Oak Ridge National Laboratory

Accurate and Timely Forecasts of Geologic Carbon Storage using Machine Learning Methods

Dan Lu (lud1@ornl.gov)

Scott Painter (ORNL)

Nicholas Azzolina (EERC, UND)

Matthew Burton-Kelly (EERC, UND)

ORNL is managed by UT-Battelle, LLC for the US Department of Energy

U.S. DEPARTMENT OF ENERGY

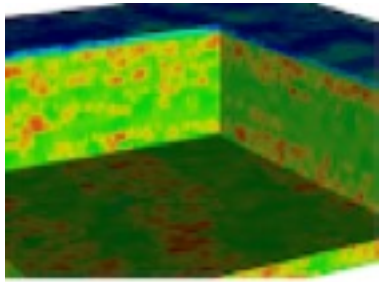
Summary of this work

- Carbon capture and storage (CCS) is one approach to help mitigate global warming.
- However, dynamics of the injected CO_2 plume is uncertain.
- This study proposes a learning-based inverse-free prediction method that can accurately and rapidly forecast CO_2 movement and distribution with uncertainty quantification based on limited simulation and observation data.
- The machine learning (ML) techniques include dimension reduction, multivariate data analysis, and Bayesian learning.
- The outcome is expected to provide CO_2 storage site operators with an effective tool for timely and informative decision making.

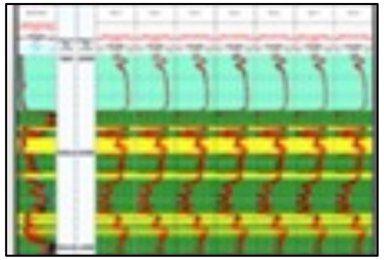
Conceptual Goal

Info we have

Uncertain permeability



Monitoring data
from wells

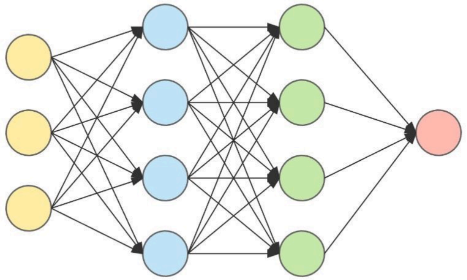


Physics-based model simulation

$$\frac{\partial}{\partial x}\left[\lambda_o\left(\frac{\partial p_o}{\partial x}-\gamma_o\frac{\partial z}{\partial x}\right)\right]=\frac{\partial}{\partial t}\left[\frac{\phi S_o}{B_o}\right]$$

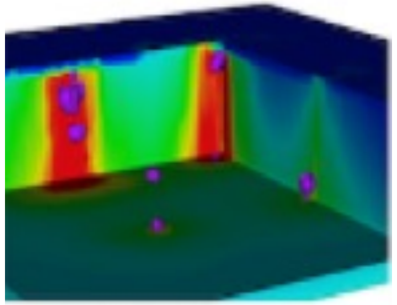
$$\frac{\partial}{\partial x}\left[\lambda_w\left(\frac{\partial p_w}{\partial x}-\gamma_w\frac{\partial z}{\partial x}\right)\right]=\frac{\partial}{\partial t}\left[\frac{\phi S_w}{B_w}\right]$$

