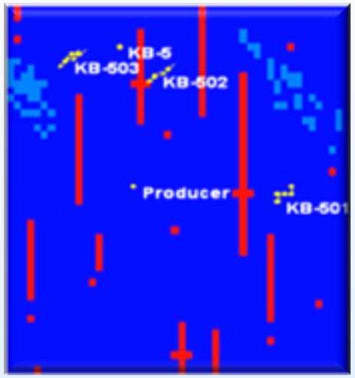
- Updated probability for each cluster:

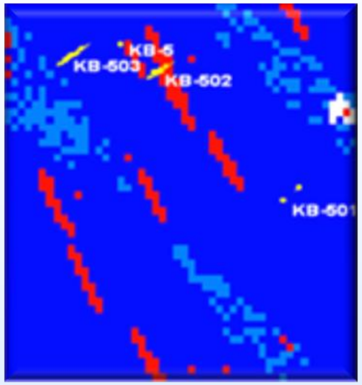
$$p\left(z^m \;\; \mathbf{u} \,\middle|\, RF_{ref}\right) = \frac{p\left(RF_{ref} \mid z^m \;\; \mathbf{u}\right)}{p\left(RF_{ref}\right)} \times p\left(z^m \;\; \mathbf{u}\right)$$

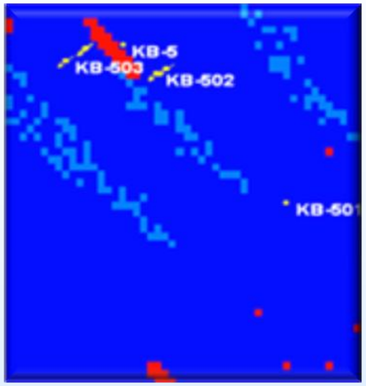
Simulated response of cluster '*m*'

