Inverse modeling of pressure data to predict CO_2 saturations using machine learning

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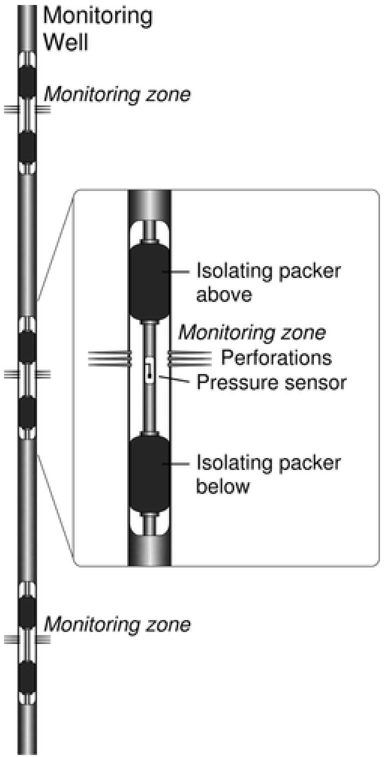
Motivation:

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

Multilevel Pressure Monitoring

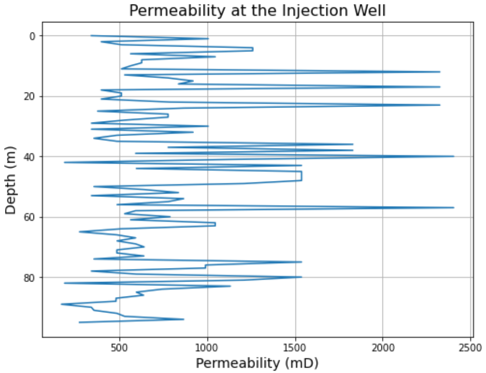
- Prior work has shown multilevel pressure transients can be used to determine the height and footprint of the CO_2 plume
- Multilevel pressure transients can also be used to history match hydrogeological models to predict future CO_2 migration
- Demonstrated using Illinois Basin – Decatur Project (IBDP) data as a case study

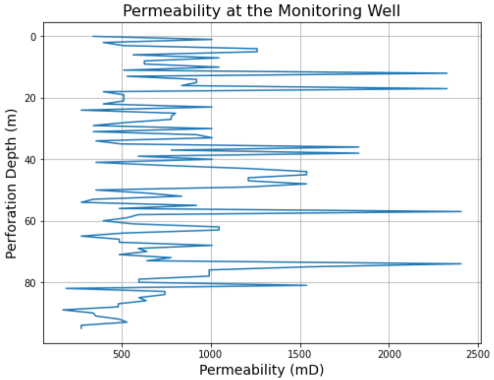


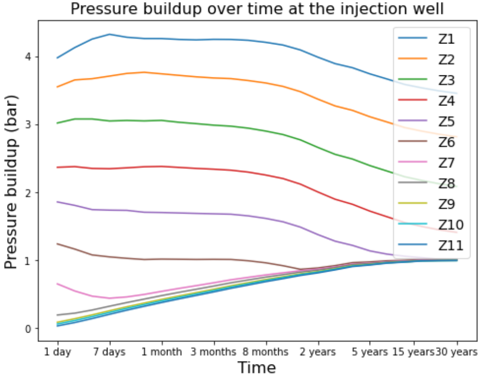
References: C. W. Strandli and S. M. Benson, "Identifying diagnostics for reservoir structure and CO_2 plume migration from multilevel pressure measurements: Diagnostics from Multilevel Pressure Measurements," *Water Resour. Res.*, vol. 49, no. 6, pp. 3462–3475, Jun. 2013, doi: 10.1002/wrcr.20285.
C.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

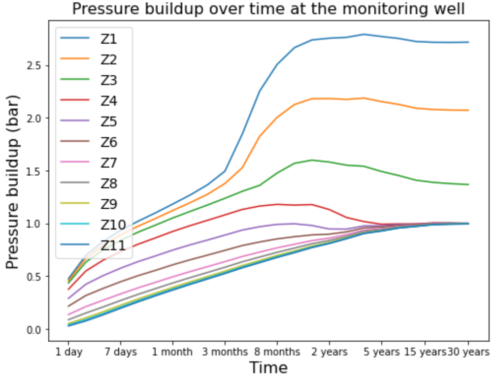
Monitoring well and injection well data

With time, buoyancy-induced migration leads to larger pressure buildups at shallower depths, upward flow of displaced brine above the plume and downward flow of displaced brine below the plume





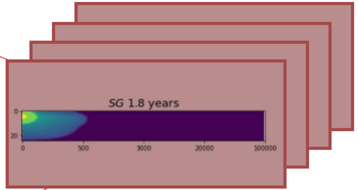




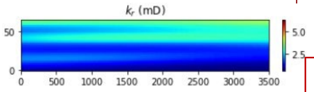
A Tale of Two Approaches

Ensemble of full saturation maps over time
Stochastic Output

If not converged iterate again



CCSNet, From Slow to Fast



Surrogate forward model in place of geologic model

Predict Pressure

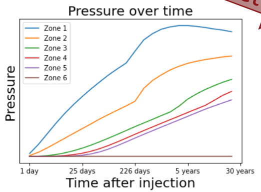
Update permeability by comparing observed and predicted ensemble

