Derisking Geological Storage w/ simulation-based seismic monitoring design & machine learning

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Challenges monitoring Geological CO₂ Storage in Saline Aquifers

Regulators & general public require transparency & assurances that supercritical CO₂ stays put in the storage complex

▶ reservoir simulations alone are uncertain due to large variability permeability
▶ risk profile storage & containment highest at start & at end
▶ there is a need for reproducibility

Develop low-cost time-lapse seismic system to monitor CO₂ plumes

▶ maximally captures information collected over many decades
▶ low-cost by being sparse w/o insisting on replication of surveys
▶ attains accuracy needed to detect early onset leakage automatically
▶ collect 1–2 orders of magnitude cheaper over a century

Systematic assessment of risks using techniques from uncertainty quantification.
Risk profiles

Uncertainties & risk storage model

- *highest at start*
- diminish when *more* time-lapse data is *collected*

**Containment risk increases**

- w/ *amount* of CO\(_2\) stored
- w/ *size area* undergoing *pressure* changes

There can be **NO lapse in monitoring** because

- any lack of *transparency* conformance
- will lead in loss in *confidence* by the *general public*

High-fidelity time-lapse information needs to be collected regularly over long periods of time!
Workflow simulation-based seismic monitoring design


proxy model
wavespeed, density

reservoir model
permeability, porosity

CO₂ dynamics
concentration, pressure

time-lapse models
wavespeed, density

time-lapse imaging

class activation mapping
deep neural classifier
time-lapse (diff) data

accuracy = 86.29%
Rock property conversion
Workflow

- Proxy model
  - Wavespeed, density
- Reservoir model
  - Permeability, porosity
- Leakage
- Regular
- Two-phase flow
- Pressure induced fault
- CO₂ dynamics
  - Concentration, pressure
- Time-lapse (diff) data
- Time-lapse (imaging)
- Deep neural classifier
- Class activation mapping

Accuracy = 86.29%
Conversion

velocity $\implies$ permeability

Converted with $v_p$ $1$km/s $\uparrow \Rightarrow K$ $1.63$mD $\uparrow$

- $K$ permeability
- $v_p$ compressional wavespeed

Three main geologic sections:

- secondary seal – Haisborough group  
  (blue, > $300$m, permeability $15 - 18$mD)

- primary seal – Rote Halite member  
  (black, $50$m, permeability $10^{-4} - 10^{-2}$mD)

- saline aquifer – Bunter sandstone  
  (red, $300 - 500$m, permeability $> 200$mD)

Values taken from Strategic UK CCS Storage Appraisal Project
Conversion

**permeability → porosity**

Kozeny-Carman relationship:

\[
K = \phi^3 \left( \frac{1.527}{0.0314(1 - \phi)} \right)^2
\]

- \( K \) permeability
- \( \phi \) porosity

Values taken from Strategic UK CCS Storage Appraisal Project

Permeability & porosity models serve as input for two-phase fluid flow simulations.

Fluid-flow modeling
proxy model
wavespeed, density

reservoir model
permeability, porosity
darcy

CO₂ dynamics
concentration, pressure
diffusion

leakage

regular
two-phase flow

time-lapse models
wavespeed, density

class activation mapping

deep neural classifier
time-lapse imaging
time-lapse (diff) data

accuracy = 86.29%
CO$_2$ dynamics

two-phase flow equations

**Mass balance equation:**
\[
\frac{\partial}{\partial t}(\phi S_i \rho_i) + \nabla \cdot (\rho_i v_i) = \rho_i q_i, \quad i = 1,2
\]

Inject CO$_2$ to replace water

\[ S_1 + S_2 = 1 \]

**Darcy’s law:**
\[
v_i = -\frac{K k_{ri}}{\tilde{\mu}_i}(\nabla P_i - g \rho_i \nabla Z), \quad i = 1,2
\]

**Fluid pressure:**
\[ P_2 = P_1 - P_c(S_2) \]

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>$K$</td>
<td>permeability</td>
</tr>
<tr>
<td>$\phi$</td>
<td>porosity</td>
</tr>
<tr>
<td>$k_{ri}$</td>
<td>relative permeability</td>
</tr>
<tr>
<td>$S_i$</td>
<td>fluid saturation</td>
</tr>
<tr>
<td>$P_i$</td>
<td>fluid pressure</td>
</tr>
<tr>
<td>$P_c$</td>
<td>capillary pressure</td>
</tr>
<tr>
<td>$\mathbf{v}_i$</td>
<td>Darcy’s velocity</td>
</tr>
<tr>
<td>$\rho_i$</td>
<td>fluid density</td>
</tr>
<tr>
<td>$\tilde{\mu}_i$</td>
<td>fluid viscosity</td>
</tr>
<tr>
<td>$q_i$</td>
<td>injection/production rate</td>
</tr>
<tr>
<td>$g$</td>
<td>gravity constant</td>
</tr>
<tr>
<td>$Z$</td>
<td>vector of vertical direction</td>
</tr>
</tbody>
</table>
Pressure-induced fractures


