Solving Inverse Problems with Machine Learning for Real-Time Monitoring of Subsurface Plumes

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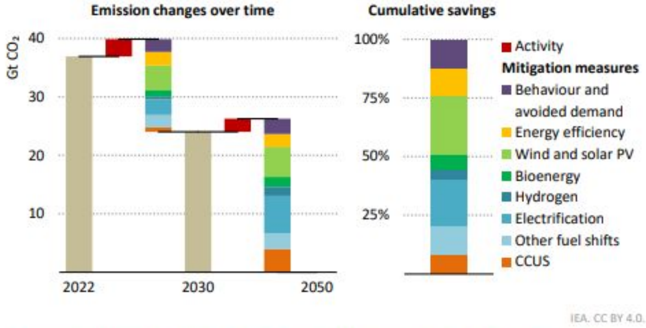
Background

- To meet the 1.5∘C target, carbon removal ranges from 5 to 16 Gt of CO_2 per year by 2050
- To meet net-zero targets, carbon management must be scaled up
- Given extensive lead times for construction, planning, and development of these projects must be happening now
- Utilization alone does not meet the Gt scale required to meet net-zero goals, so sequestration injecting supercritical CO_2 in the subsurface will be required
- IRA and LCFS tax credits mean some of these projects are profitable now

References: IEA (2023), Net Zero Roadmap: A Global Pathway to Keep the 1.5 °C Goal in Reach, IEA, Paris https://www.iea.org/reports/net-zero-roadmap-a-global-pathway-to-keep-the-15-0c-goal-in-reach , License: CC BY 4.0

Figure 2.5 ▷ CO_2 emissions reductions by mitigation measure in the NZE Scenario, 2022-2050



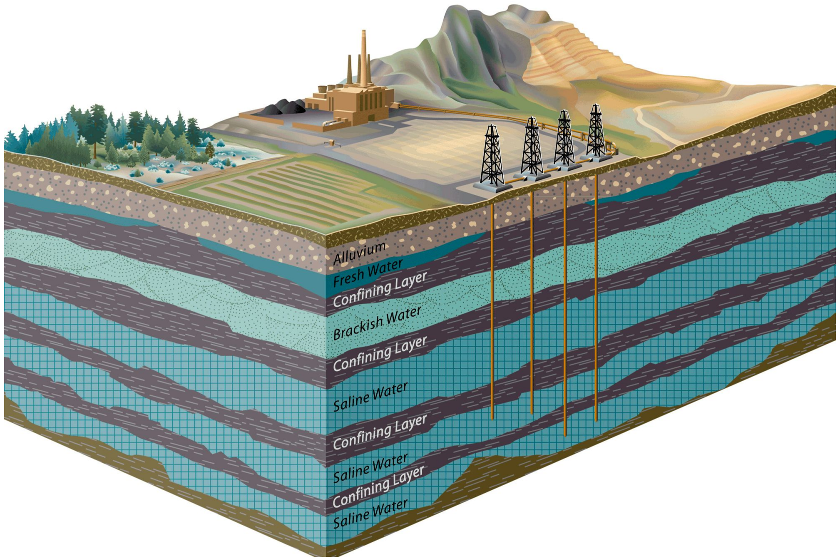
Expansion of solar PV, wind and other renewables, energy intensity improvements and direct electrification of end-uses combined contribute 80% of emission reductions by 2030

Figure 1.15 ▷ Global CO_2 capture project pipeline, 2010-2023

There has been strong growth in the project pipeline for CO_2 capture in recent years, implying that installed capacity is set to rise significantly

Background

- Saline aquifers are plentiful, have significant storage potential, and are collocated with emitters
- To get a permit, the AoR (area of review) must be well understood and a long term monitoring strategy is required
- Traditional forward models and inverse models for monitoring are computationally intensive, machine learning enables real-time monitoring



References: Young, G. B. C., Lintz, V. A., Widmann, B. L., Bird, D. A., & Cappa, J. A. (2007). CO_2 Sequestration Potential of Colorado (Resource Series 45). Colorado Geological Survey, Division of Minerals and Geology, Department of Natural Resources.

Motivation

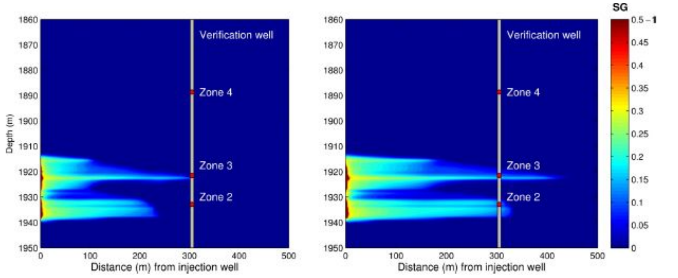
Develop a pressure-based monitoring scheme that can be used real-time, continuously, is cost-effective, and safe

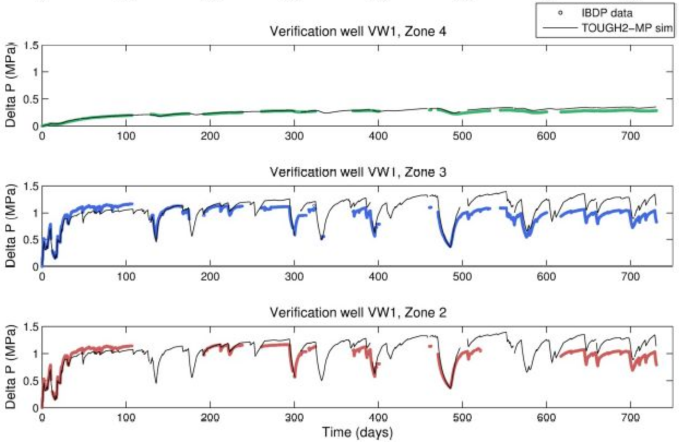
Multilevel Pressure Monitoring

Prior work has shown multilevel pressure transients can be used to determine the height and footprint of the CO2 plume

Multilevel pressure transients can also be used to history match hydrogeological models to predict future CO2 migration

Demonstrated using the Illinois Basin – Decatur Project (IBDP) data as a case study