Else Finish

Injection well and monitoring well permeability, porosity, and pressure buildup over time data

Initial Guess

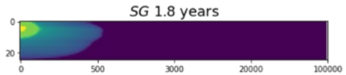
Generate Training Set



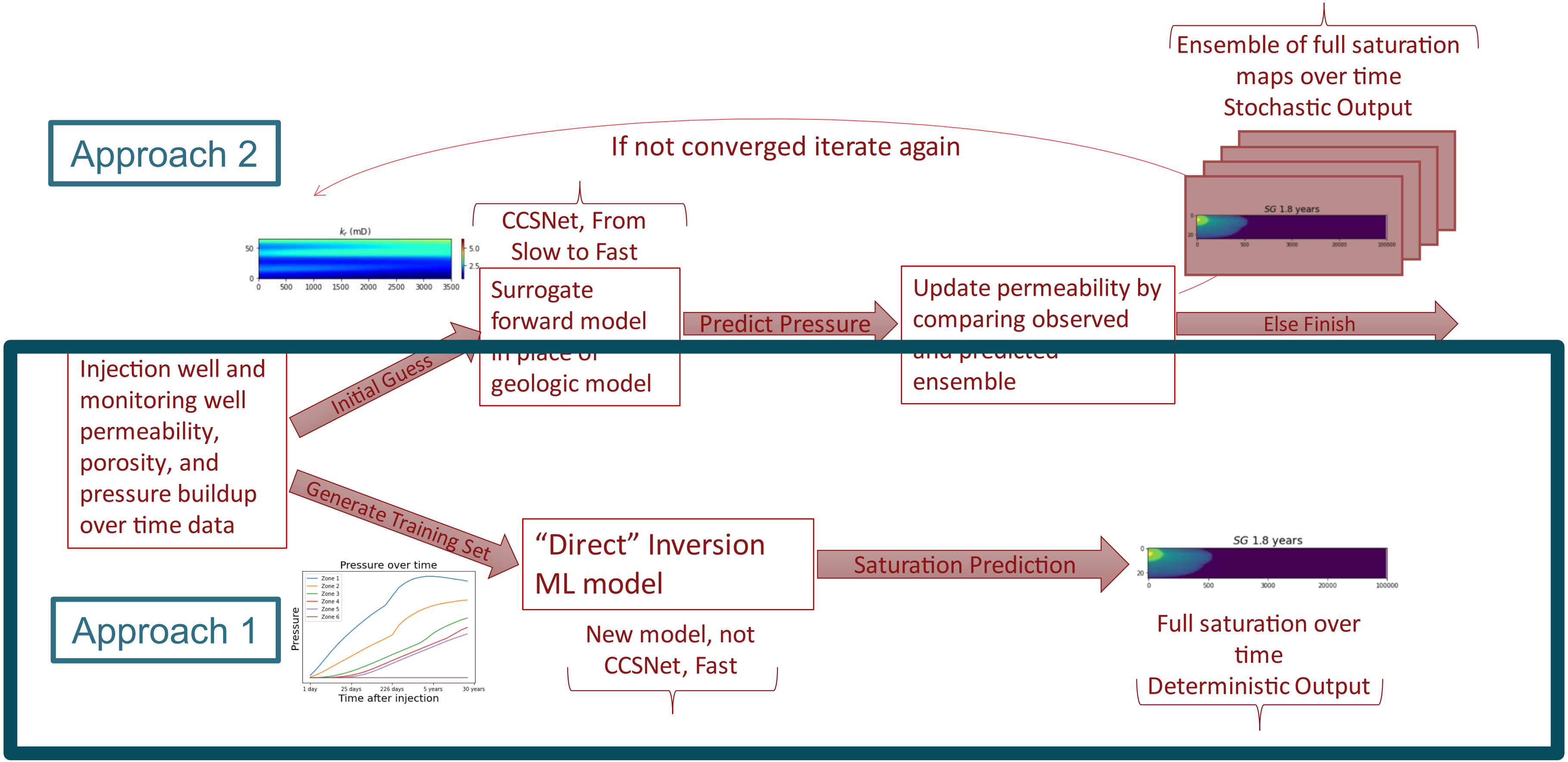
"Direct" Inversion ML model

New model, not CCSNet, Fast

Saturation Prediction



Full saturation over time
Deterministic Output


Approach 2
If not converged iterate again
Ensemble of full saturation maps over time
Stochastic Output
SG 1.8 years
k_r (mD)
CCSNet, From Slow to Fast
Surrogate forward model
geologic model
Predict Pressure
Update permeability by comparing observed
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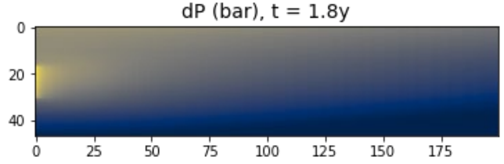
Else Finish
Injection well and monitoring well permeability, porosity, and pressure buildup over time data
Initial Guess
Generate Training Set
"Direct" Inversion ML model
Saturation Prediction
SG 1.8 years
Pressure over time
Zone 1
Zone 2
Zone 3
Zone 4
Zone 5
Zone 6
Pressure
1 day
25 days
226 days
5 years
30 years
Time after injection
Approach 1
New model, not CCSNet, Fast
Full saturation over time
Deterministic Output