Rock-physics modeling
Workflow

proxy model wavespeed, density → reservoir model permeability, porosity

CO$_2$ dynamics concentration, pressure

pressure induced fault → two-phase flow

leakage

regular

time-lapse models wavespeed, density

time-lapse (diff) data

class activation mapping

deep neural classifier

time-lapse imaging

accuracy = 86.29%
### Rock physics

#### patchy saturation model

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>$B_{r1}/B_{r2}$</td>
<td>bulk modulus of rock fully saturated with fluid 1/2</td>
</tr>
<tr>
<td>$B_{f1}/B_{f2}$</td>
<td>fluid bulk modulus</td>
</tr>
<tr>
<td>$\rho_{f1}/\rho_{f2}$</td>
<td>fluid density</td>
</tr>
<tr>
<td>$\mu_r$</td>
<td>rock shear modulus</td>
</tr>
<tr>
<td>$v_p/v_s$</td>
<td>rock P/S-wave velocity</td>
</tr>
<tr>
<td>$B_o$</td>
<td>bulk modulus of rock grains</td>
</tr>
<tr>
<td>$\rho_r$</td>
<td>rock density</td>
</tr>
<tr>
<td>$\phi$</td>
<td>rock porosity</td>
</tr>
<tr>
<td>$S$</td>
<td>CO₂ saturation</td>
</tr>
</tbody>
</table>

CO₂ concentration ↑ → $v_p$ & $\rho$ ↓

$v_p$ decrease by 0-300 m/s

localized time-lapse changes

1.68% change in acoustic impedance

\[
\begin{align*}
B_{r1} &= \rho_r \left( v_p^2 - \frac{4}{3} v_s^2 \right) \\
\mu_r &= \rho_r v_s^2 \\
\frac{B_{r2}}{B_o - B_{r2}} &= \frac{B_{r1}}{B_o - B_{r1}} - \frac{B_{f1}}{\phi(B_o - B_{f1})} + \frac{B_{f2}}{\phi(B_o - B_{f2})} \\
\hat{B}_r &= [(1 - S)(B_{r1} + \frac{4}{3} \mu_r)^{-1} + S(B_{r2} + \frac{4}{3} \mu_r)^{-1}]^{-1} - \frac{4}{3} \mu_r \\
\hat{\rho}_r &= \rho_r + \phi S(\rho_{f2} - \rho_{f1}) \\
\hat{v}_p &= \sqrt{\frac{\hat{B}_r + \frac{4}{3} \mu_r}{\hat{\rho}_r}}
\end{align*}
\]

Seismic modeling
Workflow

proxy model
wavespeed, density

reservoir model
permeability, porosity

CO2 dynamics
concentration, pressure

pressure induced fault

leakage

regular

two-phase flow

time-lapse models
wavespeed, density

time-lapse (diff) data

class activation mapping

deep neural classifier

time-lapse imaging

accuracy = 86.29%
32 non-replicated source locations (average source sampling 125m)
162 hydrophones 2m above ocean bottom (average receiver sampling 25m)
Ricker wavelet w/ central frequency 25 Hz
Seismic time-lapse simulations

- linearized Born modeling (demigration)
- SNR 8 dB by adding white noise filtered w/ source wavelet

Time-lapse imaging
proxy model wavespeed, density

reservoir model permeability, porosity

CO₂ dynamics concentration, pressure

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accuracy = 86.29%
Joint imaging
joint recovery model

Invert \( \mathbf{A} \mathbf{z} = \mathbf{b} \) where

\[
\mathbf{A} = \begin{bmatrix}
\frac{1}{\gamma} \mathbf{A}_1 & \mathbf{A}_1 \\
\frac{1}{\gamma} \mathbf{A}_2 & \mathbf{A}_2 \\
\vdots & \vdots \\
\frac{1}{\gamma} \mathbf{A}_{n_v} & \mathbf{A}_{n_v}
\end{bmatrix}
\]

\( \gamma (0 < \gamma < n_v) \) controls weight on common component

1st column adds complementary info when \( \mathbf{A}_i \neq \mathbf{A}_j \)

exploit shared information

No need to \textit{replicate} to get high degrees of repeatability

\[
\mathbf{z} = \begin{bmatrix}
\mathbf{z}_0^\top, \mathbf{z}_1^\top, \ldots, \mathbf{z}_{n_v}^\top
\end{bmatrix}^\top
\]

\( \mathbf{h} \) from https://github.com/slimgroup/GCS-CAM/blob/main/scripts/JRM.jl
Optimization

linearized Bregman Iterations

Solve via curvelet-domain sparsity promotion:

\[
\begin{align*}
\min_{x} & \quad \lambda \| Cx \|_1 + \frac{1}{2} \| Cx \|_2^2 \\
\text{subject to} & \quad \| b - Ax \|_2^2 \leq \sigma^2 
\end{align*}
\]

for \( k = 1, 2, \ldots \)

\[
\begin{align*}
 u^{k+1} &= u^k - t^k A^{(k)^T}(A^{(k)}x^k - b^{(k)}) \\
x^{k+1} &= C^T S(Cu^{k+1}, \lambda)
\end{align*}
\]