Observed field response

Result: Final Set of Best-Fit Models

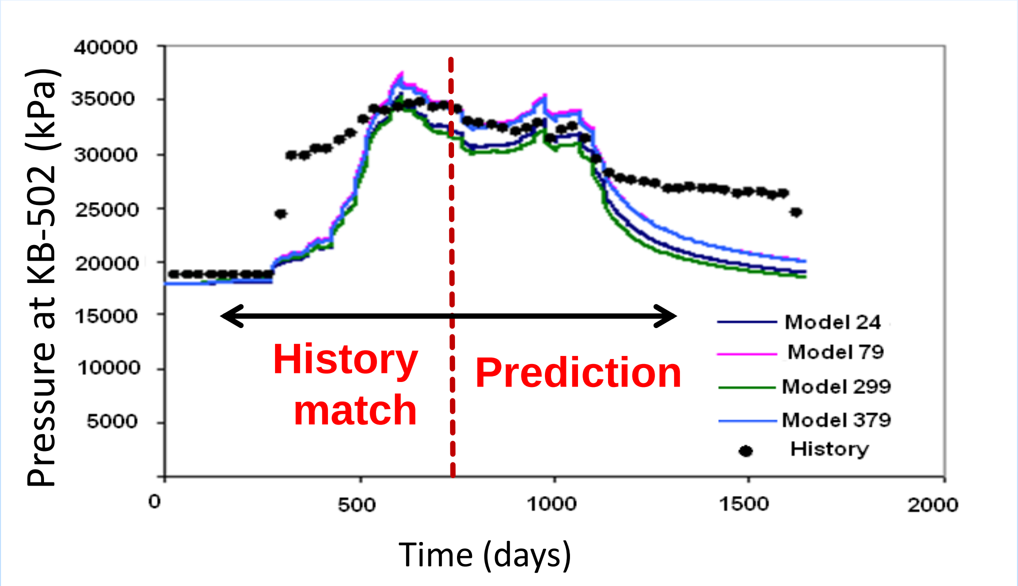




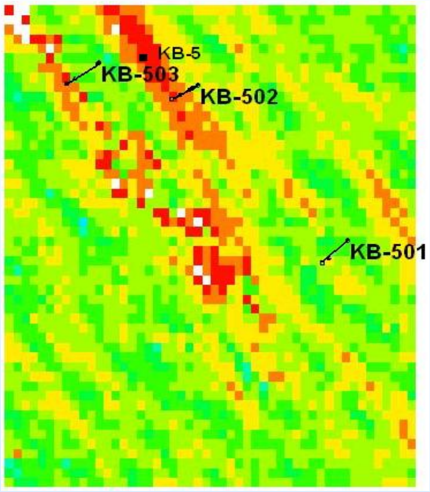


Selected models from final best-fit model set.
Note common feature: High-permeability streak from KB-502 to KB-5
Consistent with observed migration

Reasonable match to pressure history
Reasonabl e prediction of pressure

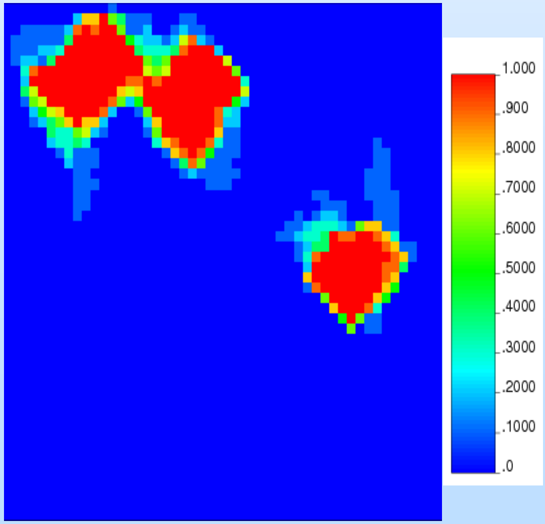


Final Set of Best-Fit Models: Further Applications



Average of all models from final cluster, showing high permeability streak highlighted over all models

Probability map created using CO_2 distribution in all models in final cluster



Research Challenges

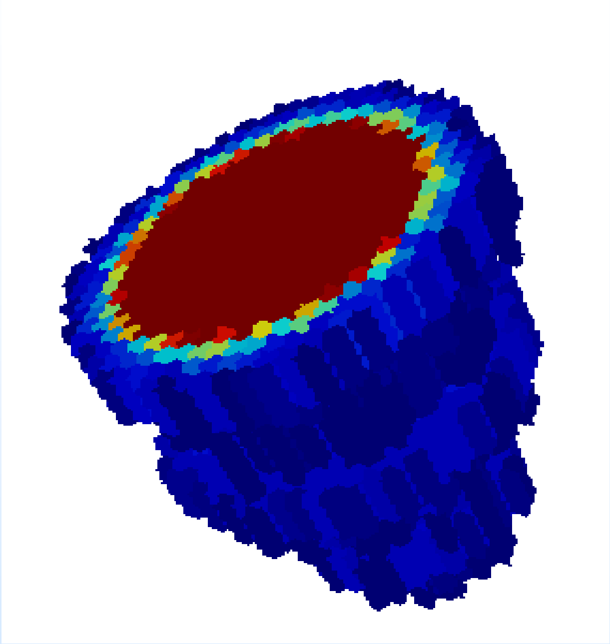
Incorporating complex physics into proxy:
need fast approximate forward model, just good enough for discriminating responses