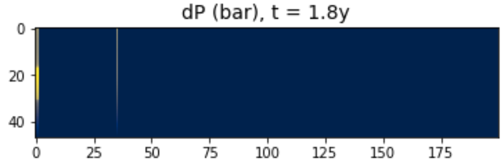
Approach 1: “Direct” Inversion

- Analogy to maximum likelihood estimation (MLE)
- Training and test sets were developed using eclipse 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

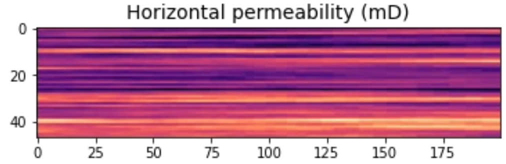
Initial data:



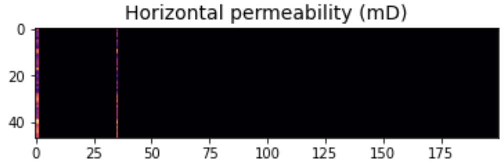
Reduced data:



Initial data:

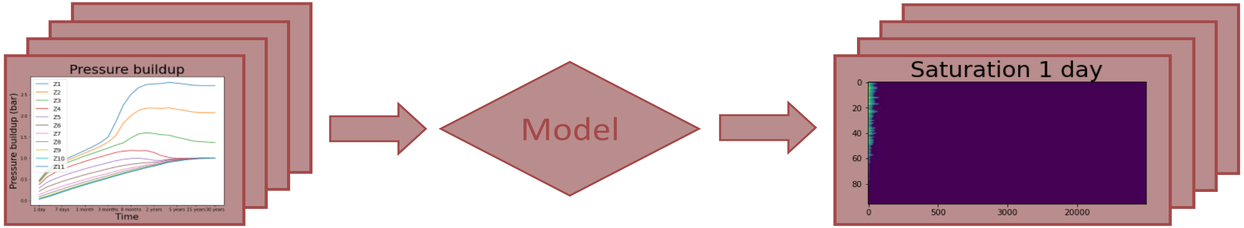


Reduced data:



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 inputs and outputs



Inputs:

Injection rate
Iso-thermal reservoir temperature
Irreducible water saturation
Perforation thickness and location
Van Genuchten scaling factor
Initial pressure
kx at the injection well and 1 monitoring well
kz at the injection well and 1 monitoring well
Porosity at the injection well and 1 monitoring well
Pressure buildup at the injection well and 1 monitoring well
Vertical gradient pressure buildup at the injection well and 1 monitoring well

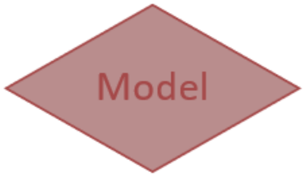
Outputs:

Full saturation map

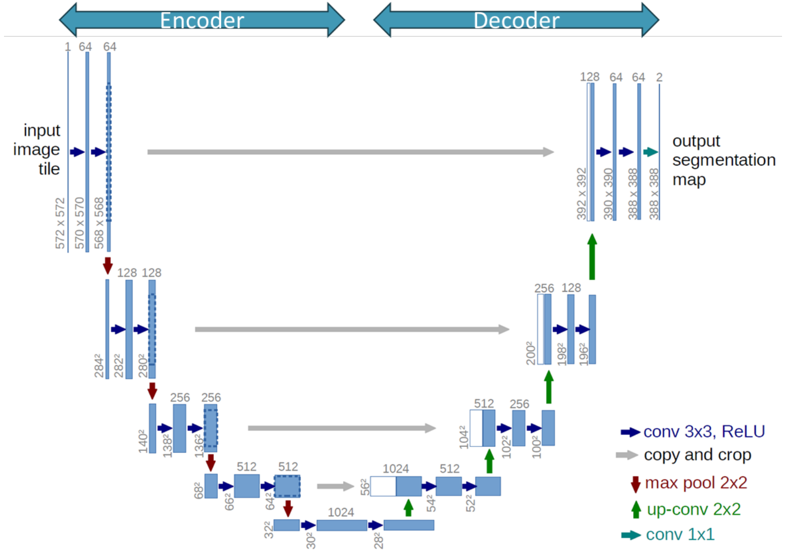
- 4500 samples in the training set, 500 samples in the test set
- 16 timesteps in one sample
- Currently always assumes the monitoring well is in the same location
- Output is a full saturation map

