Sequential Monitoring Design for Geological Carbon Storage

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November 19, 2024

Stanford | Doerr School of Sustainability | Stanford Center for Carbon Storage

Monitoring design under geological uncertainty

Spatial
- Where to monitor?

Temporal
- When to monitor?

Strategy
- How many monitoring wells or seismic surveys?

Primary focus in our current work

Monitoring well

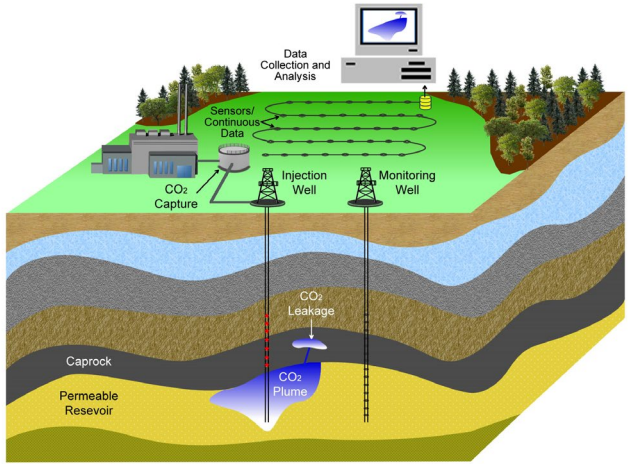
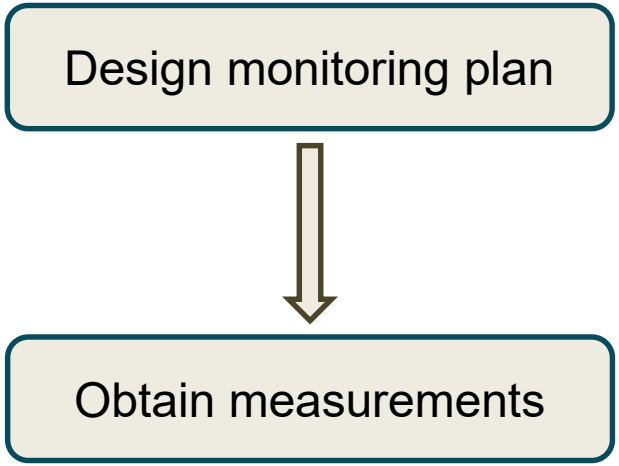


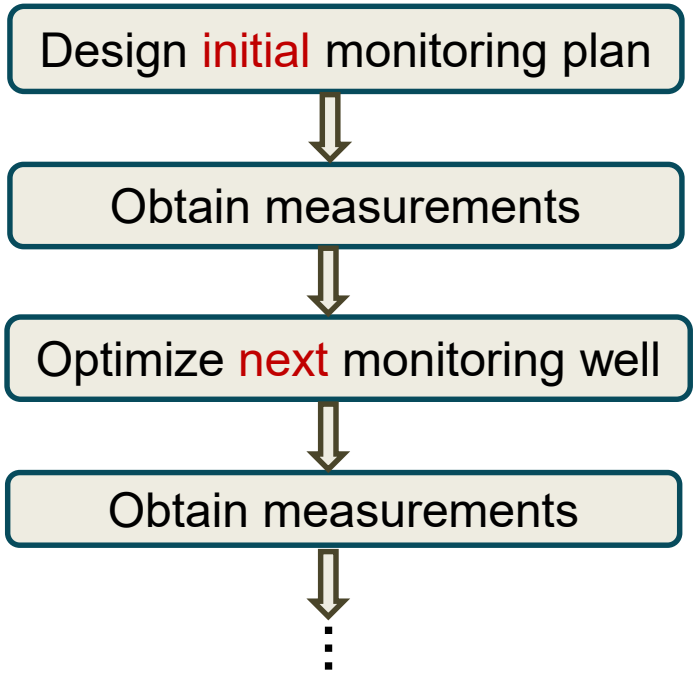
Figure source: https://www.psu.edu/news/research/story/25m-grant-funds-real-time-monitoring-underground-carbon-sequestration

Static vs. sequential monitoring design

Static monitoring design:

