

## Background

### Statement of problem:

**Can we confidently detect small leaks in large areas with a limited number of sensors?**

Many current challenges in energy require predicting the coupled behavior of multiple subsurface systems (i.e., beyond the reservoir), each of which may be governed by different physics and each with its own heterogeneity and uncertainty. This first aspect requires new simulation strategies that can address physics beyond simple porous flow; and the second aspect means these strategies must be rapid to allow for probing behavior stochastically.

One common challenge involves detection of small leaks in large areas, as shown in the example below from CO storage. Detecting these types of leaks will require new strategies that fuse simulation and monitoring. In this work, we are developing a platform to address this challenge. Predicting the anticipated signals from such leaks requires couples the physics of porous flow to the physics of flow in fracture networks and partially completed wellbores.



### Approach:

The development of efficient and accurate approaches to provide decision support for subsurface energy-related challenges requires the coupling of three components:

1. detailed knowledge of **subsurface energy-related processes**,
2. computationally efficient and accurate science-based **full-physics modeling** strategies, and
3. novel **statistical and machine learning** approaches to extract fundamental and essential relationships from full-physics simulations.

### Why this research is being done at Los Alamos National Laboratory

LANL provides a unique research environment where all three necessary components discussed above coexist. LANL also has a long history of pooling resources with other institutions to tackle subsurface energy related challenges (e.g., NETL, PNNL, LBNL, LLNL). In this poster, we present approaches to solve subsurface energy related challenges that **integrate these three components**.

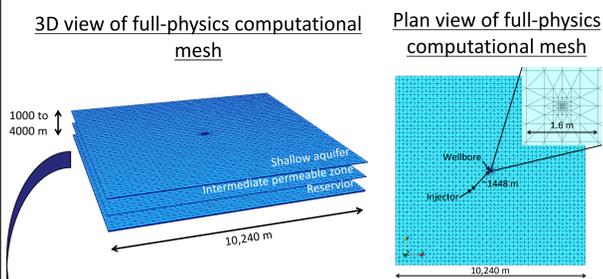
### Tools we are developing and using to address complex, subsurface energy-related challenges:

1. FEHM (fehm.lanl.gov) – Multi-component, multi-phase subsurface flow and transport simulator
2. DFNWorks (http://www.lanl.gov/.../dfnworks/index.php)– Discrete fracture network generation code
3. MATK (matk.lanl.gov)– Python package for model analysis and distributed, concurrent model execution

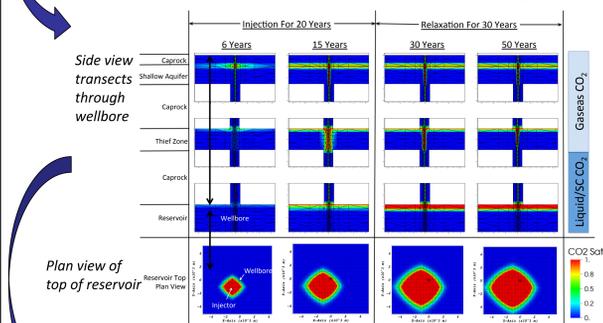
## Approach 1: Response surface modeling of leakage along cemented wellbores

Dylan Harp, Rajesh Pawar, Bill Carey, and Carl Gable

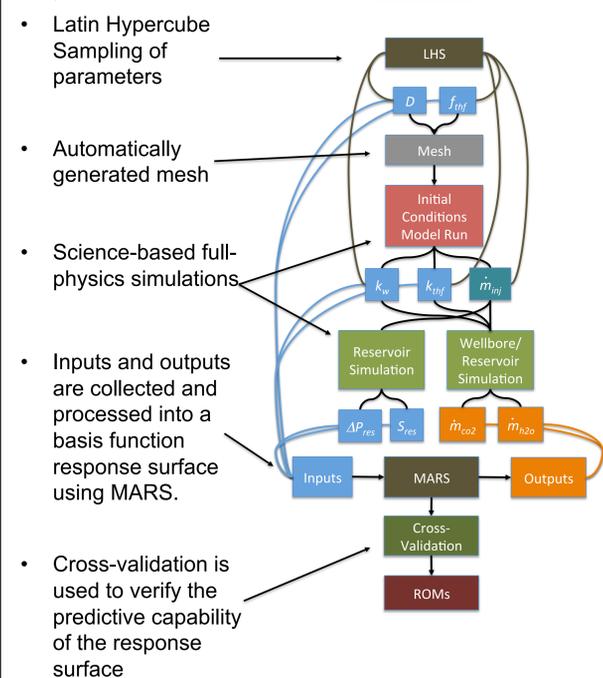
- **Abandoned wellbore leakage** is one of the primary risks in CO<sub>2</sub> sequestration.
- **Full-physics simulations** of multi-phase, multi-component brine and CO<sub>2</sub> are **computationally expensive**.
- We use **Multivariate Adaptive Regression Splines (MARS)** to **extract the fundamental relationships** between input parameters and brine and CO<sub>2</sub> leakage into **basis function response surfaces**.



Example simulation of full-physics simulations of CO<sub>2</sub> leakage



Flow diagram of response surface generation

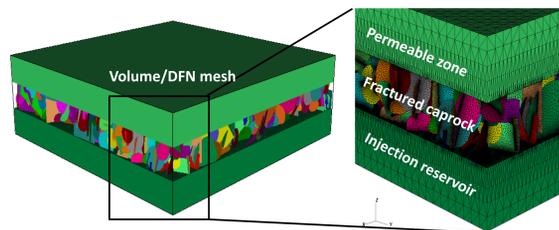


- Latin Hypercube Sampling of parameters
- Automatically generated mesh
- Science-based full-physics simulations
- Inputs and outputs are collected and processed into a basis function response surface using MARS.
- Cross-validation is used to verify the predictive capability of the response surface

## Approach 2: Improved modeling of CO<sub>2</sub> flow in fractures

Natalia Makedonska and Rajesh Pawar

- **Fractures provide dominant transport pathways** in many scenarios such as fractured caprock above CO<sub>2</sub> injection reservoirs. **Discrete Fracture Networks (DFNs)** allow us to model fracture flow more accurately and realistically.
- **Coupling DFN model with continuum approach** to study CO<sub>2</sub> flow is a computationally complex system, which provides **an example of risk quantification**.