Model architecture selection

$$L(y, \hat{y}) = \frac{\|y - \hat{y}\|_p}{\|y\|_p}$$



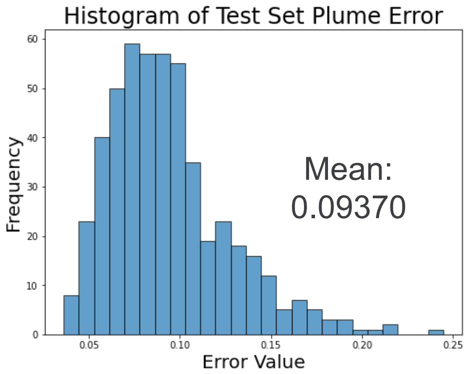
- U-Net was the best performing architecture tested for the inverse
- U-Net is ideal for localized information
- 2 million parameters in my model

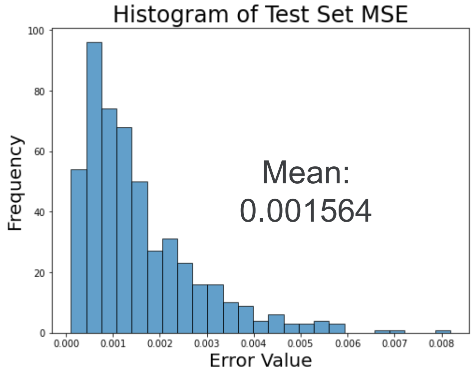


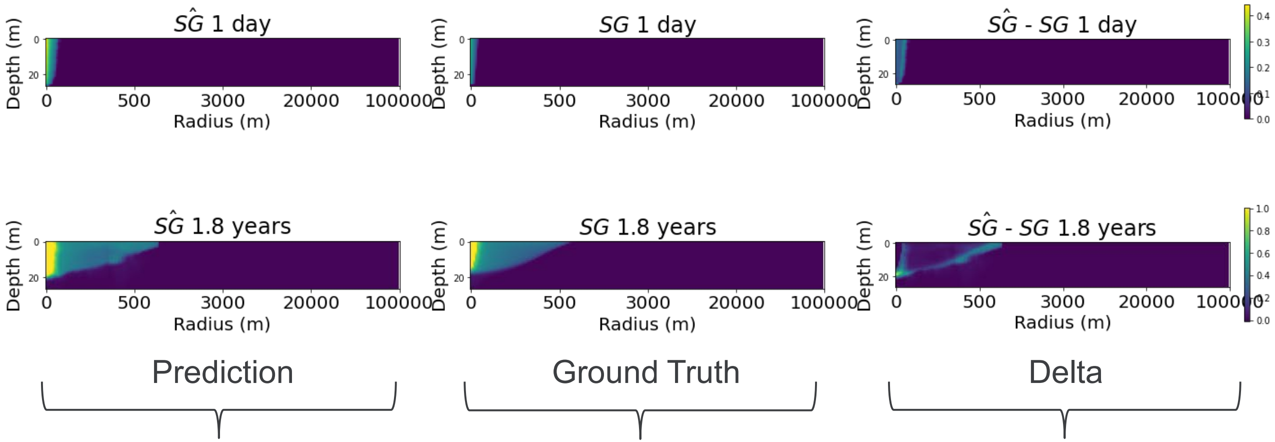
References: O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional networks for biomedical image segmentation," in Proceedings of the International Conference on Medical Image Computing and Computer-Assisted Intervention (MICCAI), Munich, Germany, Oct. 2015, pp. 234-241.

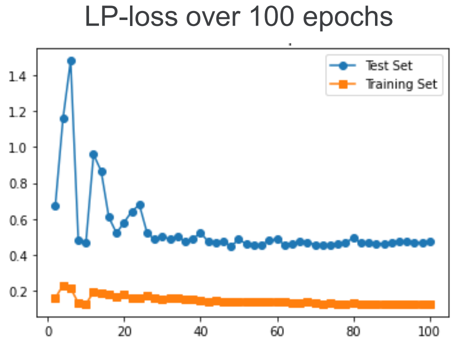
Model performance

- Good agreement for both heterogeneous and homogeneous permeability fields
- Some samples overestimate plumes and occasional samples see dispersion