Improved statistical scheme for model classification

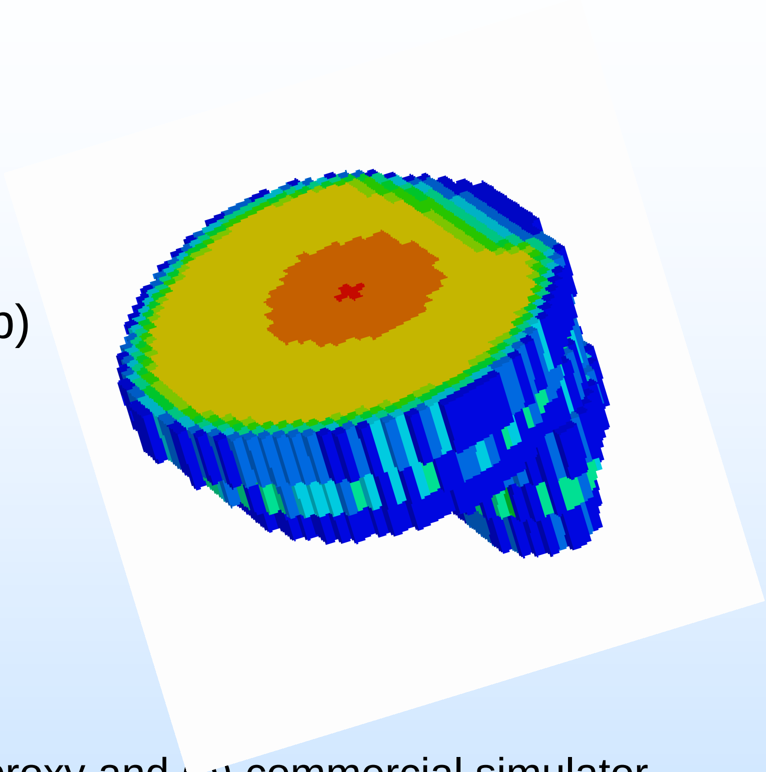
Integrated software for model selection and uncertainty quantification

Random Walker Proxy Results for Vertical Migration

(a)



(b)



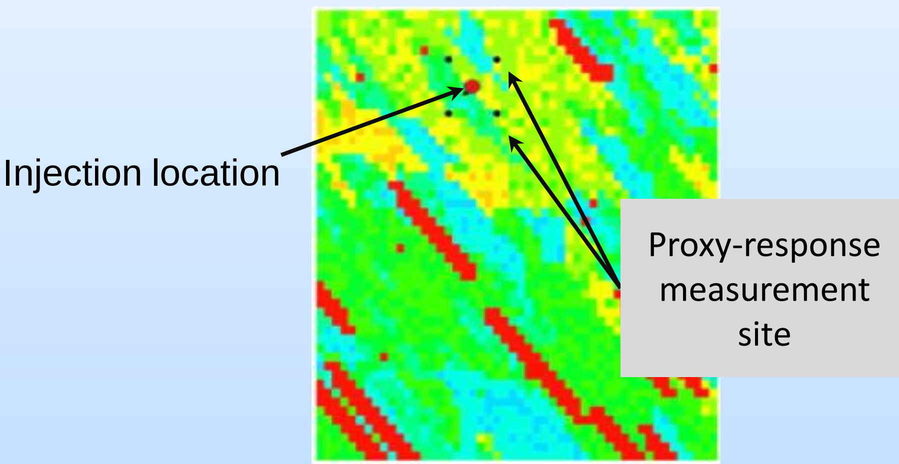
Comparison of CO_2 plume: (a) random-walk based proxy and (b) commercial simulator. Both cases run on a model with 10 layers and interbedded shales.

Limitation: **Vertical migration dominated by buoyancy not correctly captured. Needs better representation of the physics of flow.**

We need an improved proxy to capture all the physics involved in the migration and trapping process