Machine learning methods

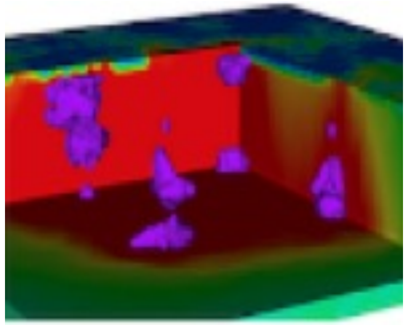


Results we want

CO_2 plume and Pressure
movement in the future



5year

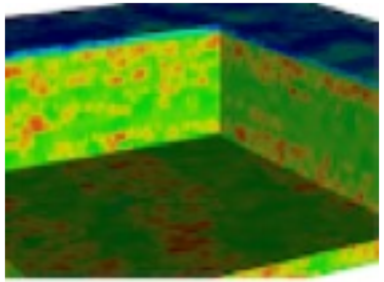


10year

State-of-the-Art: Inverse Modeling

Iterative Inverse modeling

Updated permeability



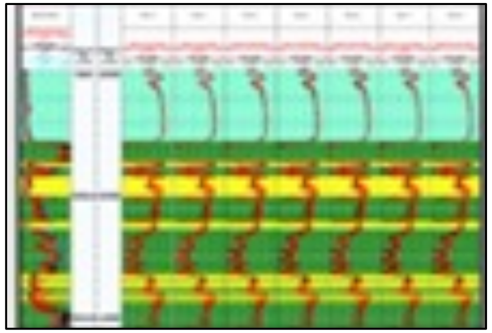
Reservoir simulation till current time

$$\frac{\partial}{\partial x}\left[\lambda_o\left(\frac{\partial p_o}{\partial x}-\gamma_o\frac{\partial z}{\partial x}\right)\right]=\frac{\partial}{\partial t}\left[\frac{\phi S_o}{B_o}\right]$$

$$\frac{\partial}{\partial x}\left[\lambda_w\left(\frac{\partial p_w}{\partial x}-\gamma_w\frac{\partial z}{\partial x}\right)\right]=\frac{\partial}{\partial t}\left[\frac{\phi S_w}{B_w}\right]$$

Fit is poor

Data matching



Fit is accepted

Challenges:

- Iterative inverse modeling;
- Time: 10,000 runs * 10 hours;
- Repeat the process for new data; incapable of automated and fast updating;
- Hard to consider various and multiscale uncertainty;
- An ill-posed problem causing poor prediction.

Forward model prediction

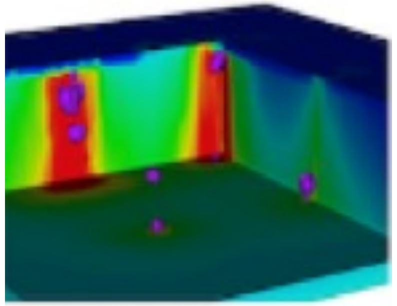
Reservoir simulation in future time

$$\frac{\partial}{\partial x}\left[\lambda_o\left(\frac{\partial p_o}{\partial x}-\gamma_o\frac{\partial z}{\partial x}\right)\right]=\frac{\partial}{\partial t}\left[\frac{\phi S_o}{B_o}\right]$$

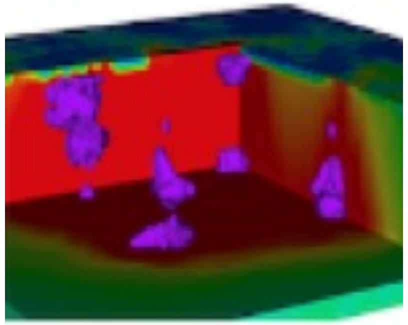
$$\frac{\partial}{\partial x}\left[\lambda_w\left(\frac{\partial p_w}{\partial x}-\gamma_w\frac{\partial z}{\partial x}\right)\right]=\frac{\partial}{\partial t}\left[\frac{\phi S_w}{B_w}\right]$$