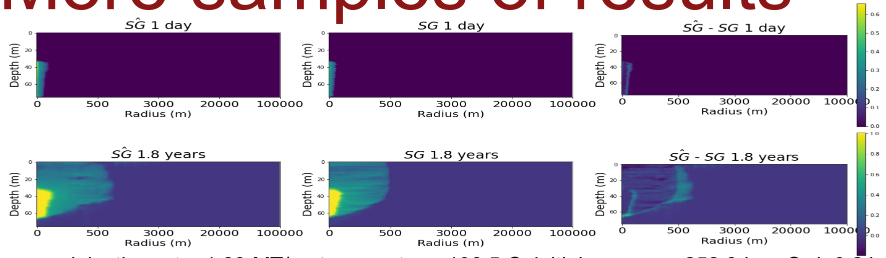




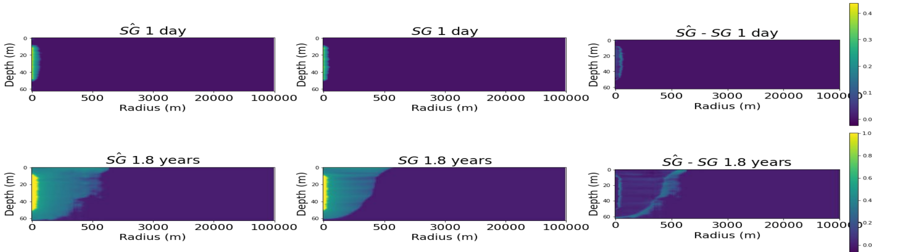




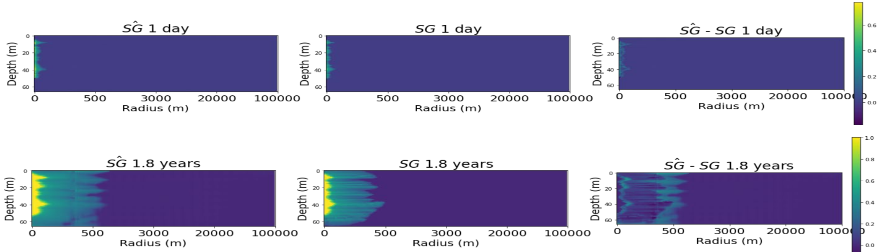
More samples of results



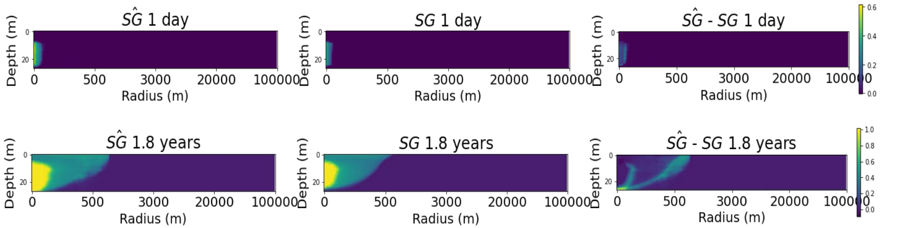
Params: injection rate: 1.83 MT/yr, temperature: 106.5 C, initial pressure: 252.8 bar, Swi: 0.24, lan: 0.42 , Mean horizontal permeability: 1110.92, Horizontal permeability standard deviation: 216.86



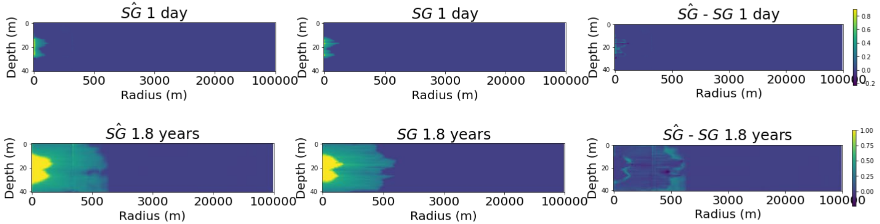
Params: injection rate: 1.34 MT/yr, temperature: 43.0 C, initial pressure: 133.9 bar, Swi: 0.23, lan: 0.61, Mean horizontal permeability: 378.01, Horizontal permeability standard deviation: 102.00



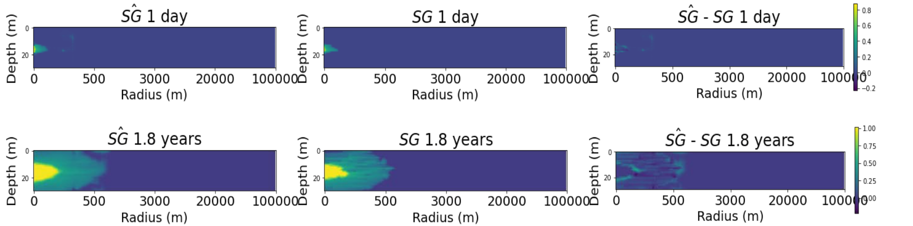
Params: injection rate: 0.76 MT/yr, temperature: 103.1 C, initial pressure: 223.5 bar, Swi: 0.24, lan: 0.40 Mean horizontal permeability: 14.71, Horizontal permeability standard deviation: 13.46