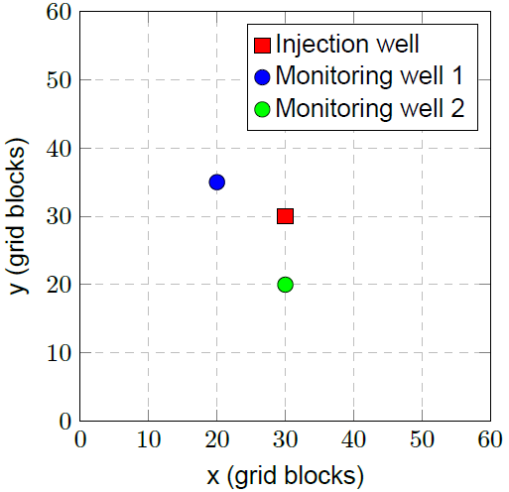


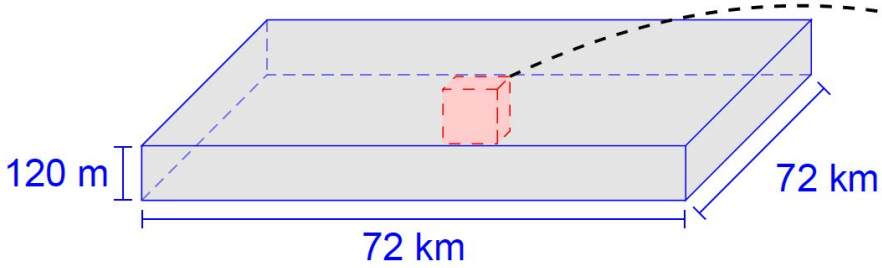
Sequential monitoring design:

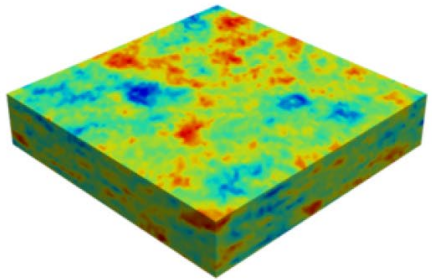


Problem setup

- Storage aquifer size: 7.2 km × 7.2 km × 120 m
- Storage aquifer: 60 × 60 × 12 blocks
- Grid size: 120 m × 120 m × 10 m
- Injection rate: 1 Mt/year
- Injection period: 30 years
- Sequential placement of two monitoring wells



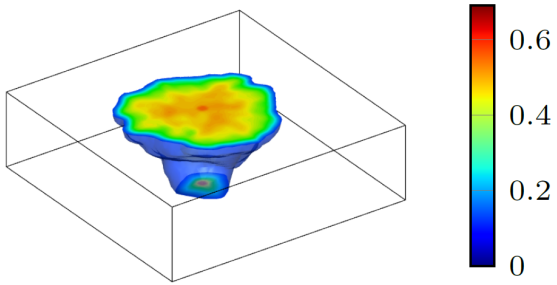




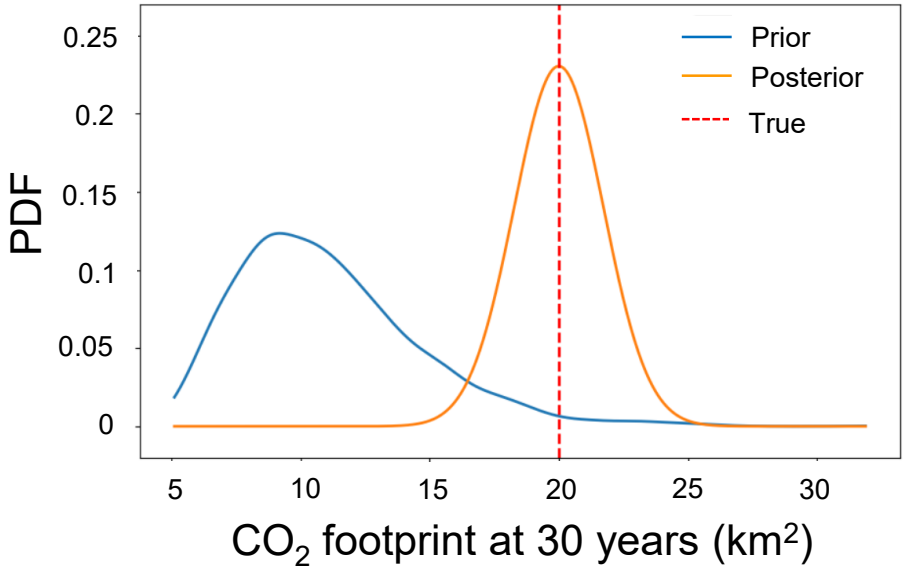
Define monitoring goal

Quantity of interest (QoI):

