Deep-learning surrogate models for history matching with in-situ and surface displacement data

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November 19, 2024

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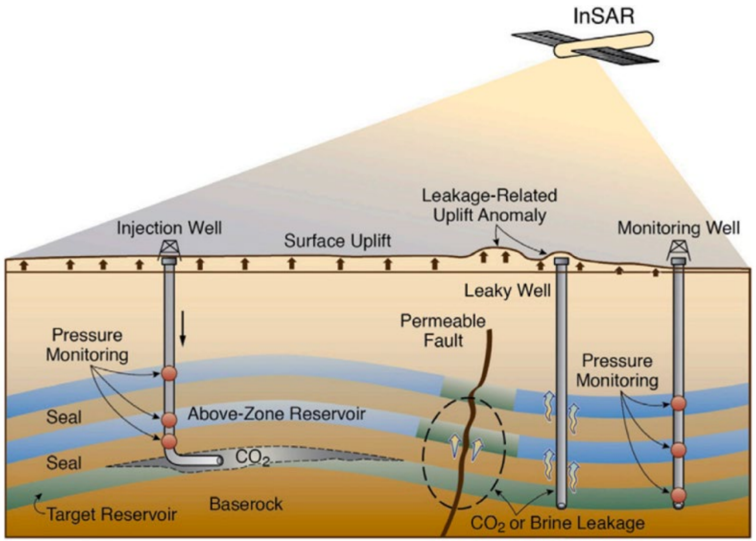
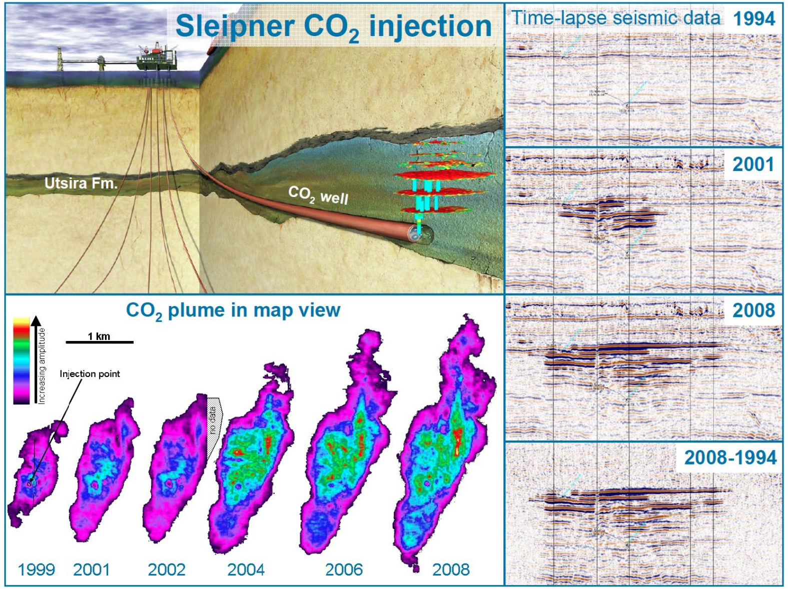
Monitoring Plan and Data Types

- InSAR satellite for surface displacement
- In-situ pressure & saturation in wells



(Peng et al., 2024; Jung et al., 2013)