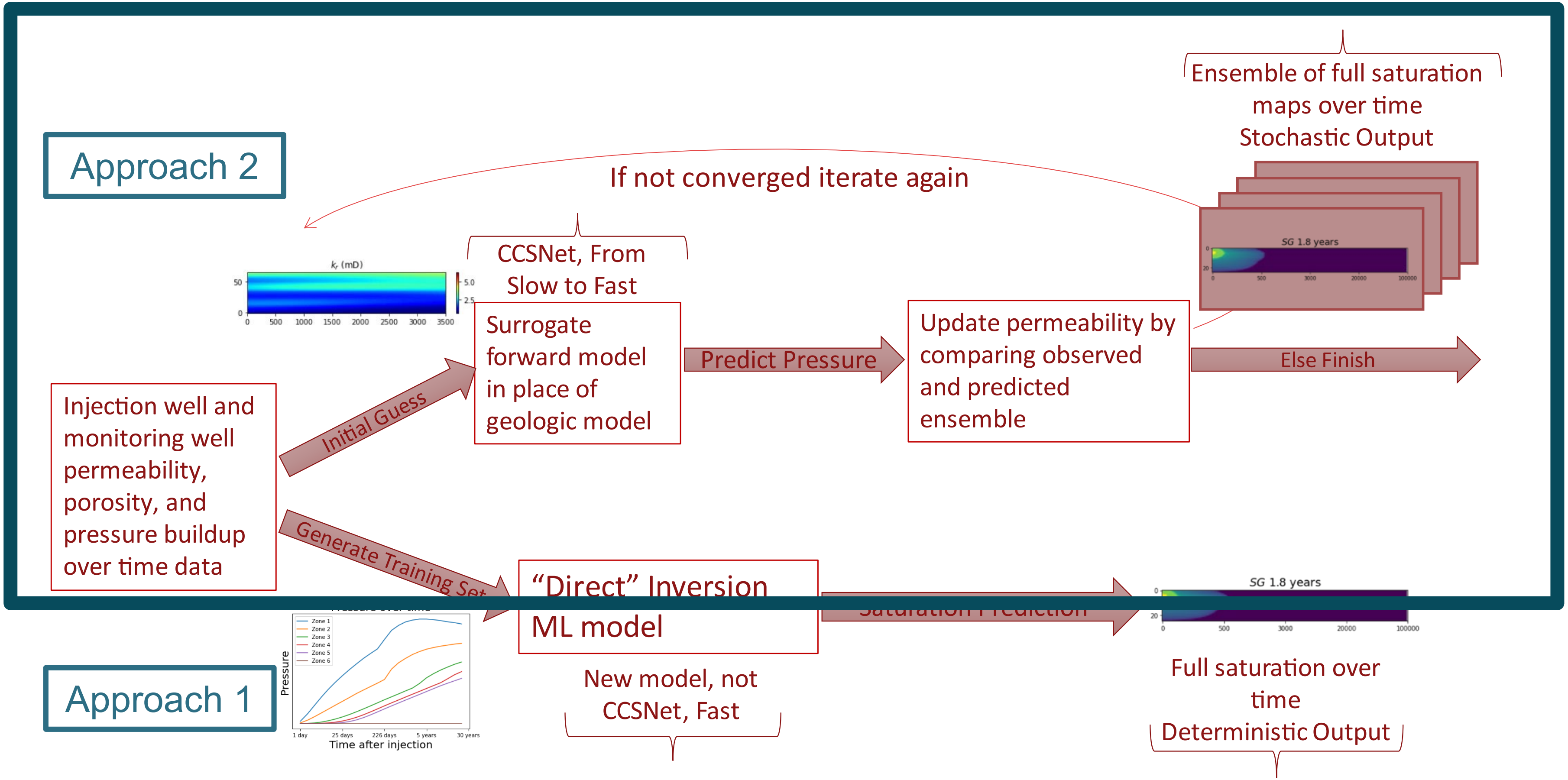
Params: injection rate: 0.79 MT/yr, temperature: 130.6 C, initial pressure: 291.7 bar, Swi: 0.13, lan: 0.42, Mean horizontal permeability: 1395.64, Horizontal permeability standard deviation: 0.00



Params: injection rate: 1.96 MT/yr, temperature: 102.5 C, initial pressure: 290.6 bar, Swi: 0.16, lan: 0.55, Mean horizontal permeability: 70.74, Horizontal permeability standard deviation: 122.20



Params: injection rate: 0.86 MT/yr, temperature: 141.6 C, initial pressure: 251.4 bar, Swi: 0.18, lan: 0.55, Mean horizontal permeability: 172.93, Horizontal permeability standard deviation: 190.05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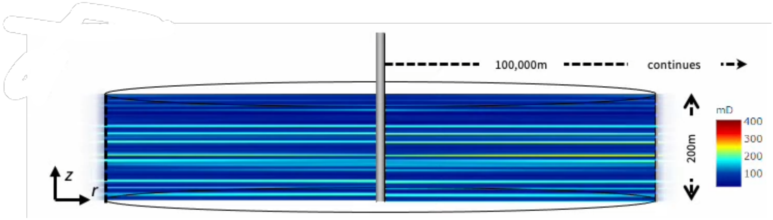
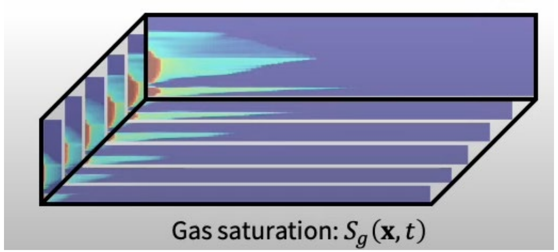
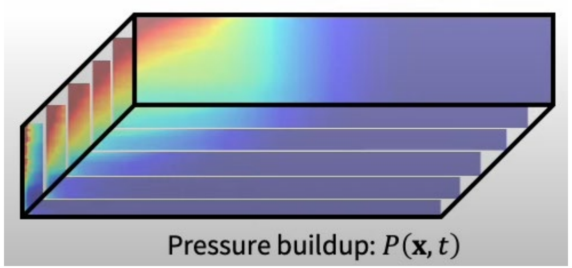
Approach 2: History matching with ES-MDA