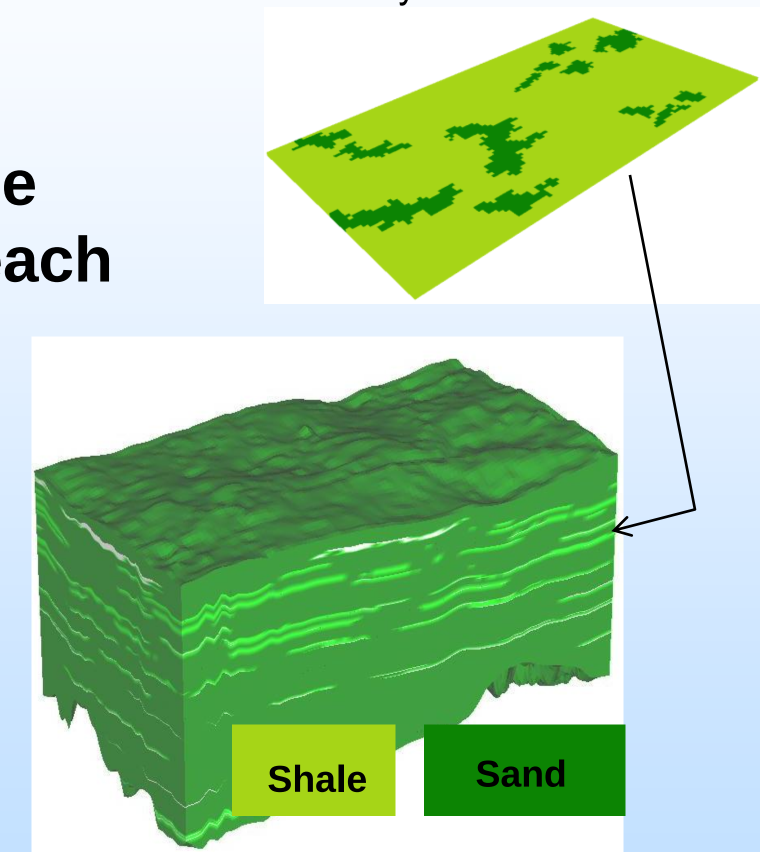
Proxy Monitoring Locations

- **Location of proxy-measurement sites critical to the process**
  - **Generic method for locating the proxy-measurement sites for each case**



Proxy measurement locations (Krechba)

Shale layers with sand ‘holes’



Where do you locate the sites in Utsira?

Research Challenges

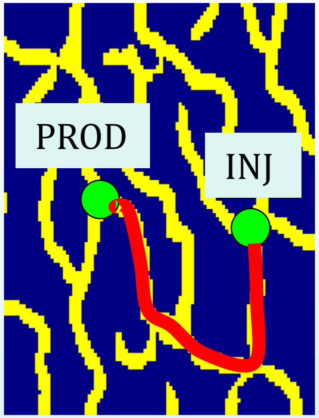
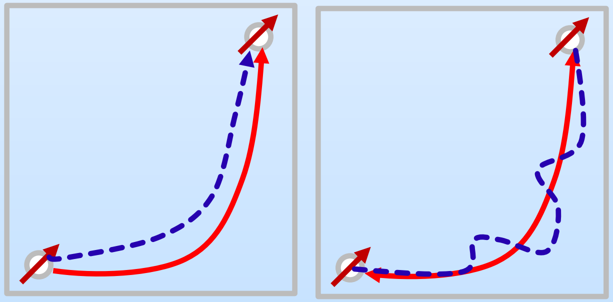
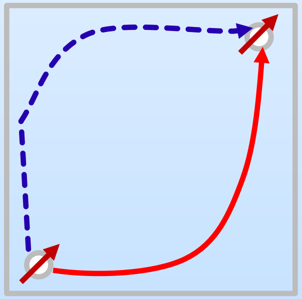
Incorporating complex physics into proxy

Improved statistical scheme for model classification

need effective way to group similar model responses

Integrated software for model selection and uncertainty quantification

Statistical approach for classifying models

Issues	Approach
How to reduce computational cost	• Injected CO_2 migrates along permeable zone. • Migration path ≈ Permeable path • Permeable path: calculated by static connectivity such as facies and permeability • To calculate permeable paths instead of migration paths without simulation 
How to quantify uncertainty	• Minor variations in paths vs Major variation   • Infer migration path from permeable path ➔ Measure similarity of permeable paths ➔ Quantify uncertainty by clustering the paths