- Seismic interpreted saturation plumes



Courtesy: Philip Ringrose, Equinor

Motivation for Surrogate Modeling for History Matching

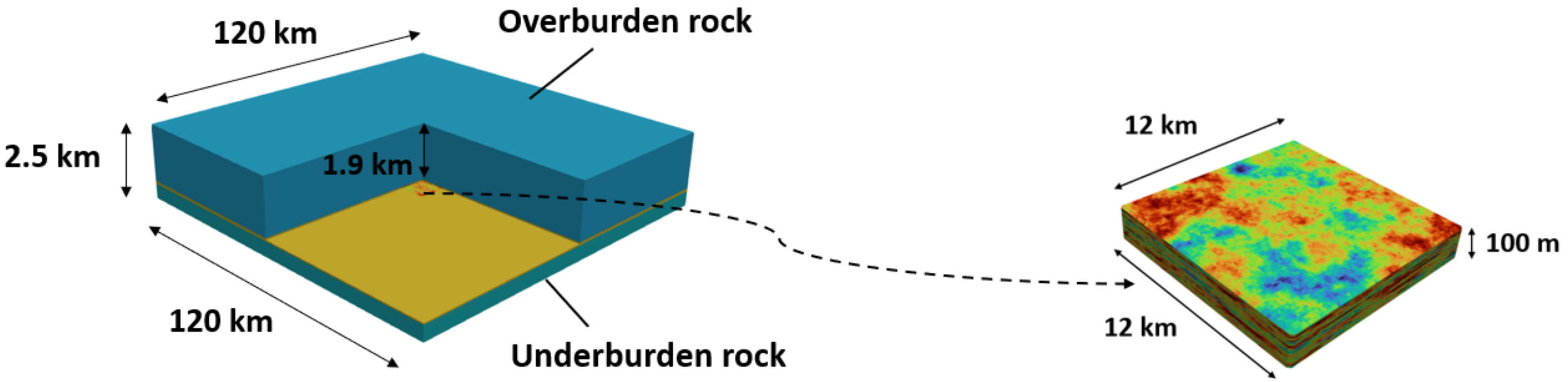
- Goal is to develop an effective surrogate model to replace the (online) simulation runs required during history matching

- This will enable the use of more formal and comprehensive history matching workflows than would otherwise be achievable

- Surrogate model is data-driven – training is based on flow simulation results from $O(10^3)$ runs

- Once trained, we can use surrogate model to assess impact of different data types and amount of data, effect of data precision and model error, …

CO_2 Storage with Geomechanics



Overall domain $\mathbf{m}_f$ contains

100×100×30 cells (300,000 cells)

Dimensions: **120 km × 120 km × 2.5 km**

Storage aquifer $\mathbf{m}_s$ contains

80×80×20 cells (128,000 cells)

Dimensions: **12 km × 12 km × 100 m**

Coupled Flow and Quasistatic Geomechanics

Flow

$$\nabla \cdot \left(\sum_j \rho_j x_j^r \mathbf{v}_j \right) + (q^{\mathrm{w}})^r = \frac{\partial}{\partial t} \left(\sum_j \phi \rho_j S_j x_j^r \right)$$

Geomechanics

$$\nabla \cdot \boldsymbol{\sigma} + \rho_m g \nabla z = 0$$

- Simulations performed using **GEOS**
- Coupled flow-geomechanics simulation required to compute surface displacement
- Coupled simulations are much more expensive (**15x**) than flow-only runs; pressure and saturation fields are well approximated using:

$$c = \frac{1-2\nu}{\phi E} \cdot \left(b^2 \frac{1+\nu}{1-\nu} + 3(b-\phi)(1-b) \right)$$

c – effective rock compressibility

E – Young's modulus

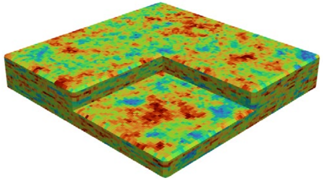
b – Biot coefficient

ν – Poisson's ratio

Deep-learning-based Surrogate Model

- Reservoir simulator (specified well locations/settings)

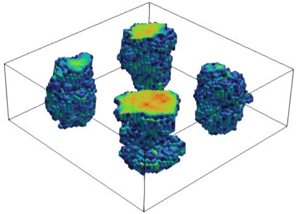
geomodel $\mathbf{m}$



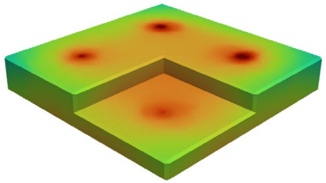
permeability, porosity

$f(\mathbf{m})$

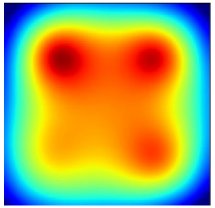
dynamic states $\mathbf{x}$



saturation



pressure



surface displ.