Forecast

CO_2 plume and Pressure movement in the future



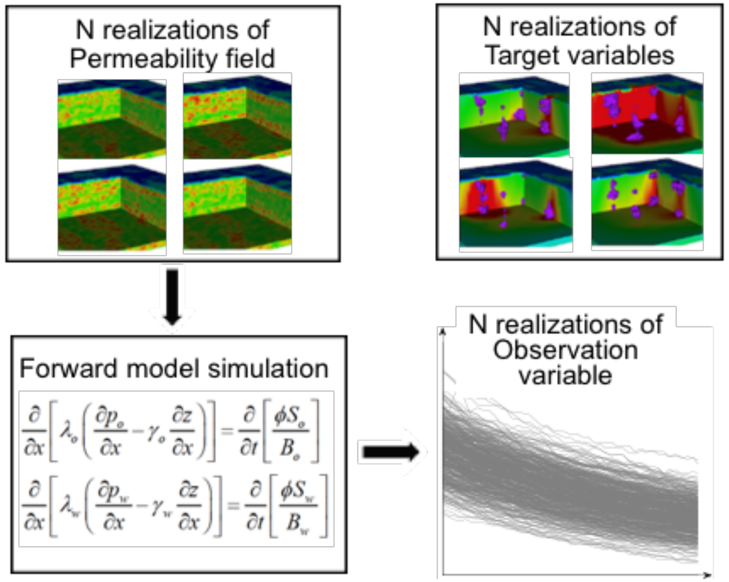
5year



10year

Our approach: Learning-based Inversion-free Prediction (LIP)

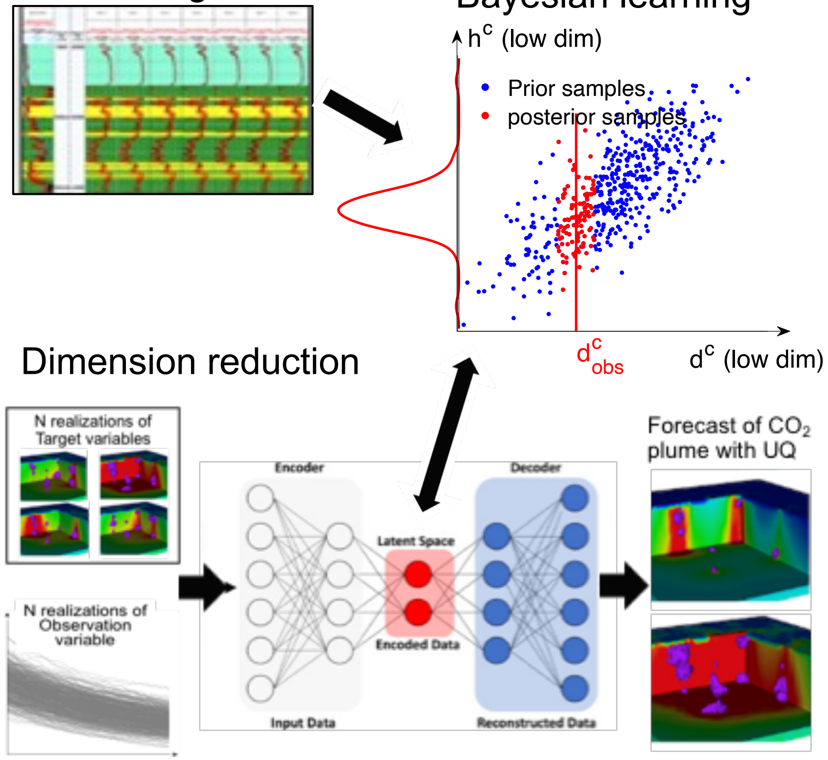
Reservoir simulations



Offline simulation

- Fully parallelizable
- Time: one forward model run
- Considers various uncertainty

Machine Learning (ML)



Online learning

- ML techniques (dimension reduction and Bayesian learning)
- Time: <1min and robust solution