Algorithm based on geologic objects

1. Decide points of interest

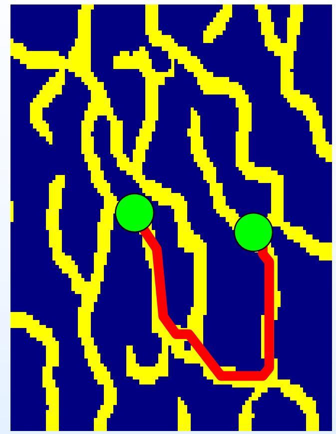
2.Compute the connected paths

3. Simplify the connected paths

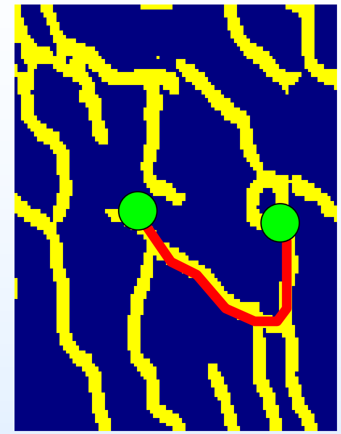
4. Calculate the discrete Frechet distance

5. Calculate the combined distance

6. Cluster analysis



Path A1 of model #1



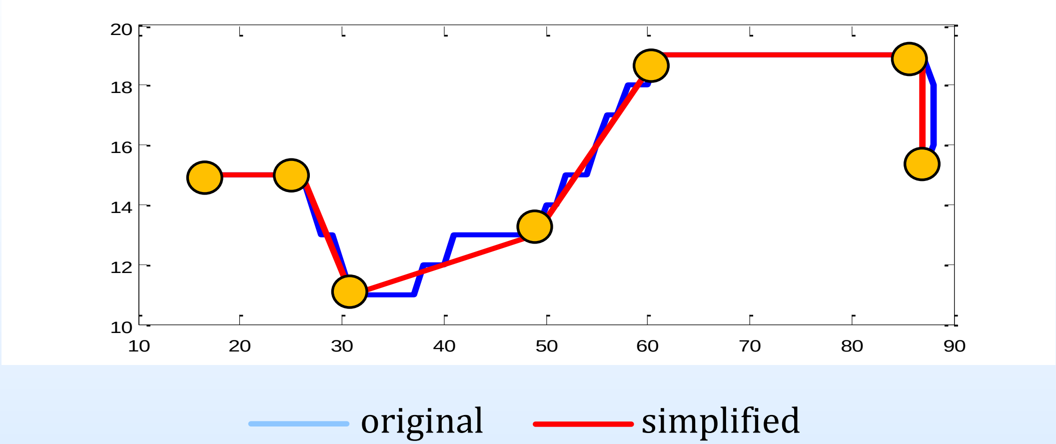
Path A2 of model #2

permeable facies
impermeable facies
shortest path
Inj / Prod

- Compute the shortest path along the connected permeable facies

Algorithm based on geologic objects

1. Decide points of interest
2. Compute the connected paths
3. Simplify the connected paths
4. Calculate the discrete Frechet distance
5. Calculate the combined distance
6. Cluster analysis



•To reduce the number of points of a path
ex) 77 points ➔ 7 points
•To reduce the computation time of calculating the discrete Frechet distance

Algorithm based on geologic objects

1. Decide points of interest
2. Compute the connected paths
3. Simplify the connected paths
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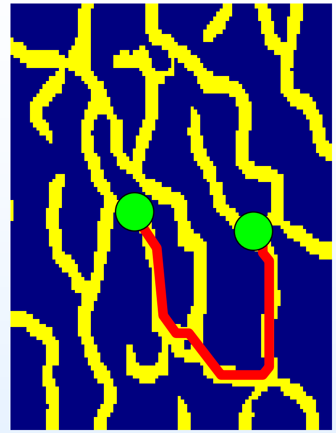
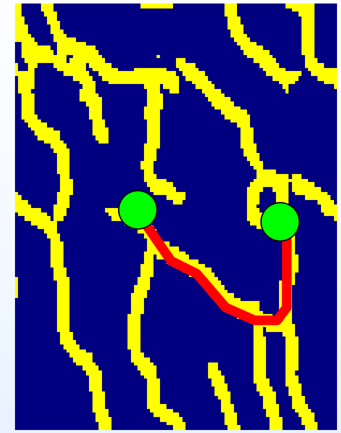
5. Calculate the combined distance
6. Cluster analysis