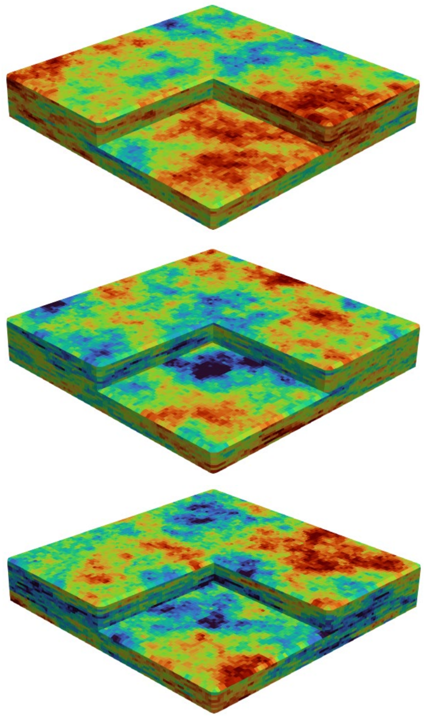
- Surrogate to evaluate new geomodel: $\hat{\mathbf{x}} = \hat{f}(\mathbf{m};\boldsymbol{\theta}) \approx f(\mathbf{m})$

  $\boldsymbol{\theta}$: deep neural network parameters

CO_2 Storage Problem Setup

- 4 vertical injectors, each injects 1 Mt/year
- 30 years continuous injection
- Uncertain geological metaparameters (mean and std. dev. of log-permeability, anisotropy ratio, Young’s moduli, etc.)
- Surrogate models: **recurrent residual U-Net** for pressure & saturation; **residual U-Net** for surface displacement
- Training set: 4000 flow-only runs, 400 coupled runs
- Training time (A100 GPU): 16 hr each for p & S, 3 hr for surface displacement