- CO_2 footprint
- Pressure buildup
- Surface displacement

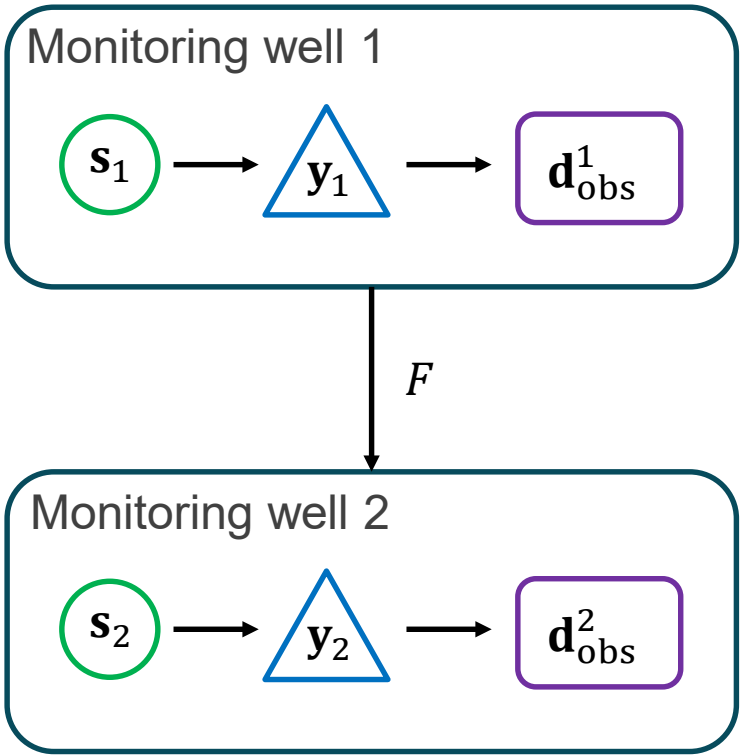


Goal: maximize uncertainty reduction of QoI

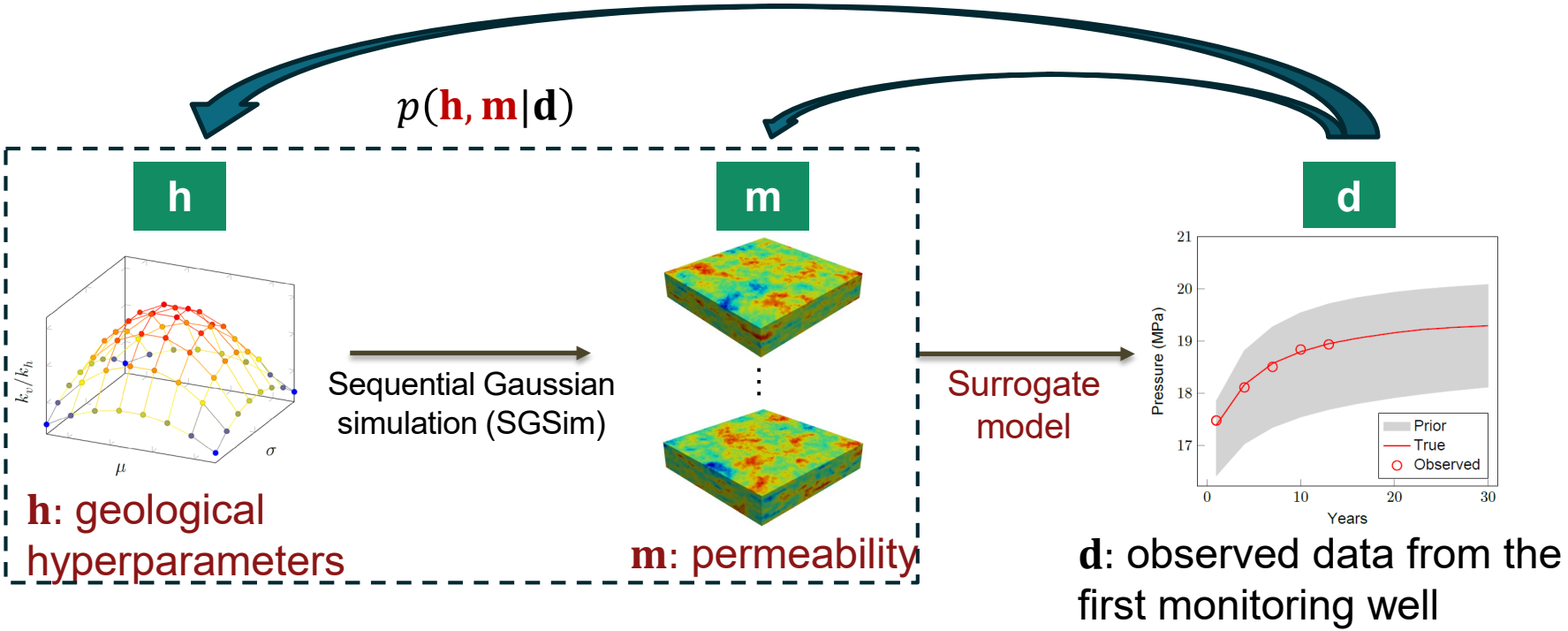


Partially Observable Markov Decision Process (POMDP)