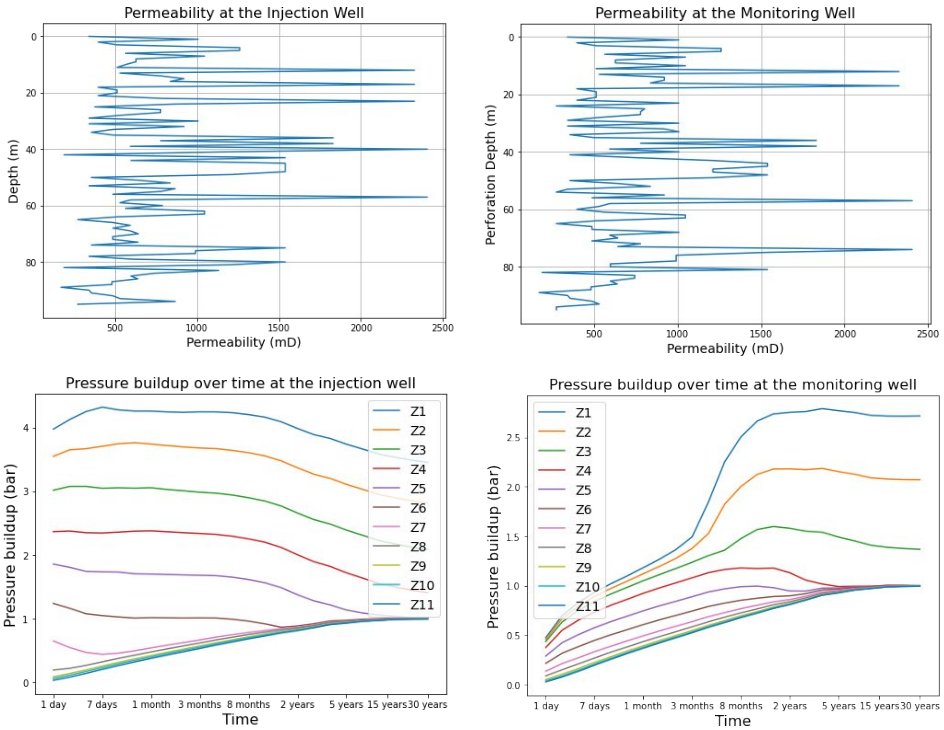


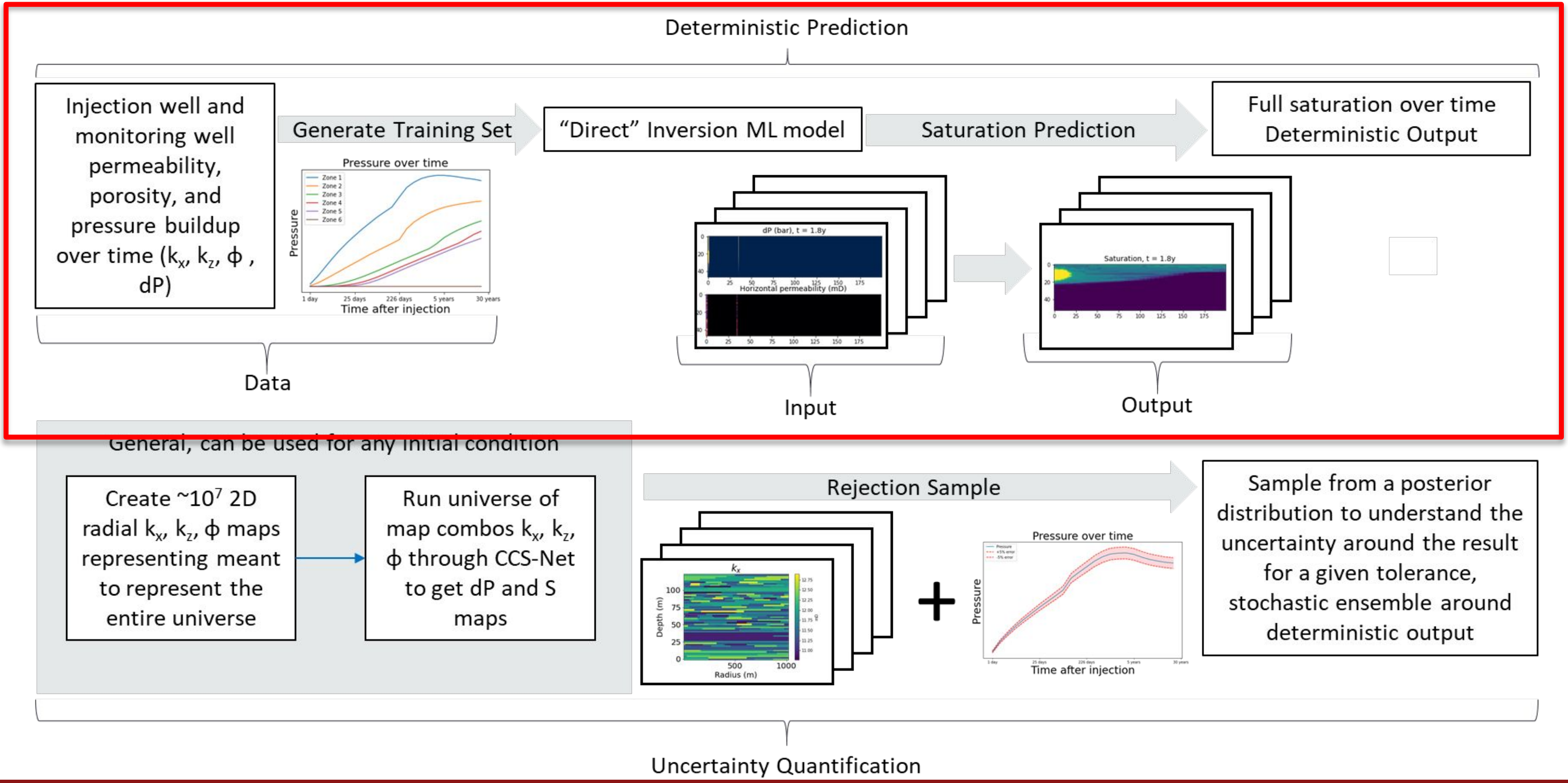
References: C. W. Strandli and S. M. Benson, “Identifying diagnostics for reservoir structure and CO_2 plume migration from multilevel pressure measurements: Diagnostics from Multilevel Pressure Measurements,” *Water Resour. Res.*, vol. 49, no. 6, pp. 3462–3475, Jun. 2013, doi: 10.1002/wrcr.20285.