Storage aquifer realizations

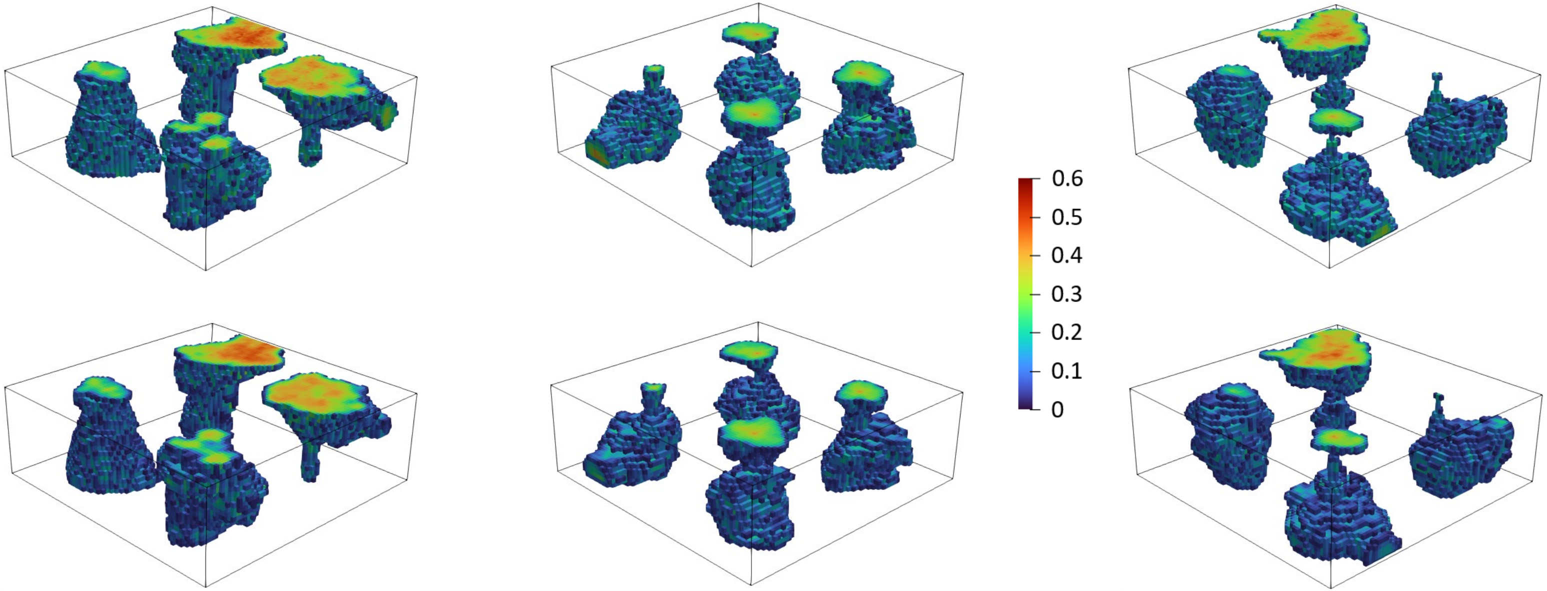


CO_2 Saturation Predictions at 30 Years (new test cases)

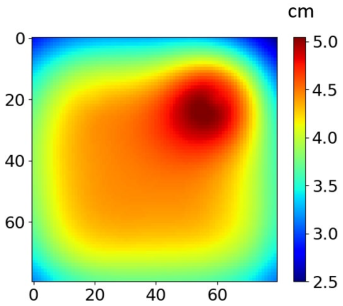
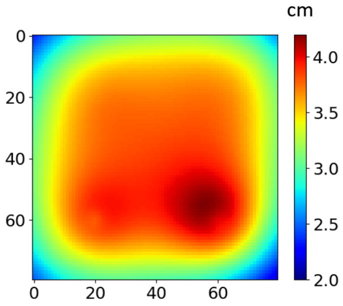
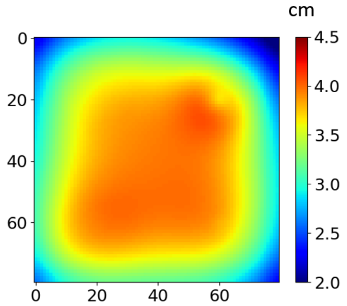
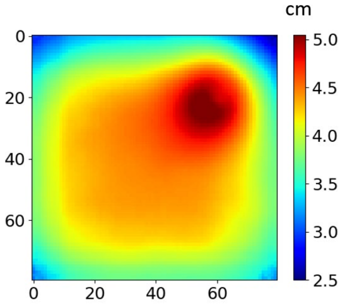
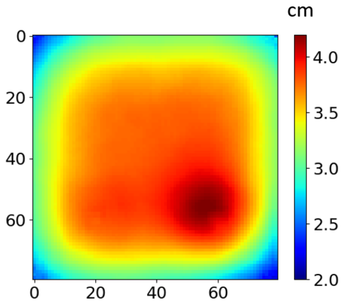
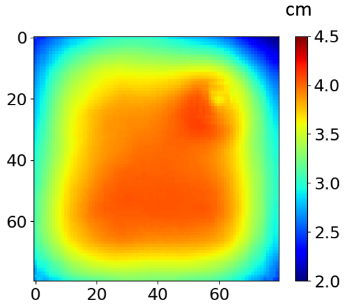
	Realization 1	Realization 2	Realization 3
	$\sigma_{\log k}$ = 1.9, k_v/k_h= 0.04	$\sigma_{\log k}$ = 2.1, k_v/k_h= 0.02	$\sigma_{\log k}$ = 2.4, k_v/k_h= 0.03