- ES-MDA (Ensemble Smoother with Multiple Data Assimilation) is an iterative scheme
- CCSNet replaces a computationally intensive geologic realization in the forward model step
- Use the CCSNet 2D radial U-FNO forward model which uses **full horizontal permeability, vertical permeability, and porosity fields** to predict either **pressure or saturation**
- Use ES-MDA to update permeability and porosity maps using observed pressure data
- After all assimilation steps, use the final updated permeability and porosity maps to predict saturation using CCSNet







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Full workflow

Start with an initial guess conditioned to injection well and monitoring well data with correct mean and standard deviation

Add Gaussian noise to observed pressure data and the initial guess to generate an ensemble

Begin ES-MDA loop:

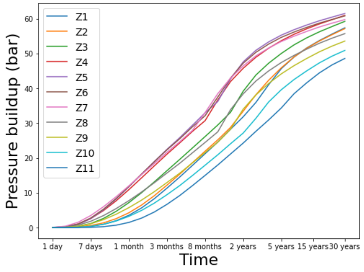
- Run surrogate for the forward model using the initial guess and get an ensemble of pressure predictions
- Calculate Kalman gain using covariances
- Calculate the innovation comparing true observed pressure measurements with pressure measurement predictions generated using the permeability ensemble
- The update to permeability is calculated by multiplying the Kalman gain and the innovation which is then added to the ensemble

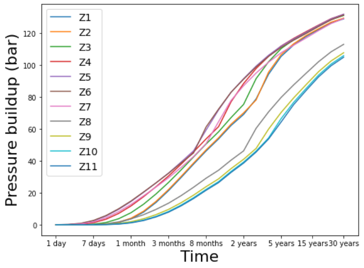
Use final permeability maps to generate an ensemble of saturation maps after multiple assimilations

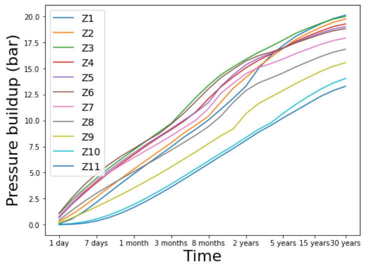
Example problems

Use sequential Gaussian simulation conditioned to 2 vertical columns of data with noise and the mean and standard deviation of the real permeability map to generate an ensemble of initial guesses for horizontal permeability, vertical permeability and porosity

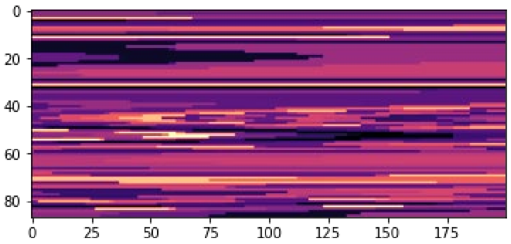
Test set observed pressure data at the monitoring well

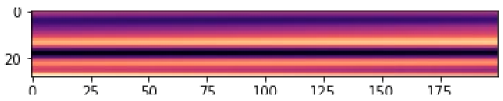


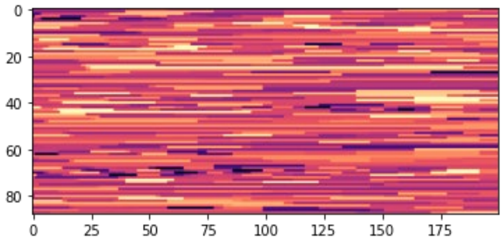




Test set ground truth horizontal permeability map

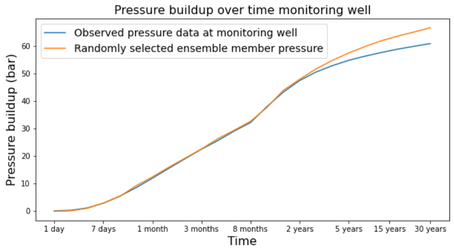


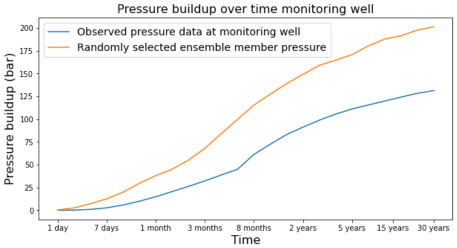


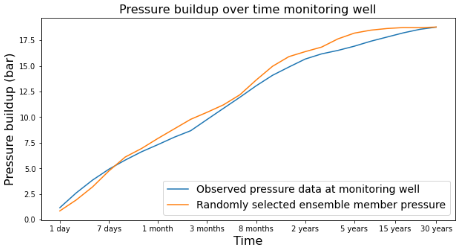


History matching with ES-MDA results

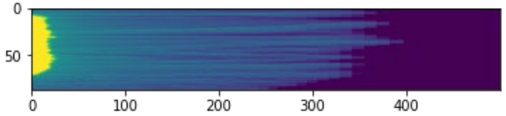
Comparing ensemble member pressure and observed data