C. W. Strandli, E. Mehnert, and S. M. Benson, “CO2 Plume Tracking and History Matching Using Multilevel Pressure Monitoring at the Illinois Basin – Decatur Project,” *Energy Procedia*, vol. 63, pp. 4473–4484, 2014, doi: 10.1016/j.egypro.2014.11.483.

Sparse data for automated history matching

The generalized problem statement involves trying to predict plume migration in a storage reservoir using sparse data, we are history matching the pressure data




Deterministic Prediction
Injection well and monitoring well permeability, porosity, and pressure buildup over time (kx, kz, ϕ , dP)
Generate Training Set
Pressure over time
Zone 1
Zone 2
Zone 3
Zone 4
Zone 5
Zone 6
Pressure
1 day
25 days
226 days
5 years
30 years
Time after injection
Data
"Direct" Inversion ML model
Saturation Prediction
Full saturation over time Deterministic Output
dP (bar), t = 1.8y
Horizontal permeability (mD)
Input
Saturation, t = 1.8y
Output
General, can be used for any initial condition
Create ~10^7 2D radial kx, kz, ϕ maps representing meant to represent the entire universe
Run universe of map combos kx, kz, ϕ through CCS-Net to get dP and S maps
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kx
Depth (m)
Radius (m)
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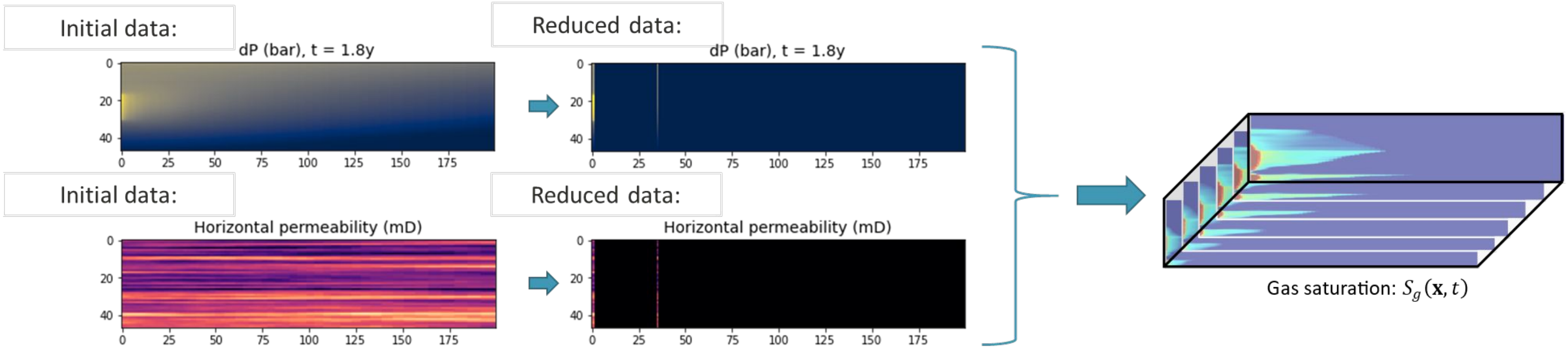
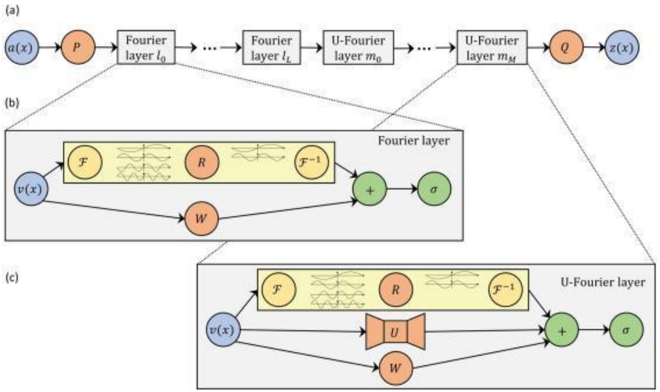
Time after injection
Sample from a posterior distribution to understand the uncertainty around the result for a given tolerance, stochastic ensemble around deterministic output
Uncertainty Quantification

"Direct" Inversion





Training and test sets were developed using a commercial simulator and are treated as the ground truth, they're modified from same data sets as CCSNet

Train a model to predict the full saturation plume with permeability, porosity and pressure buildup input data from the injection well and monitoring well

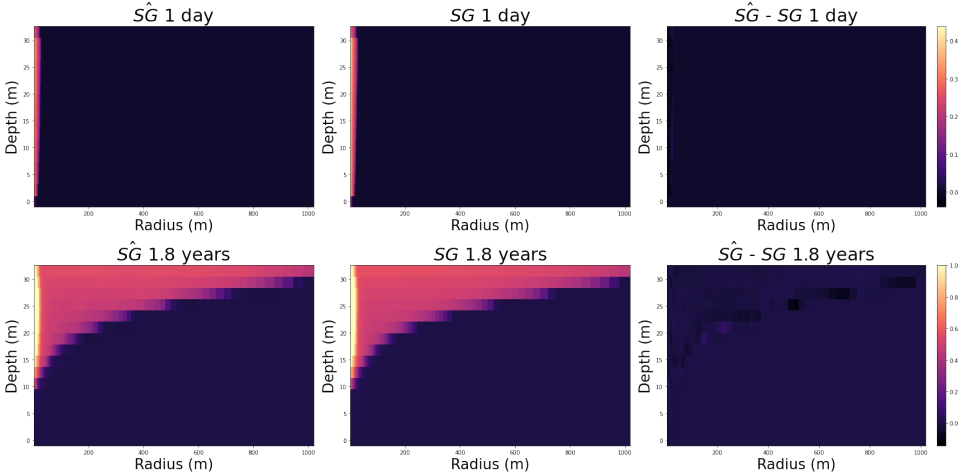
Leverages the fact that pressure and saturation are coupled

2D radial system

References: G. Wen, Z. Li, K. Azizzadenesheli, A. Anandkumar, and S. M. Benson, "U-FNO—An enhanced Fourier neural operator-based deep-learning model for multiphase flow," *Advances in Water Resources*, 2022.