Deploy

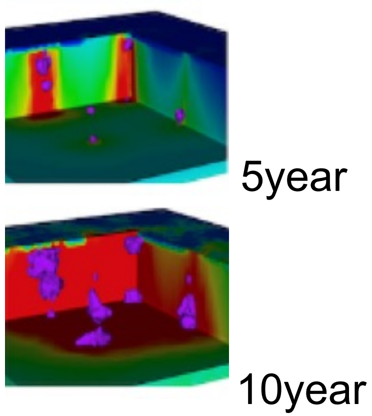
Observations

↓

Trained ML model

↓

Forecast with uncertainty



Deploy an automated and timely forecast workflow

Oak Ridge National Laboratory

Experiment

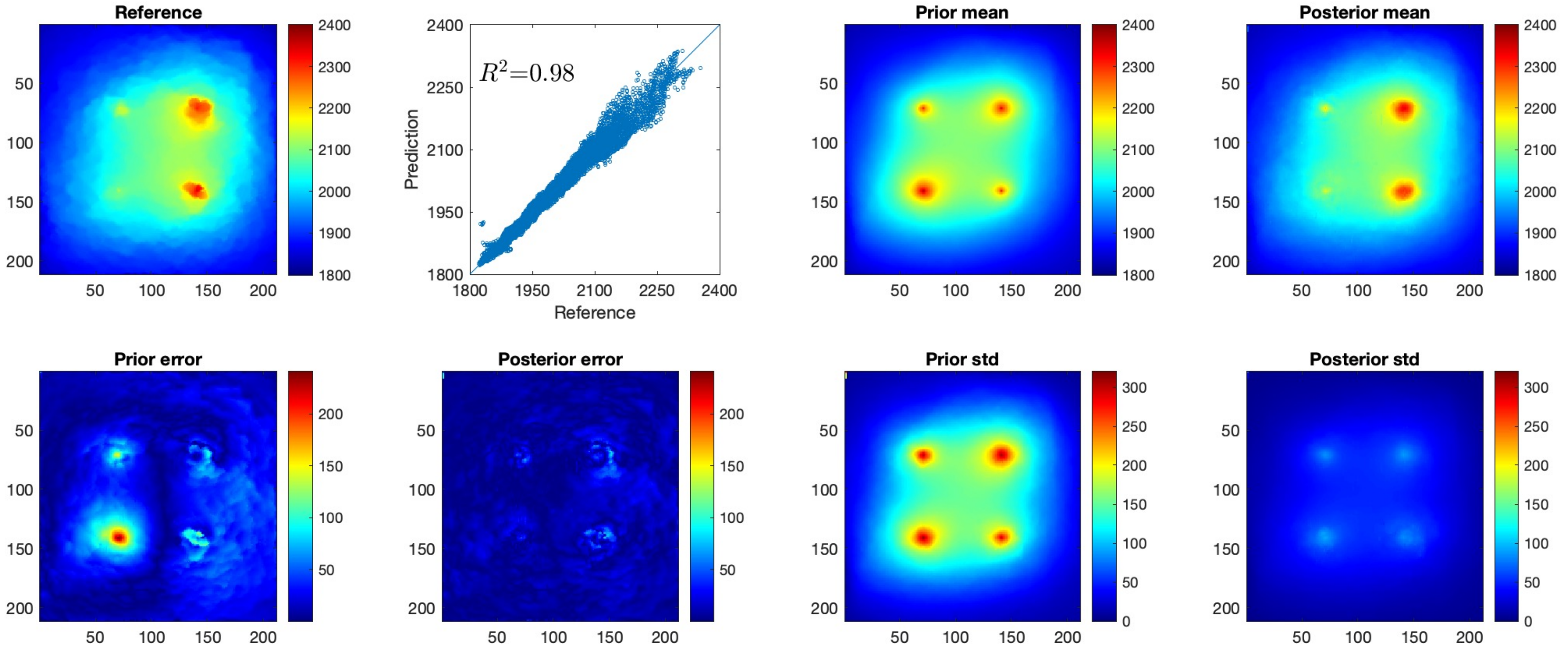
- Data source: 100 samples of CO_2 pressure in the 3D domain simulated from the 100 geomodels with low-, mid-, and high-porosity.
- Problem: Use CO_2 pressure measurements at layer 3 of four injection wells to predict the spatial distribution of pressure in layer 3 after 10 years of injection.