Simulation

Surrogate

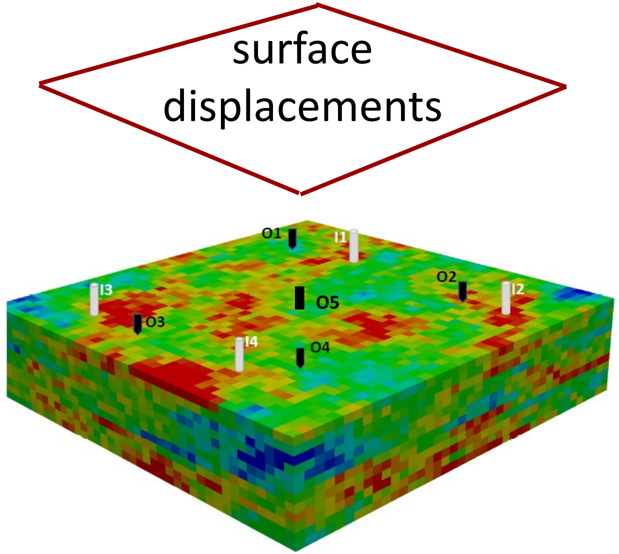


Surface Displacement Predictions at 30 Years

	Realization 1	Realization 2	Realization 3
	E_s = 9.2 GPa, E_o = 25.5 GPa	E_s = 11.6 GPa, E_o = 37.7 GPa	E_s = 18.7 GPa, E_o = 31.3 GPa
Simulation			
Surrogate			

History Matching Problem Setup

- CO_2 saturation and pressure (measured in observation wells) and surface displacement (at **81** observation locations) at 1, 2, 4, 6 & 9 years
- Total of 905 measurements (incl. 405 surf. displ.)
- **Hierarchical Markov Chain Monte Carlo** (MCMC) requires ~95,000 function evaluations
- 1 coupled run of GEOS – 120 min on 32 cores;
  1 surrogate run ~0.15 sec on 1 GPU (~4 hours total)
  (MCMC would take ~**21 years** with GEOS runs)

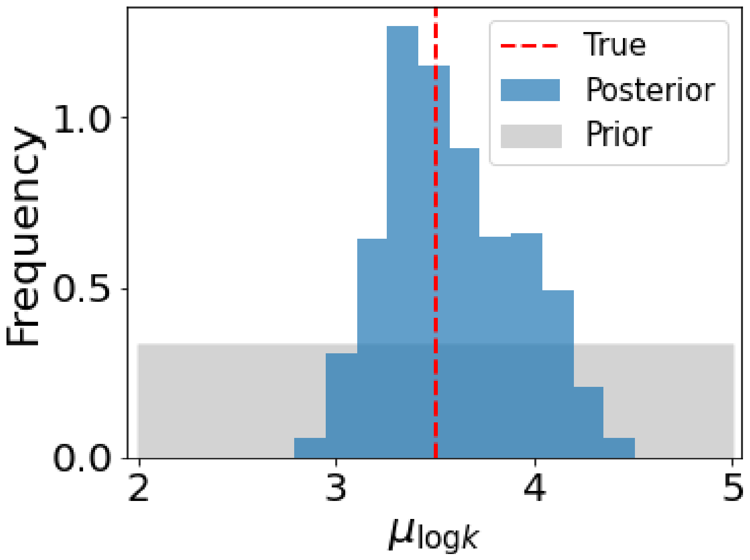


synthetic true model

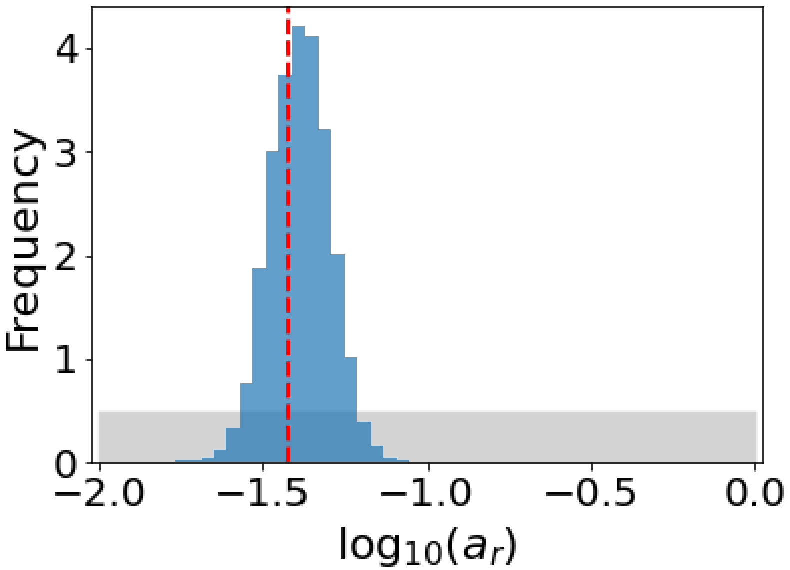
Observations in aquifer (p, S) in **O1 – O5** and at the surface (d_g)