- Sequential decision making problem
- Number of monitoring wells: 2
- Uncertain parameters: geological hyperparameters and permeability fields
- Prior: $\mathbf{s}_1$, Posterior: $\mathbf{s}_2$
- Locations of two monitoring wells: $\mathbf{y}_1$, $\mathbf{y}_2$
- Monitoring-well data: $\mathbf{d}_{\text{obs}}$
- History matching: $\mathbf{s}_2 = F\left(\mathbf{s}_1, \mathbf{y}_1, \mathbf{d}_{\text{obs}}^1\right)$



History matching – hierarchical data assimilation

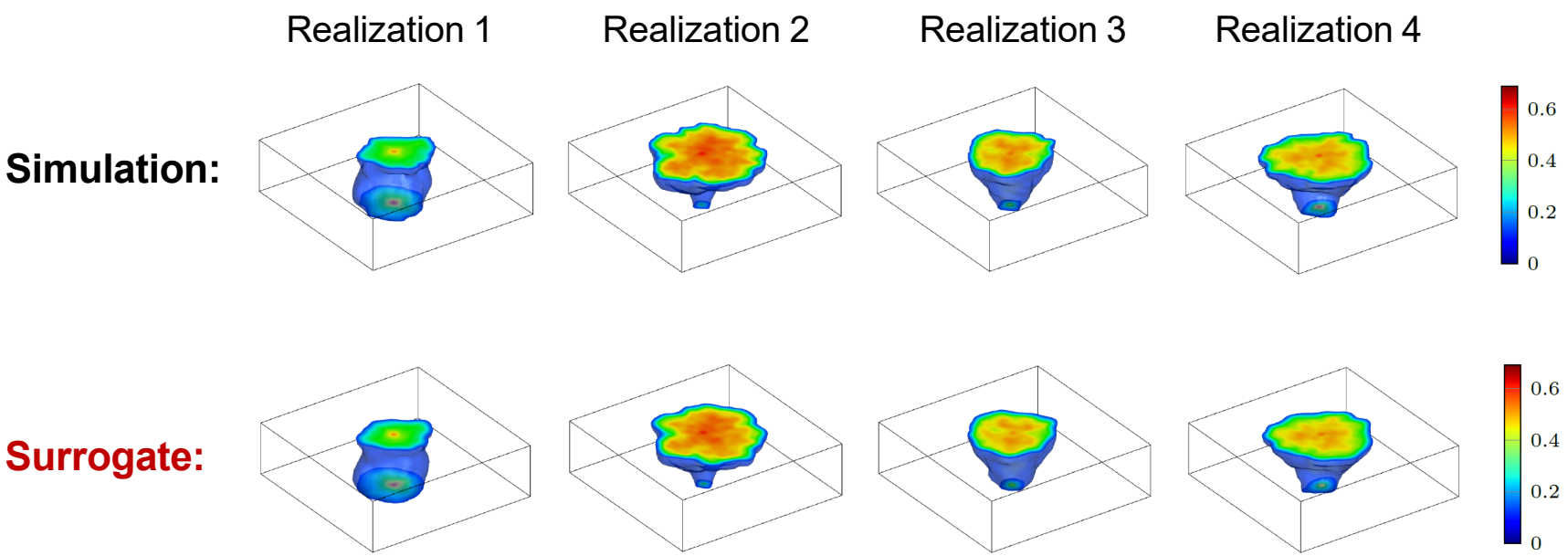


h: geological hyperparameters

m: permeability

d: observed data from the first monitoring well

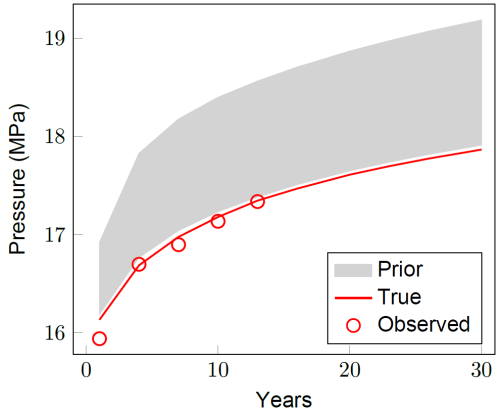
Surrogate comparisons – CO_2 plume at 30 years