Path A1 of model #1



Path A2 of model #2

Discrete Frechet Distance (points of path A1, points of path A2)

Dissimilarity between path A1 and path A2

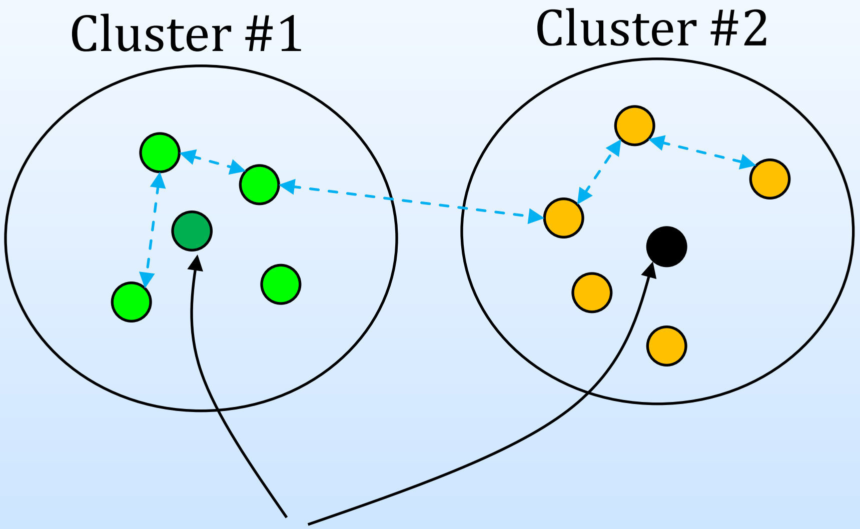
How different is A1 from A2? / How dissimilar is A1 to A2?

- Similar Path1 & Path2 ➔ low
  Dissimilar Path1 & Path2 ➔ high
- Calculate for all corresponding paths

Algorithm based on geologic objects

1. Decide points of interest
2. Compute the connected paths
3. Simplify the connected paths
4. Calculate the discrete Frechet distance
5. Calculate the combined distance
6. Cluster analysis

- K-medoids clustering
  ➔ All of the distances between all of the models
  ➔ Cluster by the distances