History Matching Results for Metaparameters
(using both in-situ and surface data)

mean log permeability

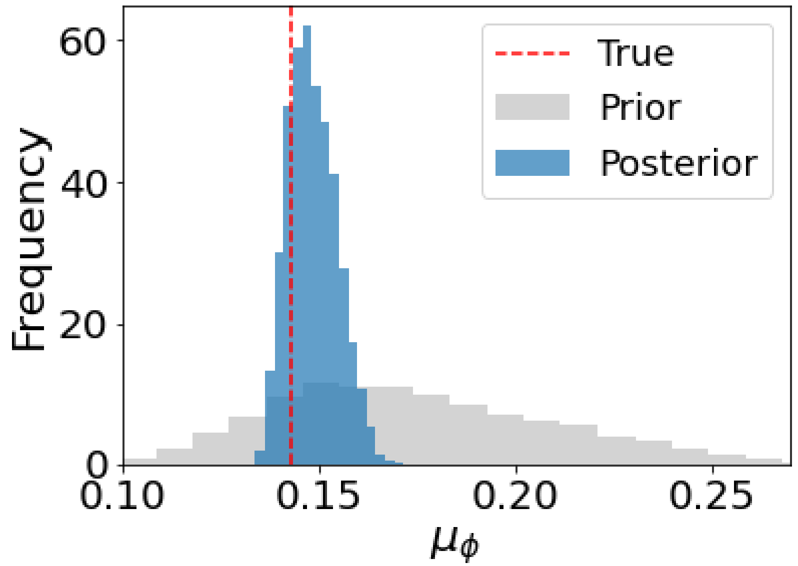


$\log_{10}(k_v / k_h)$

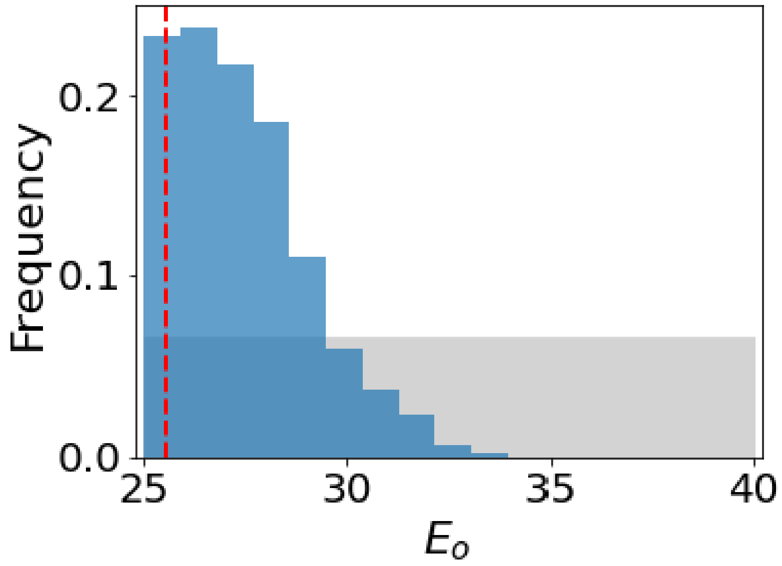


History Matching Results for Metaparameters
(using both in-situ and surface data)