Model Performance

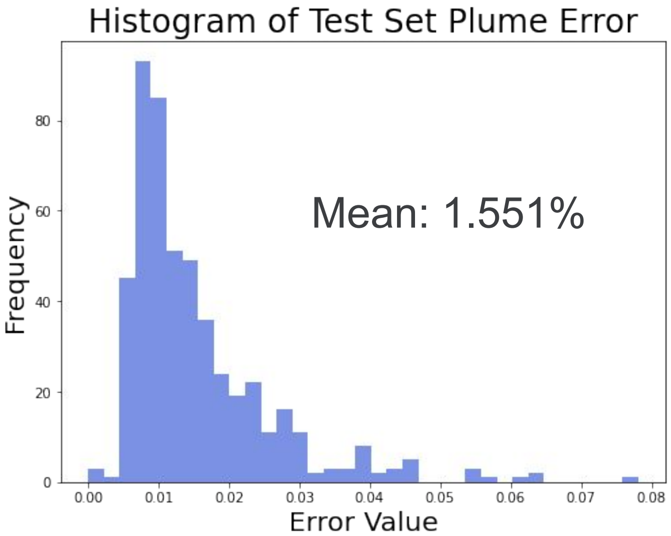
Good statistical agreement for both heterogeneous and homogeneous permeability fields