Medoid: representative model
the closest to the members of its cluster

Research Challenges

Incorporating complex physics into proxy

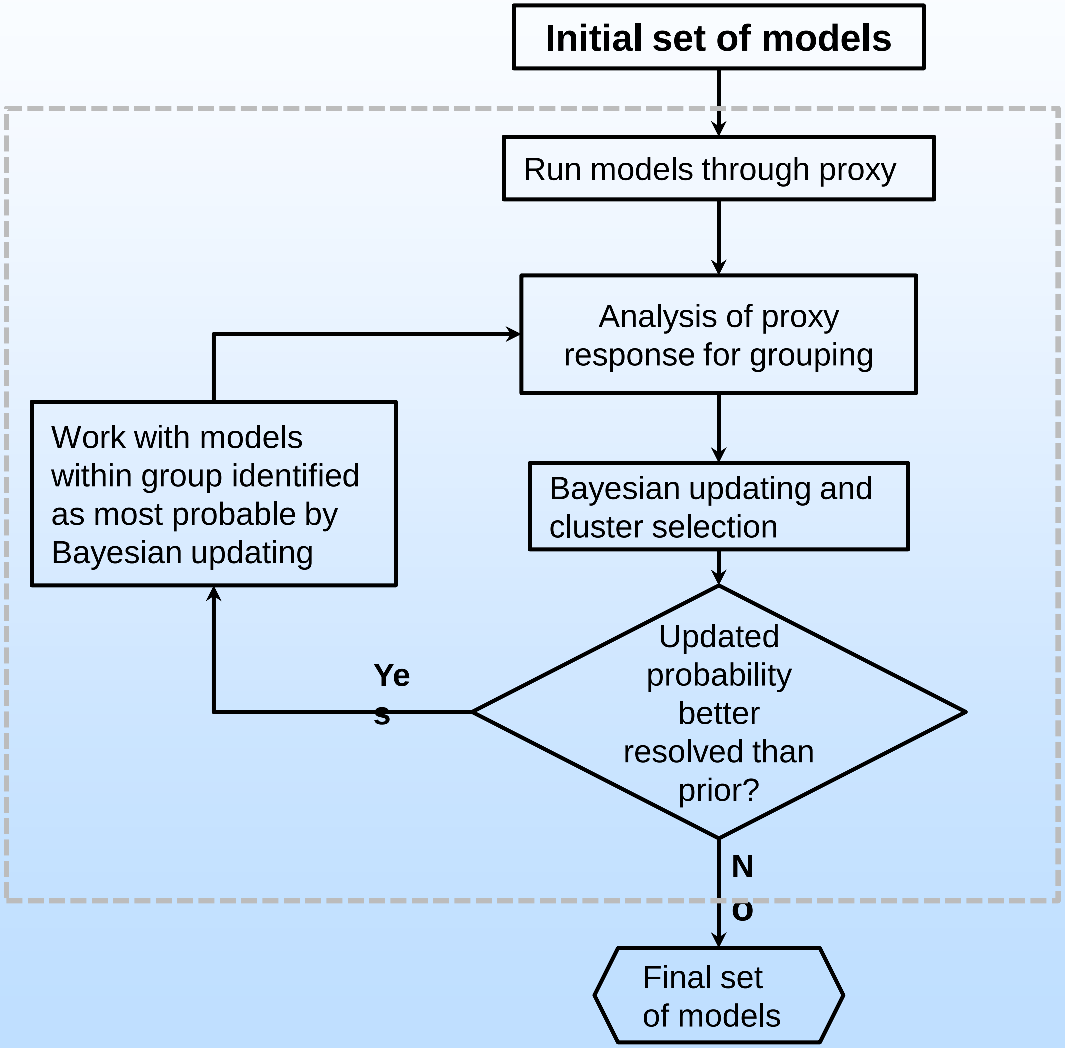
Improved statistical scheme for model classification

Integrated software for model selection and uncertainty quantification

put tools together for sequestration project management workflow

Integrated software for model selection/probabilistic plume monitoring

- Important decisions:
  - develop own modules for PCA, MDS, Medoid Clustering?
  - What language – Python, C++
  - Data structures for geological model input, flow simulation input/output



Accomplishments to Date

- Sensitivity analysis of impact of subsurface heterogeneity on injection response
- Fast model responses
  - Proxy to account for permeability heterogeneity, fluid compressibility, buoyancy effect
  - Proxy monitoring scheme accounting for multiphysics/multiscale CO_2 transport
- Effective model classification
  - using PCA, Kernel PCA, Multi-dimensional scaling methods
  - Statistical classification using Frechet distance between shortest connected path between wells
- Resampling schemes for posterior uncertainty modeling
- Modular software development