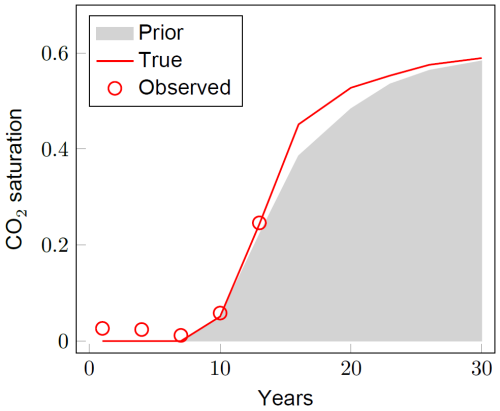


History matching problem setup

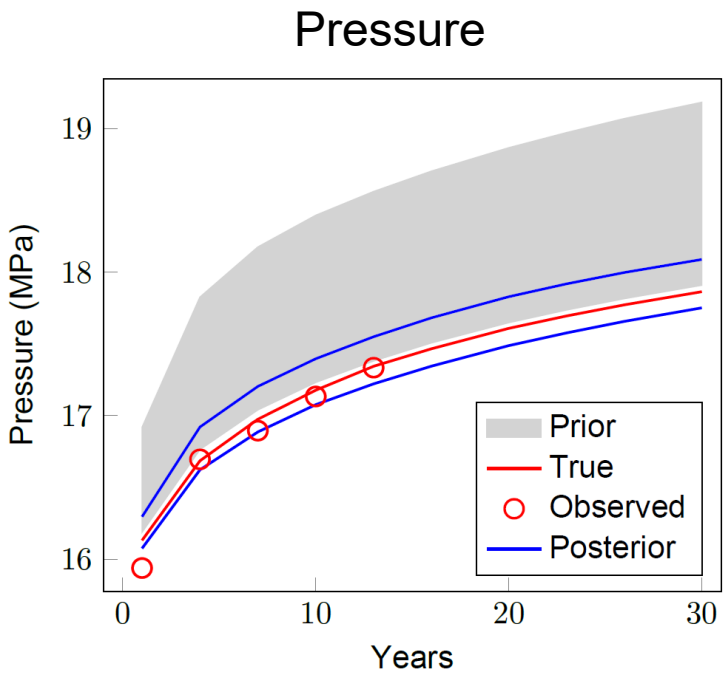
- Observed data from the first monitoring well: pressure and CO_2 saturation
- Uncertain parameters: $\mathbf{h}, \mathbf{m}$
- Sequential Monte Carlo-based approximate Bayesian computation (SMC-ABC)
- One-to-two order of magnitude speedup relative to reference method (rejection sampling)

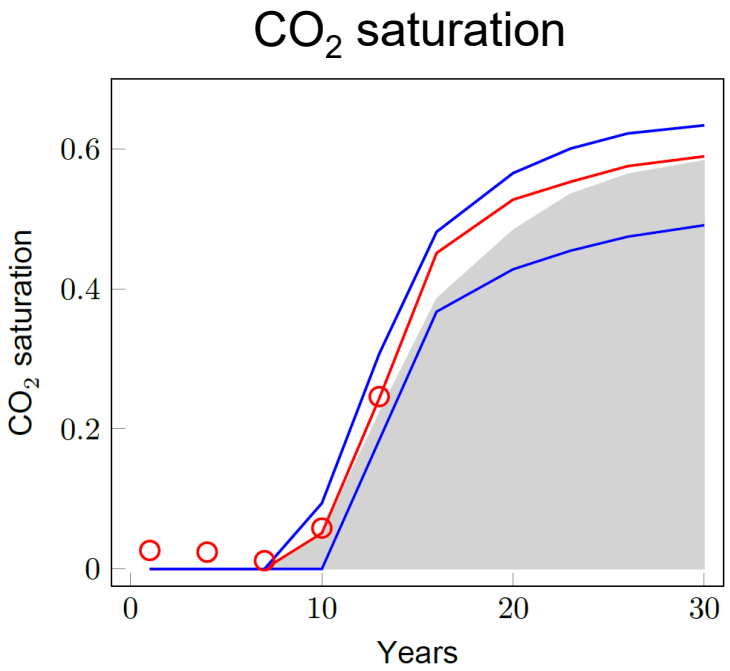
$\mathbf{h}$: hyperparameters $\mathbf{m}$: permeability