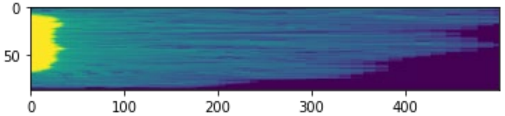




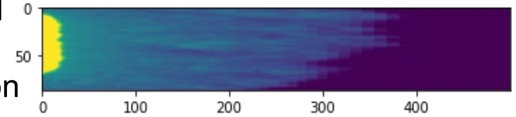


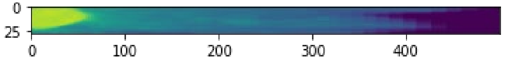
Test set ground truth saturation

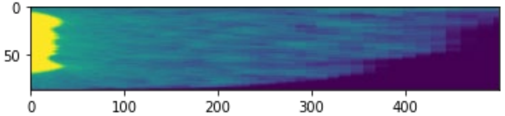




Randomly selected ensemble member saturation prediction



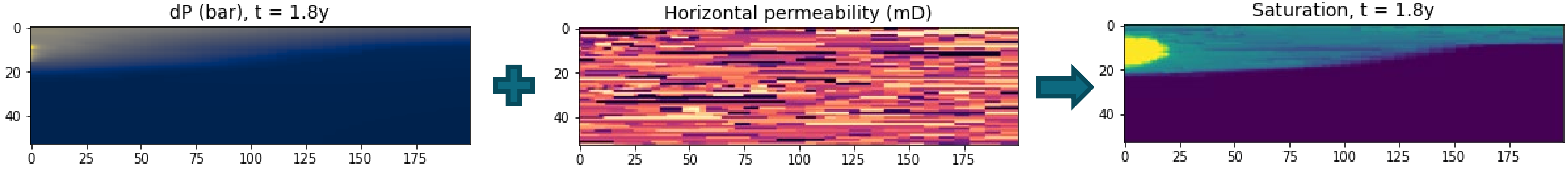




Understanding uncertainty

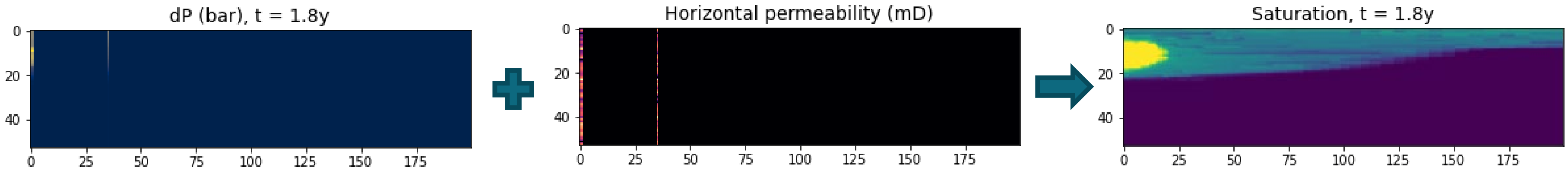
$$\underbrace{\boxed{\frac{\partial(\phi\sum_p S_p\rho_p X_p^{CO_2})}{\partial t}}}_{LHS} = \underbrace{\boxed{-\nabla\cdot[\sum_p X_p^{CO_2}(-k\frac{k_{r,p}(S_p)\rho_p}{\mu_p}(\nabla(P+P_c(S_p))-\rho_p g))]+q^{CO_2}}}_{RHS}$$

Can we mathematically prove that this is unique using the governing equation from eclipse:



Instinct is yes

What about this:



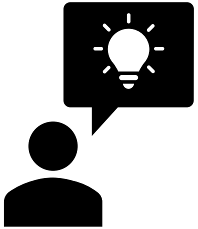
Instinct is no, what formal implications about uncertainty and uncertainty quantification are there if this is the case

Looking Ahead

We're not ready to call one approach better than the other, both can produce good visual agreement

We're interested in how much less data can we give corresponding to what trade-off in performance

We want to make this work as useful as possible for real applications – including understanding uncertainty



Thank You

Results – Binary Classification Loss Function

Threshold saturation >=0.05 = 1, otherwise 0

Inspired by desire to handle dispersion

Experimented with image segmentation to track plume envelope over time with contours using quick shift

$$l_n = -w_n \left[y_n \cdot \log \sigma(x_n) + (1 - y_n) \cdot \log(1 - \sigma(x_n)) \right]$$