mean porosity

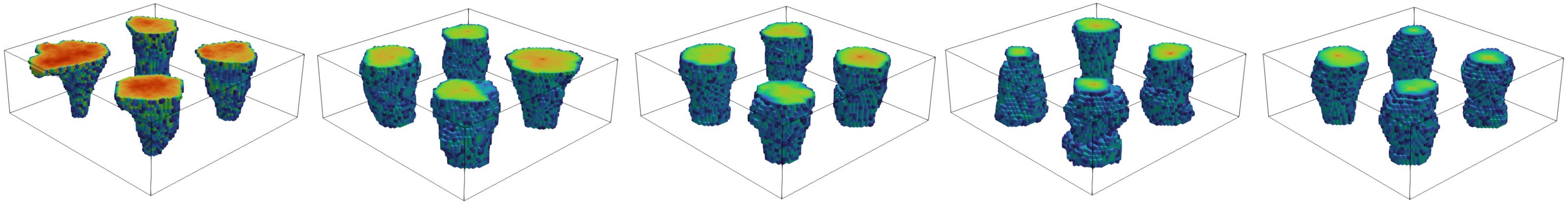


Young's modulus in overburden

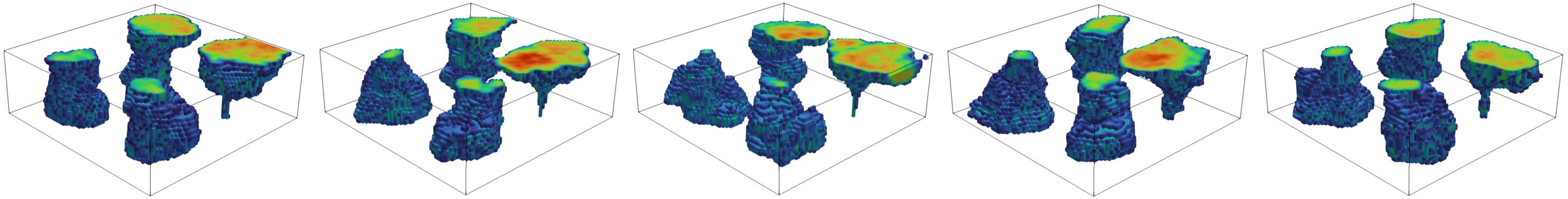


Prior and Posterior CO_2 Saturation (30 years, K-means clustering)

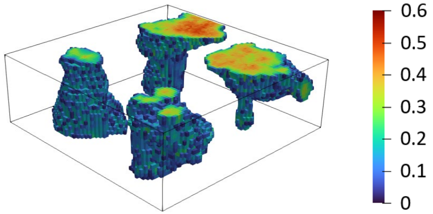
Prior:



Posterior:



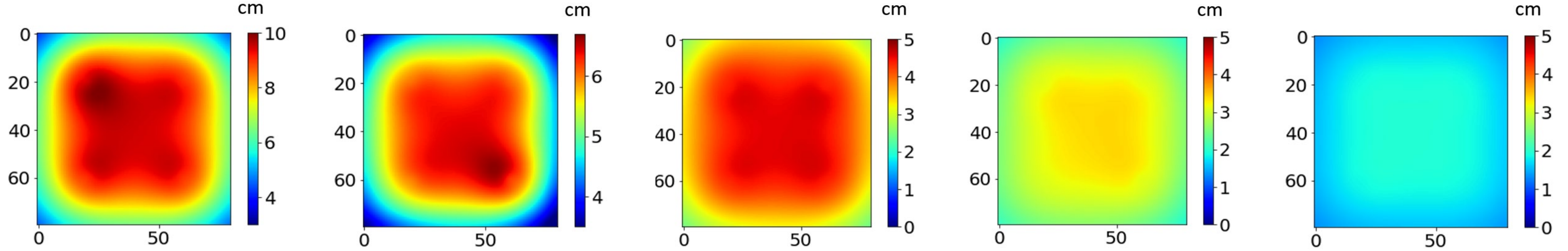
True :