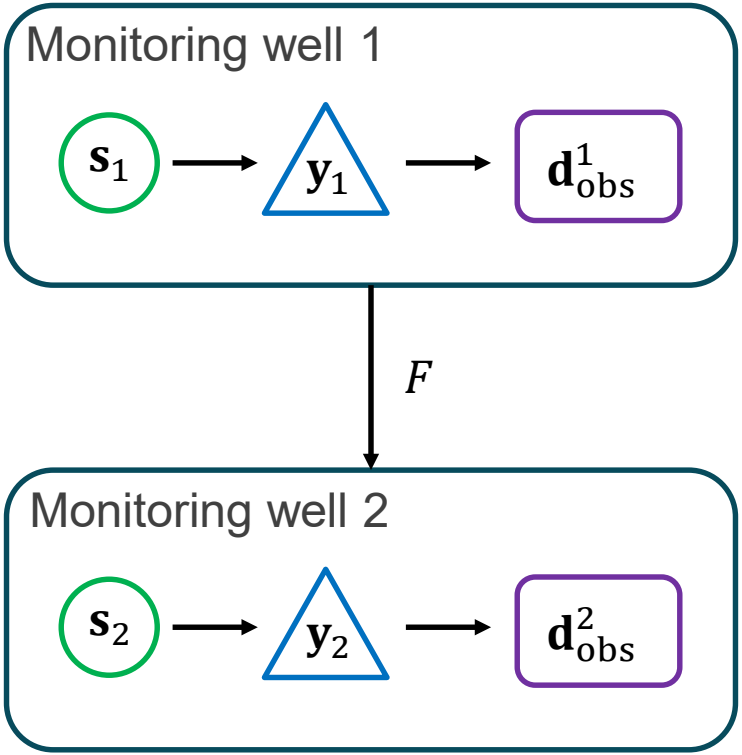


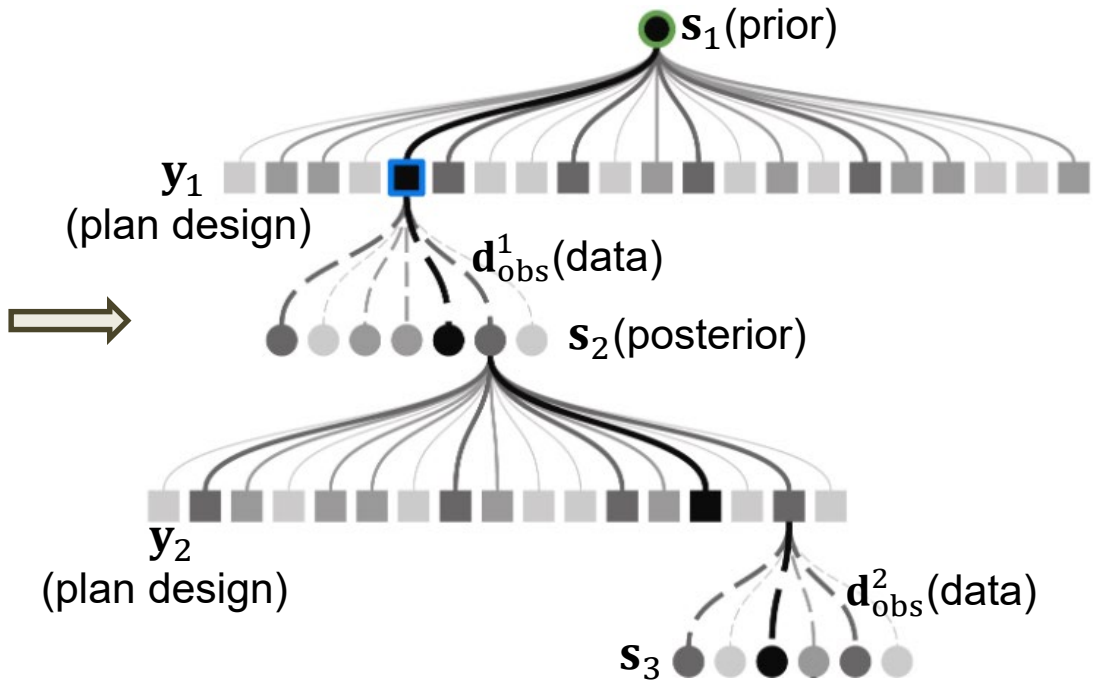
History matching results





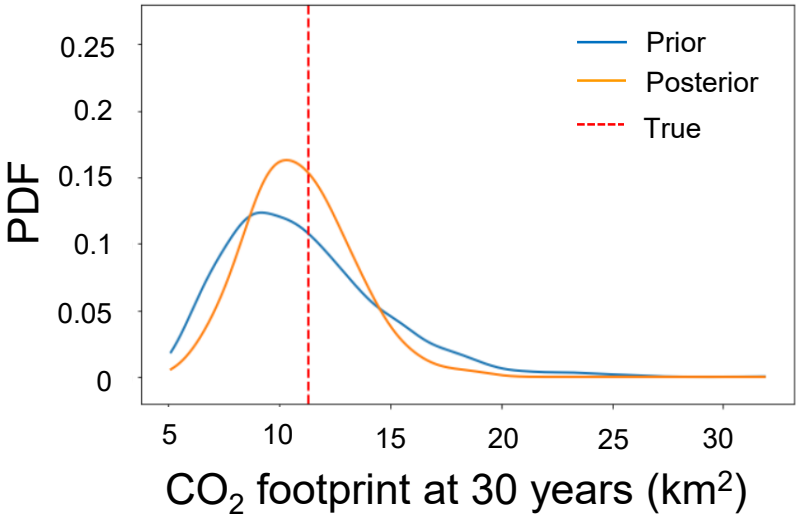
Online planning – Monte Carlo tree search