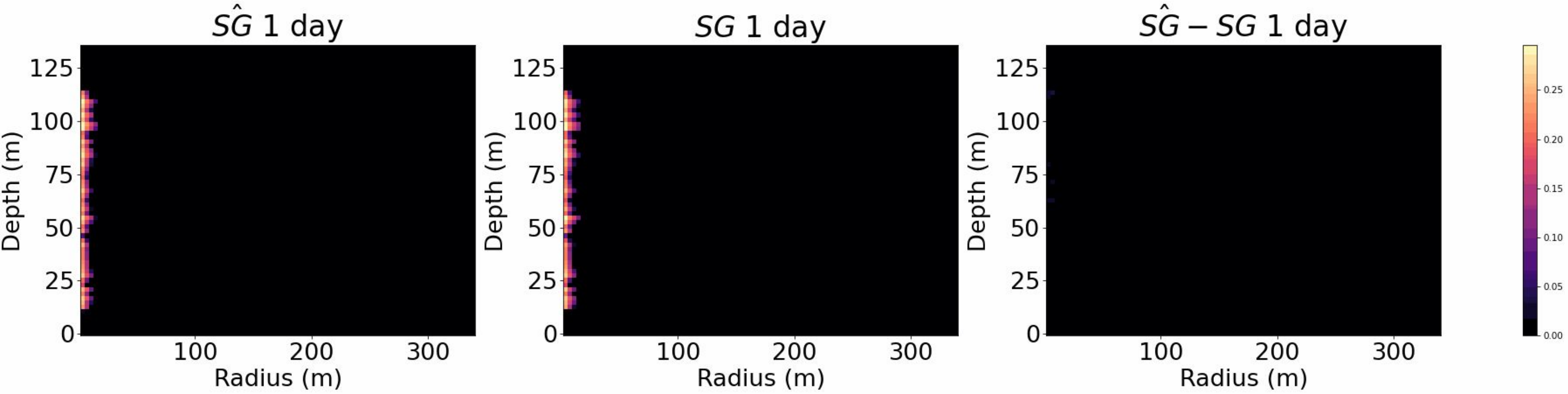
Prediction

Ground Truth

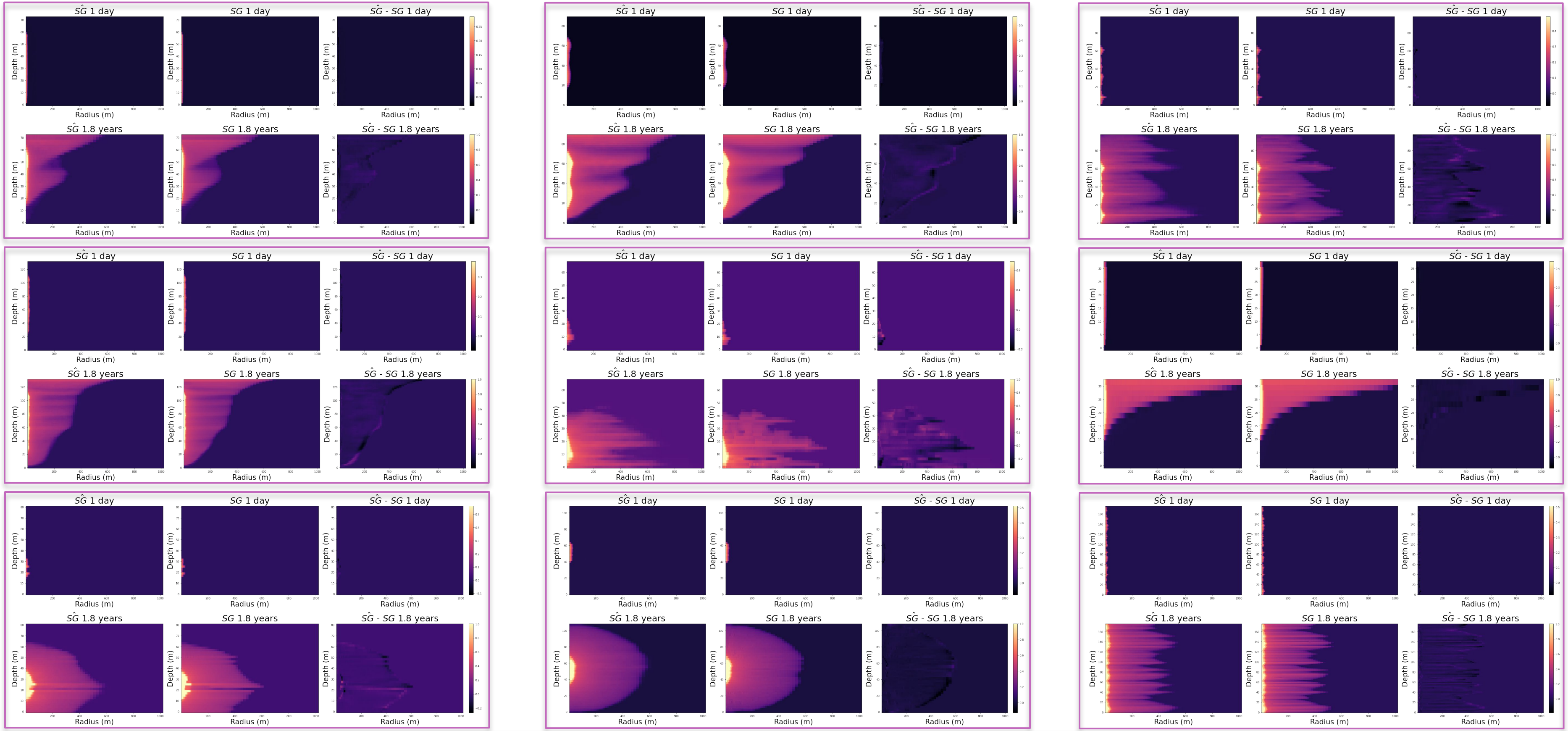
Delta



$$\text{Gas Plume Error} = \begin{cases} \frac{\sum_i |s_g^{(i)} - \hat{s}_g^{(i)}| \cdot \delta\left(|s_g^{(i)}| > 0.01 \vee |\hat{s}_g^{(i)}| > 0.01\right)}{\sum_i \delta\left(|s_g^{(i)}| > 0.01 \vee |\hat{s}_g^{(i)}| > 0.01\right)}, & \text{if } \sum_i \delta\left(|s_g^{(i)}| > 0.01 \vee |\hat{s}_g^{(i)}| > 0.01\right) \geq \epsilon, \\ 0, & \text{otherwise.} \end{cases}$$

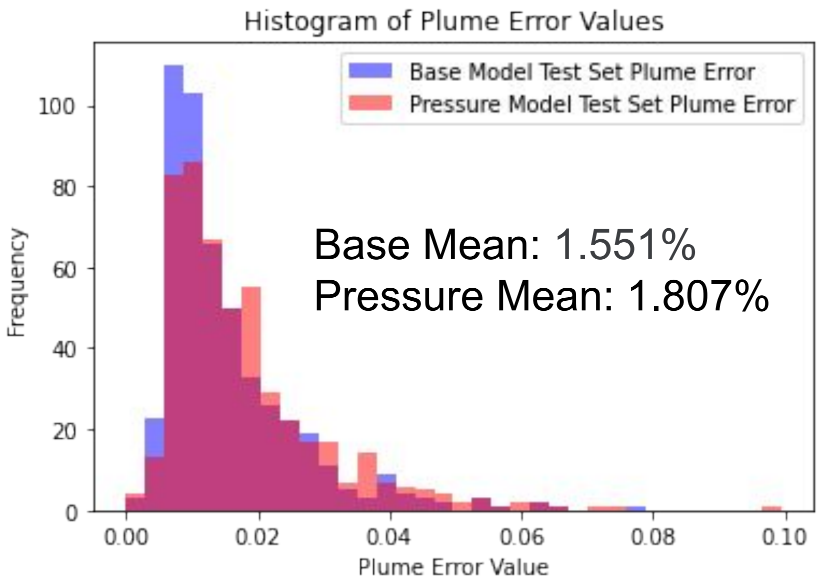

$\hat{SG}$ 1 day
SG 1 day
$\hat{SG} - SG$ 1 day
Depth (m)
Radius (m)
125
100
75
50
25
0
100
200
300
0.25
0.20
0.15
0.10
0.05
0.00

The model is performant across geologies and configurations



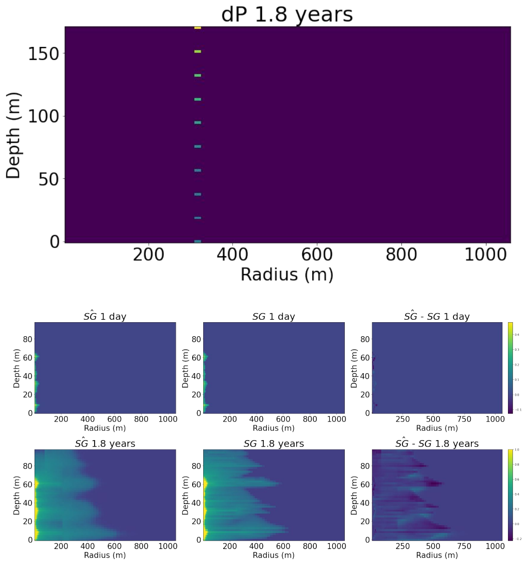
Pressure by itself can tell the story

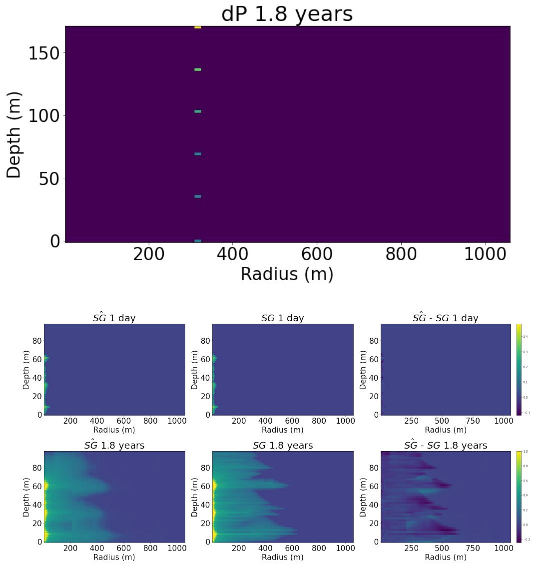
Removing horizontal permeability, vertical permeability, and porosity