Target variable (h): CO_2 pressure map at year 10, 211 * 211 grid cells = 44521 variables.					
Observation variable (d): CO_2 pressure observations from the 4 injection wells	Case I	Case II	Case III	Case IV	Case V
	5 years of observations	6 years of observations	7 years of observations	8 years of observations	9 years of observations

- Objective: Evaluate LIP method's accuracy, efficiency, and capacity to incorporate streaming observations to improve predictions.
- Synthetic study: Choose one sample as synthetic "truth" and the other 99 samples for learning. We had 3 choices of synthetic "truth" corresponding to low-, mid-, and high-porosity datasets to evaluate the method's robustness and generalizability.

Results: Fast and accurate prediction with UQ

- Results indicate that our method can effectively incorporate observations to improve prediction accuracy and reduce predictive uncertainty.
- The analysis takes about **2 sec** after we have the 100 simulation samples.



- Prior: results based on the 99 prior simulation samples.
- Posterior: results after incorporating observations using our method.

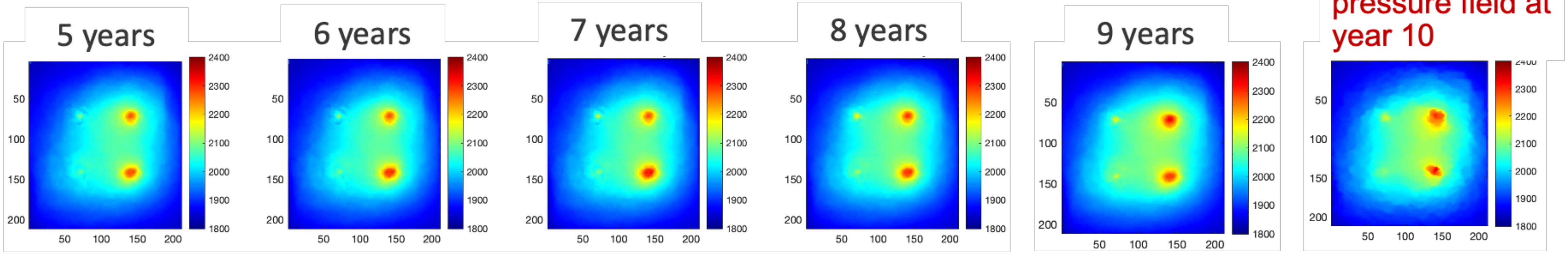
- Targe variable: CO_2 pressure plume in layer 3 after 10 years injection.
- Observations: 9 years of pressure measurements from four injection wells in layer 3.

Results: Timely forecasts via rapid measurements integration

- Results indicate that our method can effectively assimilate observation streams to gradually improve predictions.
- The data assimilation does not require additional reservoir simulations which promises the incorporation of real-time measurements for timely forecasts in field operations.

Predicted pressure fields at year 10 using observations from wells up to 5, 6, 7, 8, 9 years

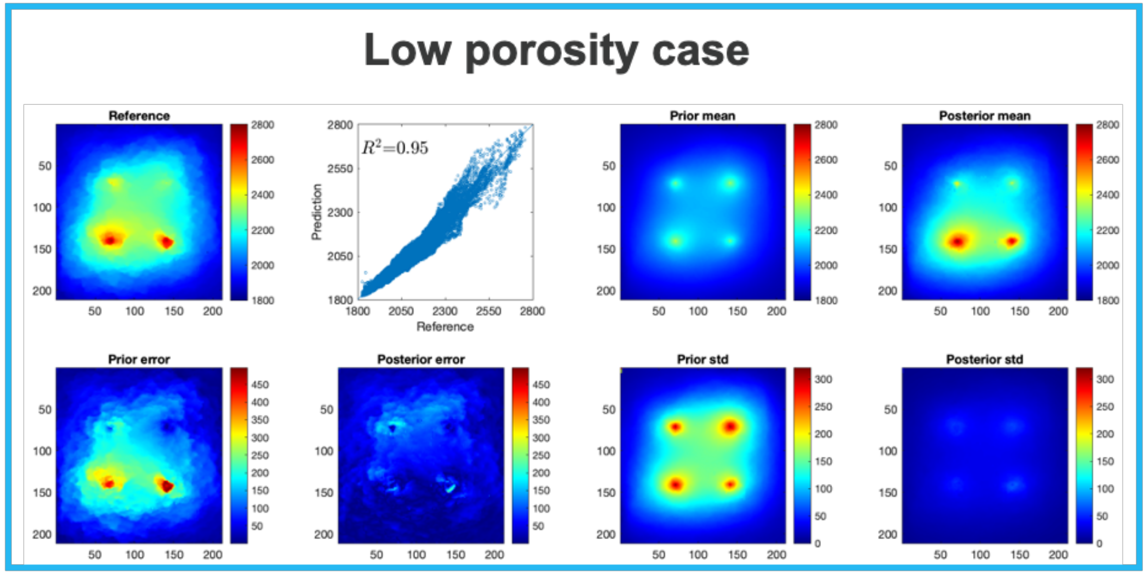
Synthetic "truth" pressure field at year 10