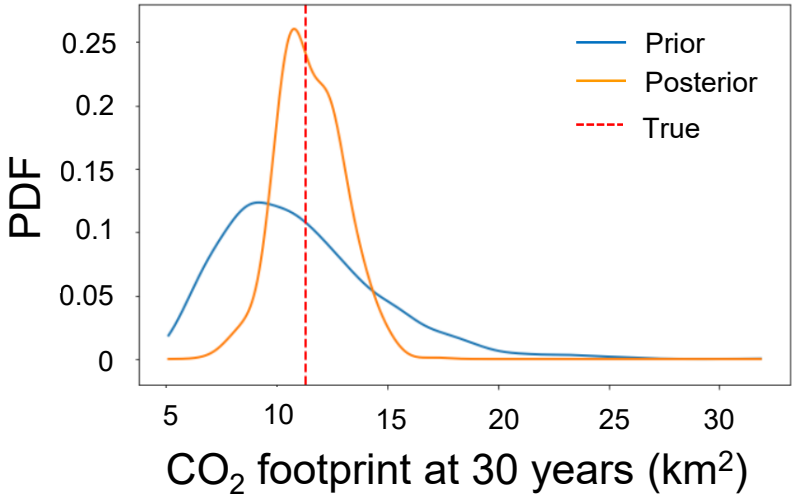


Comparison of static and sequential design

Static monitoring design

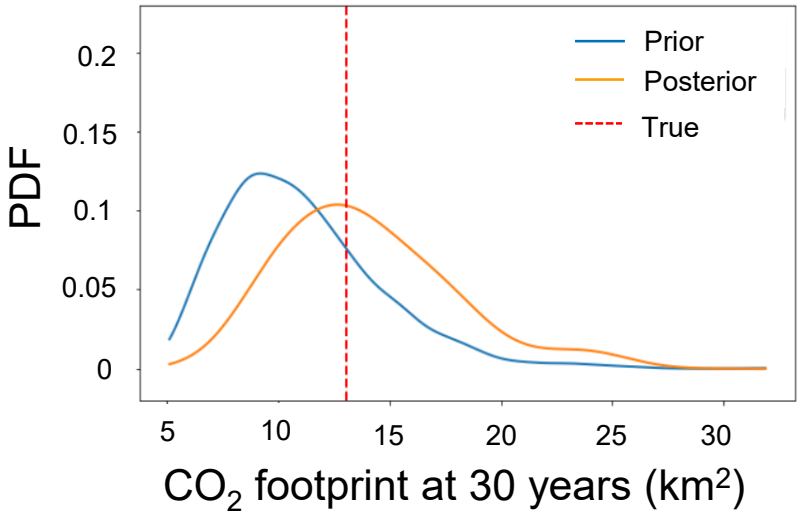


Sequential monitoring design

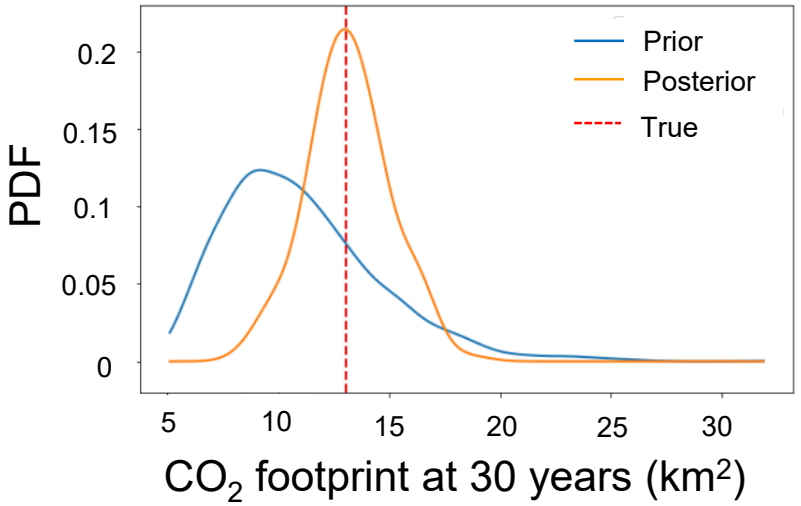


True model 2: static vs. sequential design

Static monitoring design



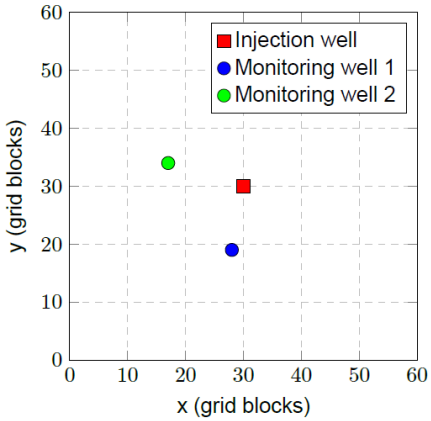
Sequential monitoring design



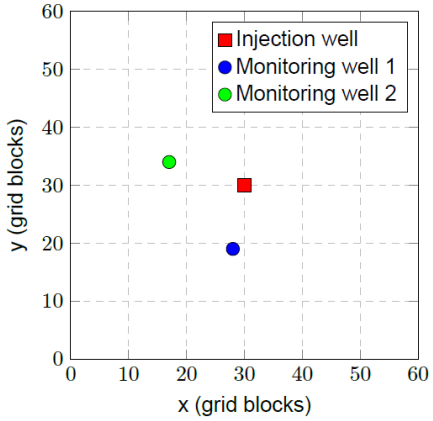
Locations of monitoring wells for the two true models

Static monitoring design

True model 1

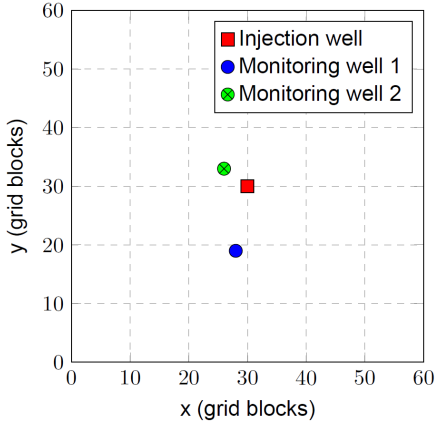


True model 2

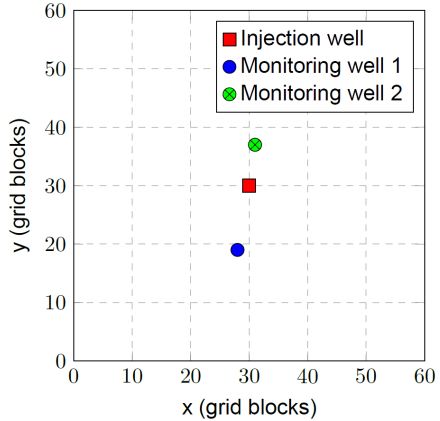


Sequential monitoring design

True model 1



True model 2



Summary and Future Work

- Developed a sequential monitoring design framework based on surrogate modeling, hierarchical data assimilation, and online planning algorithms