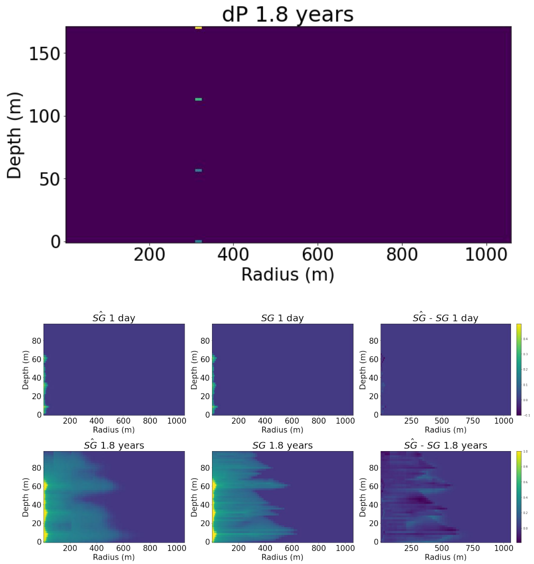


Sparse pressure model and sensitivity to pressure availability

Case	Mean Plume Error %
10 vertical sensors	4.421
6 vertical sensors	4.855
4 vertical sensors	5.067







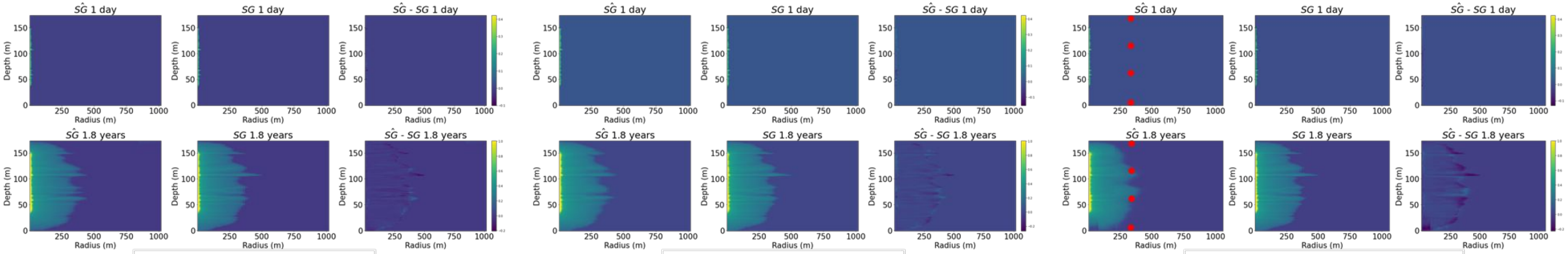
Model comparison - all learn the footprint and height of the plume

Successfully directly predict saturation using well data with the ability to generalize to unseen data

Learn the height and footprint of the plume for a wide variety of initial configurations

Pressure is the most important input even when sparse

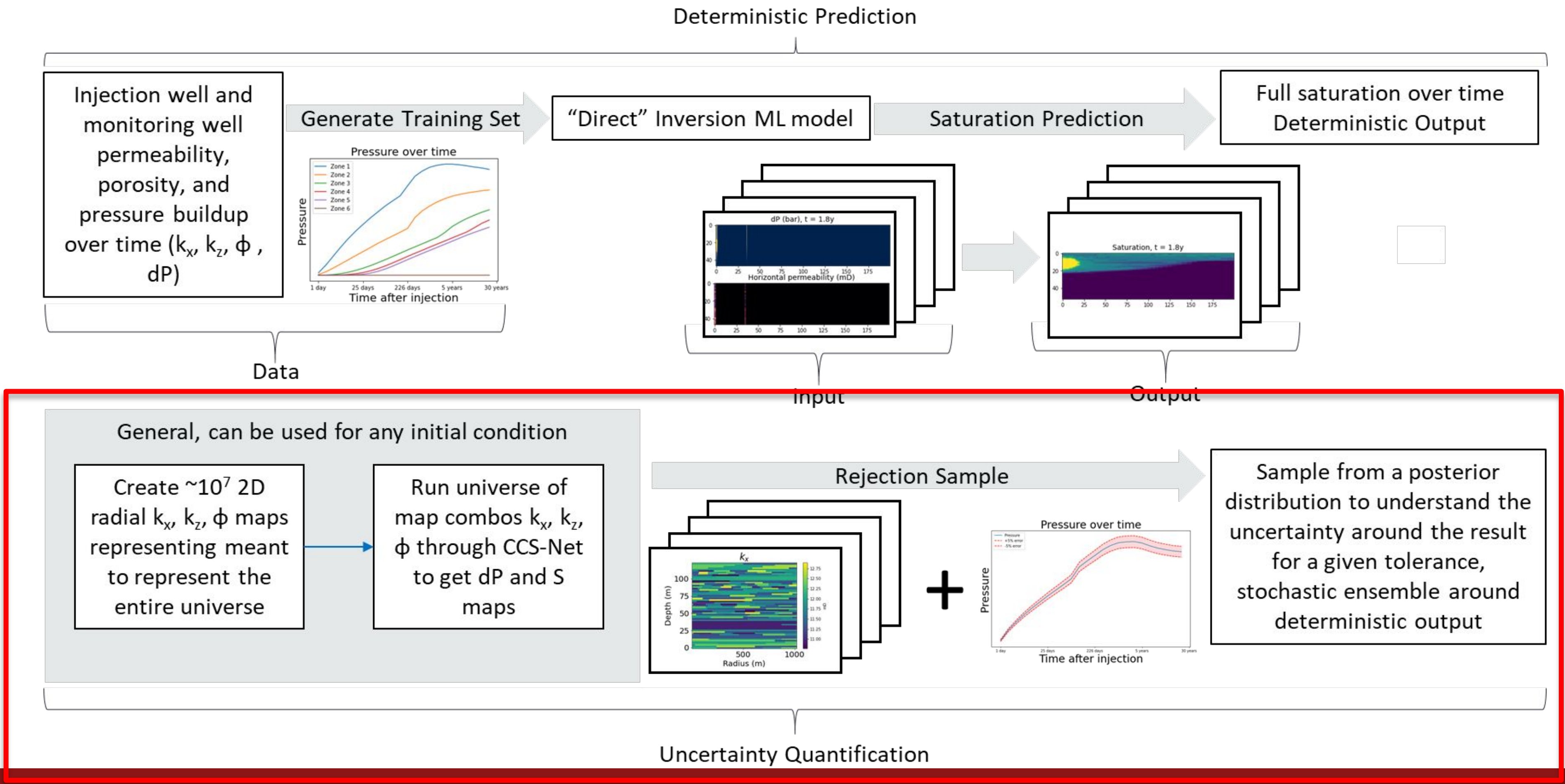
Case	Mean Plume Error %
Base Model	1.551
Pressure Model	1.807
Sparse Pressure Model	5.067