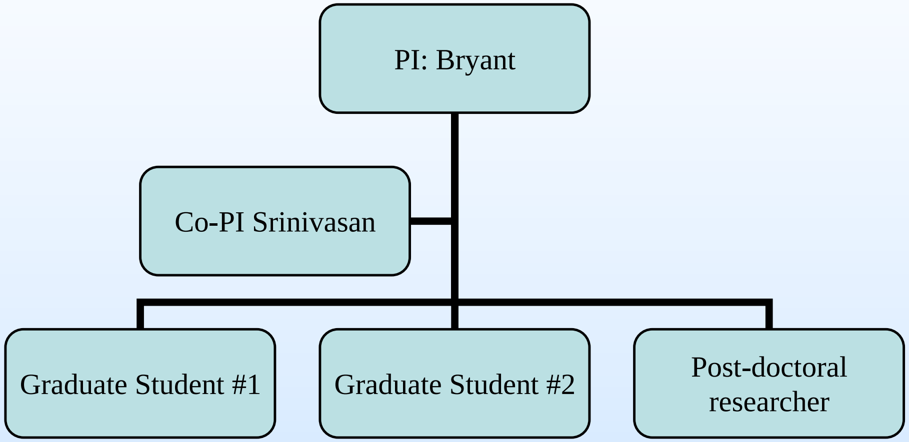
Summary and Future Plans

- Injection data carry useful information
  - Sensitive to large geologic heterogeneities
  - Can be used to predict future plume migration
- Combination of efficient proxy, rigorous model classification scheme enables quantitative uncertainty assessment
  - Useful for monitoring process
  - Valuable in managing process
- Development of a modular software underway
  - will render algorithms, workflows accessible to field operators and planners

Appendix

Organization Chart

- Team:
  - PI Steven Bryant
  - Co-PI Sanjay Srinivasan
  - Researchers
    - Sayantan Bhomik
    - Hoonyeong Jeong
    - Haiyan Zhou
- Organization
  - Center for Petroleum and Geosystems Engineering
  - Cockrell School of Engineering
  - The University of Texas at Austin



Gantt Chart

Phase	Task	Milestone	YEAR 1				YEAR 2				YEAR 3				Interdependencies
			1	2	3	4	1	2	3	4	1	2	3	4	
	1														Project management
1	2	1.A			X										Verify feasibility for Phase 2
	3.1														Pre-requisite for software development in Phase 2
	3.2	1.B				X									
	4.1														Provides geologic consistency to interpretation of injection data
	4.2														
2	5	2.A								X					Combines Tasks 2-4 into software platform
	6	2.B									X				Validates Task 5
	7														Uses Phases 1, 2 to quantify uncertainty
3	8.1														Uses Phase 2 to apply concept to field data
	8.2	3.A										X			Applies Phase 2 to In Salah
	8.3	3.B												X	Applies Phase 2 to RCSPs
			Phase 1						Phase 2			Phase 3			

Milestone Number	Milestone Title	Planned Completion Date	Actual Completion Date	Variance Comment
1.A	Set of model storage formations	End Q4 YR 1		
1.B	Estimate maximum pore volume	End Q2 YR 2		
1.C	Method for observing accumulation	End Q3 YR 1		
2.A	Validation of concept	End Q2 YR3		
2.B	Preliminary assessment of filling of local capillary traps	End Q4 Y3		
2.C	Trend of the fraction	End Q1 Y3		
2.D	Preliminary assessment of trend of the fraction of CO2	End Q2 Y3		
2.E	Preliminary version	End Q3 Y3		

Bibliography

- Journal, multiple authors:
  - Srinivasan, S., and Jeong, H., 2012, Modeling the Uncertainty in CO_2 Plume Migration During Sequestration Using a Model Selection Approach. Accepted for publication in Mathematical Geosciences.
- Publication:
  - Jeong, H., Srinivasan, S. and Bryant, S.L., 2012, Uncertainty Quantification of CO_2 Plume Migration Using Static Connectivity, proceedings of International Conference on Greenhouse Gas Technologies (GHGT), Kyoto, Japan.
  - Bhowmick, S., Srinivasan, S. and Bryant, S.L., 2012, DON'T KNOW THE TITLE EXACTLY, proceedings of International Conference on Greenhouse Gas Technologies (GHGT), Kyoto, Japan.