- Formulated sequential monitoring design problem as a partially observable Markov decision process (POMDP)
- Applied sequential Monte Carlo-based approximate Bayesian computation algorithm for the history matching (data assimilation) step
- In future work, plan to refine sequential hierarchical data assimilation and apply the monitoring design framework to more realistic problems

Acknowledgments

Surrogate model code from Yifu Han and Dylan Crain

Stanford Center for Carbon Storage

Stanford Smart Fields Consortium

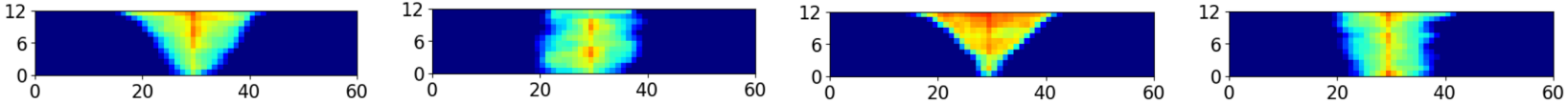
Stanford Graduate Fellowship

SDSS Center for Computation

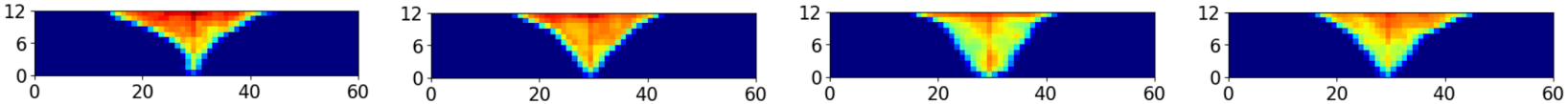
Backup slides

Saturation comparison (y-z cross-sections)

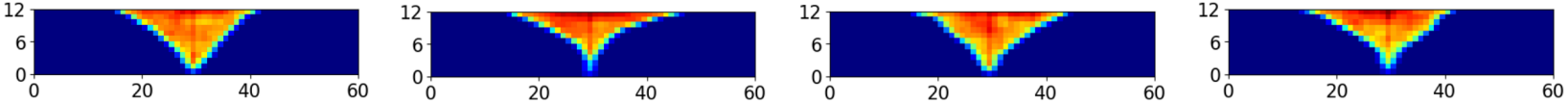
Prior saturation samples



Static monitoring design



Sequential monitoring design



True model