Base Model: Full columns of k_x, k_z, ϕ, dP

Pressure Model: Full columns of dP

Sparse Pressure Model: Full columns of k_x, ϕ, sparse columns of dP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Full saturation over time Deterministic Output
General, can be used for any initial condition
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Run universe of map combos kx, kz, ϕ through CCS-Net to get dP and S maps
Rejection Sample
Depth (m)
Radius (m)
+
Pressure over time
Pressure
Time after injection
Sample from a posterior distribution to understand the uncertainty around the result for a given tolerance, stochastic ensemble around deterministic output
Uncertainty Quantification

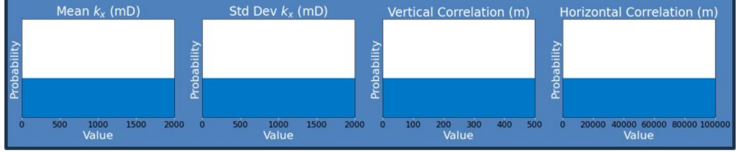
Rejection Sampling: Make a Rigorous Posterior Ensemble for a given initial condition

Initial condition: start with 1 input, columns of dP, k_x, k_z, and ϕ

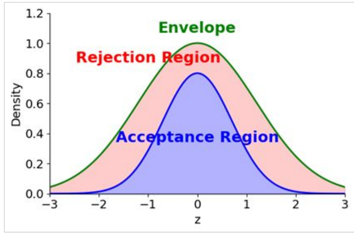
General, can be used for any initial condition

Create ~10^7 2D radial k_x, k_z, ϕ maps representing all possible parameter combinations -> meant to represent the entire universe

Run universe of map combos k_x, k_z, ϕ through CCS-Net to get dP and S maps instead of running ~10^6 eclipse simulations



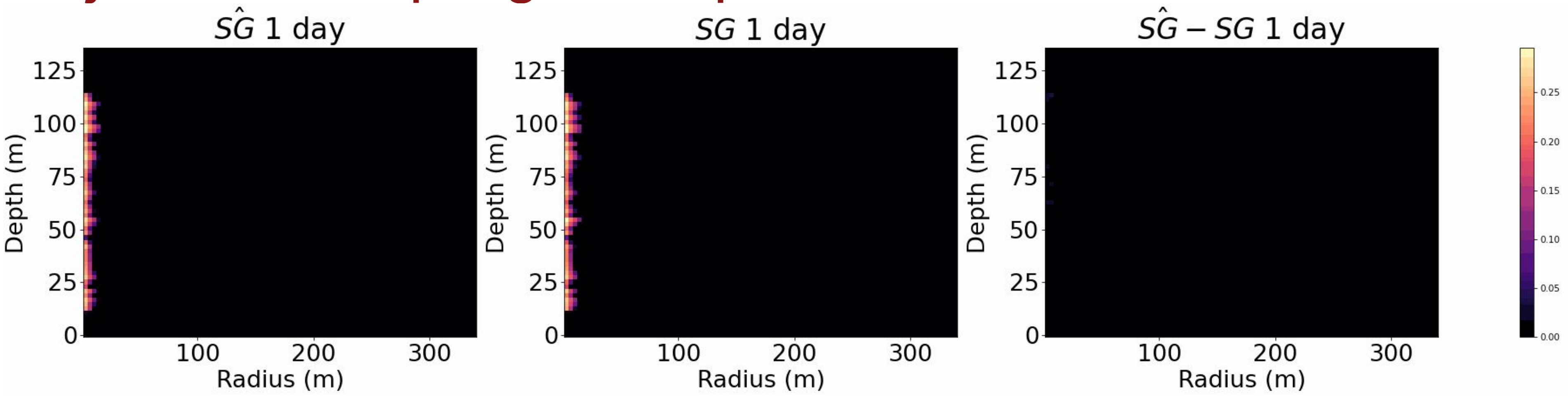
Compare full dP at monitoring well locations to observed data (the columns of dP in the initial condition)



Accept all within some tolerance of observed dP data and reject the rest

Each full S output corresponding to an accepted dP is a member of the posterior ensemble

Rejection Sampling Set-Up



Tracking one sample shown here over the first year

5% tolerance for pressure buildup

$$p(d_{\text{obs}} \mid \mathbf{k}, \mathbf{m}) = \det(2\pi\mathbf{R})^{-\frac{1}{2}} \exp\left(-\frac{1}{2}(d_{\text{obs}} - f(\mathbf{m}))^{\top}\mathbf{R}^{-1}(d_{\text{obs}} - f(\mathbf{m}))\right)$$

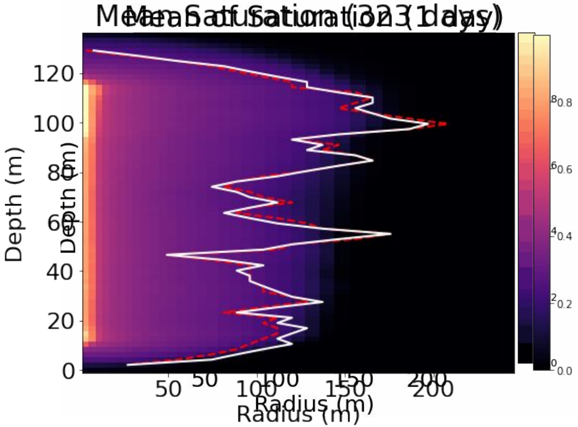
Accept or reject based on likelihood value