### Merging Discrete Fracture Network (DFN) and Volume Mesh

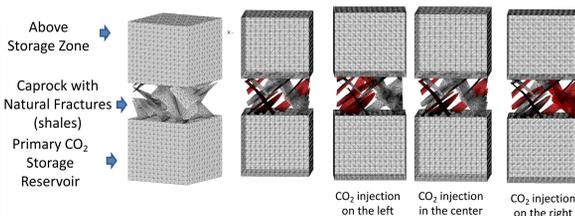
- The DFN is generated using dfnWorks simulation tool
- The 2D fracture network is meshed by conforming Delaunay triangulation (LaGrIT)
- The simulation domain size can be extended up to kilometers
- Different fracture densities can be considered ( $0.1 < P_{32} < 0.6$ )

### Application to Characterize Caprock Leakage

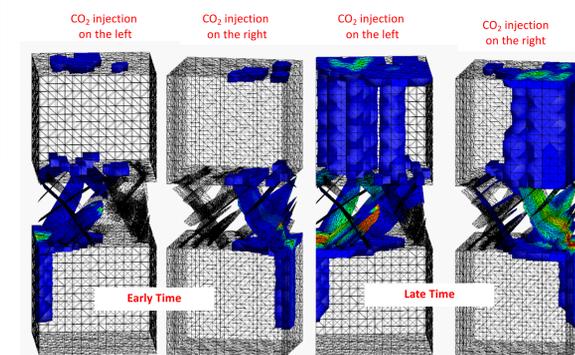
Realistic simulations, representing not only geologic complexity but also operational conditions

### Important insights

Not all fractures contribute to flow  
Operational scenario and plume evolution in reservoir affect fluid migration



### Example of CO<sub>2</sub> Saturation at Earlier and Later Times After CO<sub>2</sub> Injection

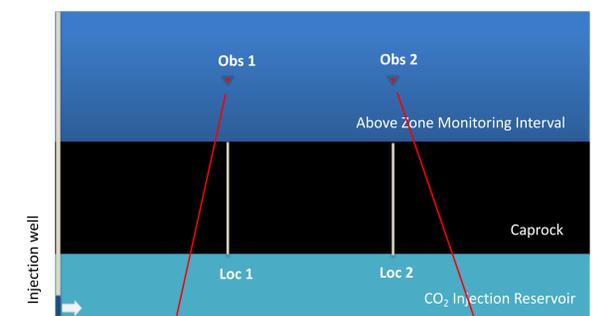


## Approach 3: Using machine learning to detect CO<sub>2</sub> leakage

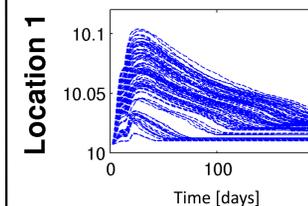
Youzuo Lin, Dylan Harp, and Rajesh Pawar

- **Machine learning** is a powerful tool to effectively detect unknown pattern from datasets.
- We employ machine-learning to **detect the leak location** of the stored CO<sub>2</sub>.
- We generate training datasets using **FEHM** to simulate the actual leaks of CO<sub>2</sub>.
- Our detection algorithm is trained with pressures resulting due to leaks at 2 locations only, but **can detect leakage from any location in the caprock based on monitoring observations at 2 locations**.

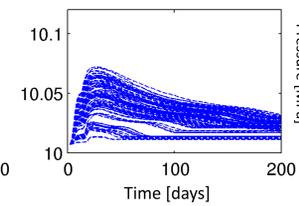
### Model and Training Data



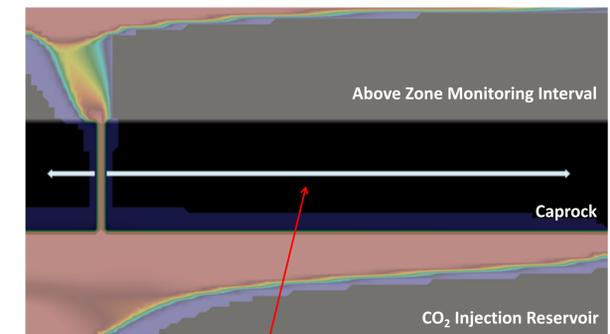
### Observation 1



### Observation 2

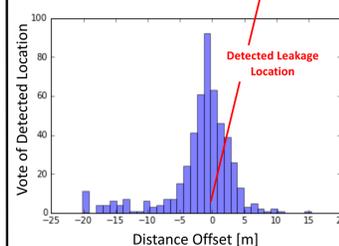


### Detection Test



### Methods and Results

#### Example histogram of error in location estimation



- We employ the above training data to train our supervised learning methods.
- 500 unknown leak cases are created by varying the CO<sub>2</sub> injection rate.
- Prediction error is measured by Mean Absolute Error (MAE):

$$MAE = \frac{\sum_{i=1}^n |y_i^{gt} - y_i^{pred}|}{n}$$

- Overall MAE  $\approx$  3 grid points.
- Detection error:
  - > within 1 grid point: **41.4%**
  - > within 2 grid points: **60.6%**
  - > within 3 grid points: **72.8%**

## Acknowledgments

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