\( C \) – curvelet transform

\( A^{(k)}, b^{(k)} \) – the demigration operator for randomly (w/ replacement) selected shots

\( S(t, \lambda) = \max\{ |t| - \lambda, 0 \} \text{sign}(t) \) – soft thresholding w/ threshold \( \lambda \)
**Seismic imaging**

**JRM vs RTM**

**JRM**

**RTM**

Number of iterations: 22

Batch size: 4

Number of sources: 32

Number of data passes: 3
**Time-lapse differences**

**Independent RTMs**

\[ \text{NRMS} = 8.48\% \]

**JRM**

\[ \text{NRMS} = 3.20\% \]

**NRMS**

\[ \text{NRMS} = 200\% \times \frac{\|x_1 - x_2\|}{\|x_1\| + \|x_2\|} \]
Automatic leakage detection w/ explainable ML

Training set
Compass model

Five different 2D velocity slices

1000 leak/no leak scenarios

Retrieved from Jones (2008)
Training dataset
densely sampled seismic data

- pressure $\geq 15$ MPa seal opens (12.5 m – 62.5 m) randomly
- permeability $10^{-4}$ md $\rightarrow$ 500 md
- linear time-lapse data generated w/ & w/o leakage
- time-lapse data inverted after 200 days w/ JRM

Seismic imaging
no leakage

10X no leakage difference image

Difference images will be network input
Seismic imaging
leakage

Difference images will be network input

10X leakage difference image
JRM vs independent Imaging
NRMS histogram

JRM:

- lower NRMS
- narrower range
- 6~7% → 2~3%
- more *repeatable* recovery
Class activation mapping
Classification network training

Convert time-lapse difference images to 224x224 size w/ 3 channels

Use state-of-the-art pre-trained vision transformer


Results
Class Activation Mapping

leakage

regular

plume

CAM
Examples

Thresholded CAM maps (<0.2)
Localized areas of (potential) leakage
Results

Overall 86.29% accuracy

- relied on dense receiver sampling
- relatively high percentage false negatives
- fewer false positives
- may need improvement

Improved leakage detection w/ data augmentation
Problem
leakage detection deteriorates

- accuracy decreases w/ receiver density
- solution augment training set
Issue
sparse receiver sampling

200 Receiver Configuration

100 Receiver Configuration

20 Receiver Configuration

RTM

RTM

RTM
Solution
data augmentation

- produce difference images w/ random number of receivers
- add new images to training dataset
- retrain the model w/ augmented dataset
- test on different receiver configurations
Results after data augmentation

Accuracy vs Number of receivers

Confusion matrix (rec = 160)

- True neg: 50 (50.00%)
- False pos: 0 (0.00%)

Confusion matrix (rec = 120)

- True neg: 44 (44.00%)
- False pos: 6 (6.00%)

Confusion matrix (rec = 80)

- True neg: 36 (36.00%)
- False pos: 14 (14.00%)

Confusion matrix (rec = 40)

- True neg: 11 (11.00%)
- False pos: 39 (39.00%)
Results after data augmentation

- **Classifier accuracy vs Number of receivers**
  - Trained on augmented dataset
  - Trained on one geometry dataset

- **Confusion matrix for augmented**
  - True neg: 550 (36.42%)
  - False pos: 200 (13.25%)
  - False neg: 192 (12.72%)
  - True pos: 568 (37.62%)

- **Confusion matrix for one configuration**
  - True neg: 382 (25.30%)
  - False pos: 368 (24.37%)
  - False neg: 148 (9.80%)
  - True pos: 612 (40.53%)
Permeability inversion from time-lapse seismic data

End-to-end inversion permeability

\[
\text{minimize } K \quad \| \mathcal{F} \circ \mathcal{R} \circ \mathcal{S} (K) - d \|_2^2
\]

permeability \( K \)

\( \mathcal{F} \)

\( \mathcal{R} \)

\( \mathcal{S} \)

fluid-flow physics

rock physics

wave physics

\( \text{CO}_2 \) concentration \( c \)

wavespeed \( v \)

time-lapse data \( d \)

Mathias Louboutin, Ziyi Yin, Rafael Orozco, Thomas J. Grady II, Ali Siahkoohi, Gabrio Rizzuti, Philipp A. Witte, Olav Meyner, Gerard J. Gorman, and Felix J. Herrmann, "Learned multiphysics inversion with differentiable programming and machine learning", 2023
CO$_2$ plume predictions & forecast

physical time

<table>
<thead>
<tr>
<th>Initial</th>
<th>Ground truth</th>
<th>Inverted</th>
</tr>
</thead>
<tbody>
<tr>
<td>year 10</td>
<td>year 20</td>
<td>year 30</td>
</tr>
<tr>
<td>year 20</td>
<td>year 30</td>
<td>year 40</td>
</tr>
<tr>
<td>year 30</td>
<td>year 40</td>
<td>year 50</td>
</tr>
</tbody>
</table>

Monitor | year 25 | Forecast
Permeability inversion


Julia packages can be found on the SLIM GitHub page (https://github.com/slimgroup).
Acknowledgements

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https://slim.gatech.edu/