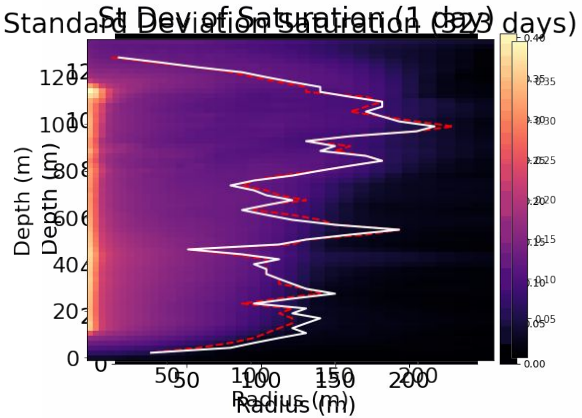
$$u \leq \frac{p(d_{\text{obs}} \mid \mathbf{k}, \mathbf{m})}{\mathcal{L}}$$

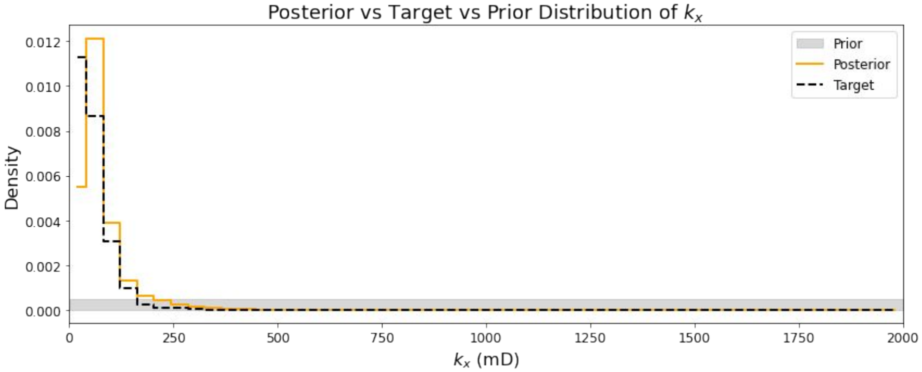
Accepted samples form the posterior distribution

References: W. Teng and L. J. Durlofsky, “Likelihood-free inference and hierarchical data assimilation for geological carbon storage,” Advances in Water Resources, 2025.

Rejection Sampling Results







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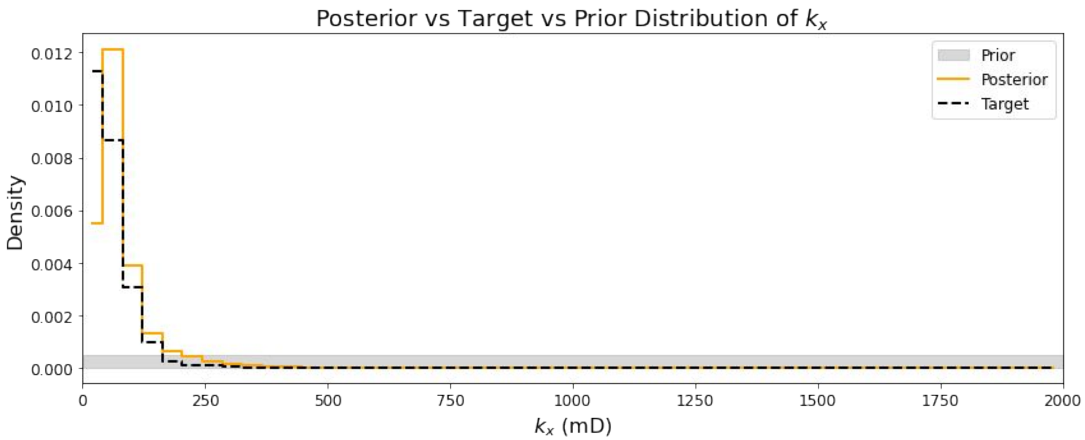

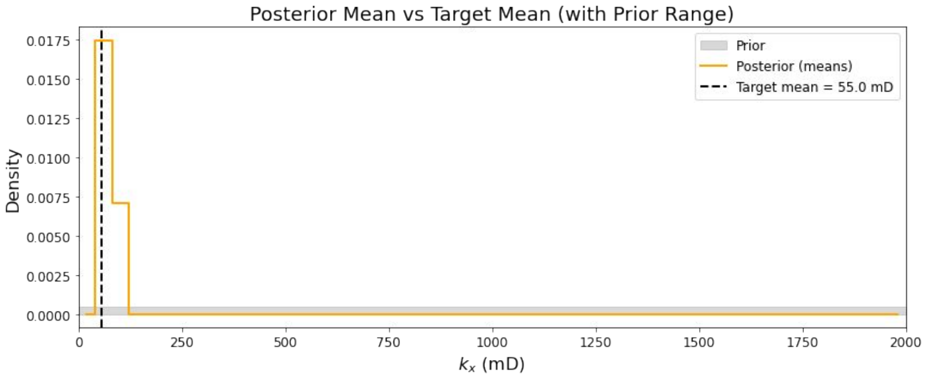

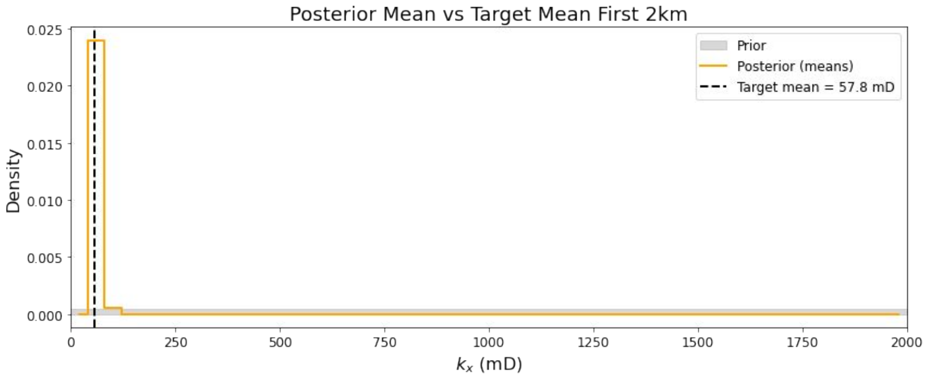

Thank you!

Multilevel pressure measurements can be used to recover the height and footprint of the plume

Machine learning enables real-time monitoring

Probabilistic modeling enables projects to be safer and more efficient

Useful for problems with fine spatial and temporal scale, but limited and uncertain actual data

Questions?