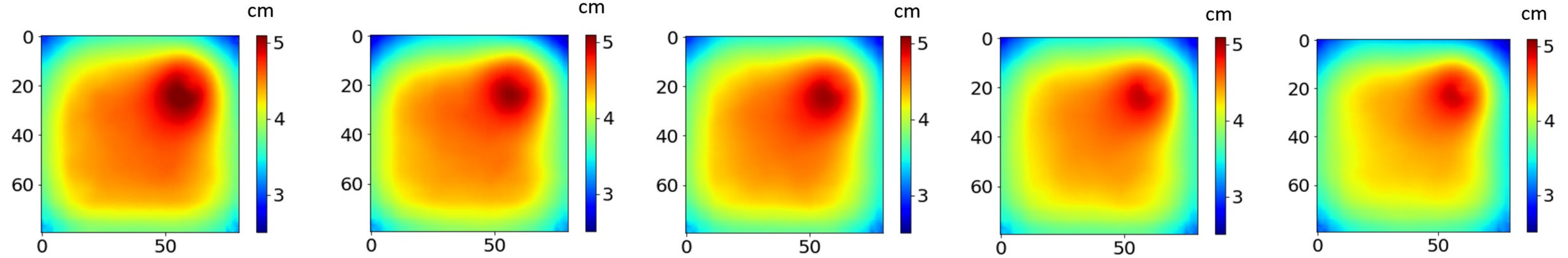
- Uncertainty in CO2 plume shapes/sizes reduced

Prior and Posterior Surface Displacement (30 years, K-means clustering)

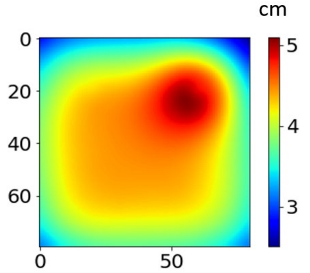
Prior:



Posterior:



True :



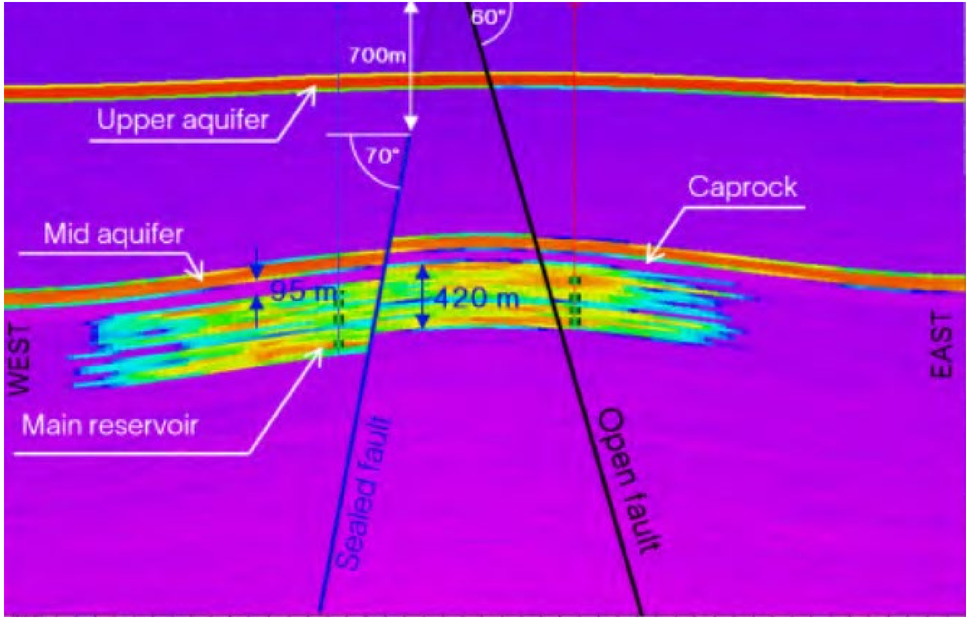
- Uncertainty in surface displacement reduced

Summary & Current Directions

- Developed deep-learning surrogate models to enable formal history matching in carbon storage problems
- Implemented surrogate modeling framework for coupled problems
- Demonstrated applicability of Markov Chain Monte Carlo history matching with coupled flow and geomechanics, using in-situ pressure & saturation data and surface displacement data
- *Now applying the workflow to realistic geomodels with faults*

Summary & Current Directions

- *Now applying the workflow to realistic geomodels with faults*



SEG Advanced Modeling Corporation (SEAM) CO_2 Project in Gulf of Mexico

(Yoon et al., 2024)

Acknowledgements

- Stanford Center for Carbon Storage
- Stanford Smart Fields Consortium
- SDSS Center for Computation

Thank you