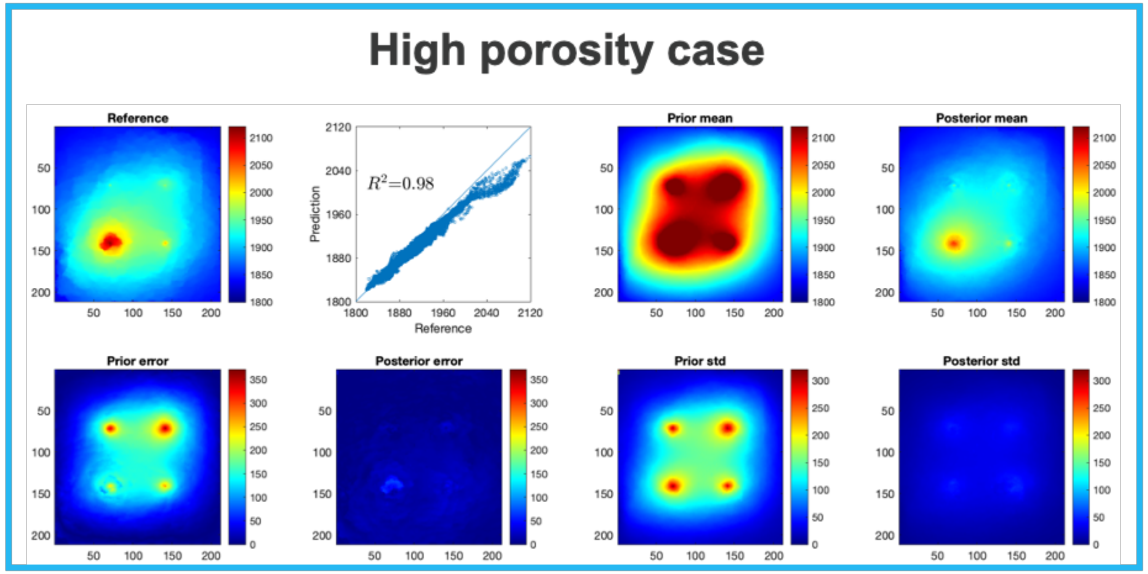


Incorporating observation streams to improve prediction

Results: Robust prediction performance

- We applied our method to several synthetic datasets with different porosities.
- All the numerical experiments indicate that our method can effectively incorporate observations to improve prediction accuracy and reduce predictive uncertainty, giving robust performance.





Impacts and Future work

- The proposed LIP method has potential to fundamentally change how real-time decisions are made about CO_2 storage operations.
- Bypassing the traditional workflow of history matching and then forward simulations, LIP makes direct forecasting by learning observation-prediction relationship and provides continually updating forecasts of CO_2 distributions from streaming observations, thus providing operators with earlier warning of off-normal behavior and more time to implement mitigation measures.
- In the future, we will apply LIP to actual measurements from the field and deploy it to CO_2 storage operators for real-time decisions.