The Value of Information metric for synthesizing the uncertainty of diverse CCUS monitoring techniques

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Well Integrity Workshop
Your Next Proposal or Monitoring Plan

- Assign discrete value to different data and/or sensor placements you propose to collect

- VOI = Value of Information

\[
\text{VOI}_{\text{seismic}} = $$$
\]
\[
\text{VOI}_{\text{MT}} = $$$
\]
\[
\text{VOI}_{\text{specialized sensor}} = $$$
\]

- Decision that can be influenced by this information
Value of Information (VOI)

\[
V_{\text{imperfect}} = \sum_{j=1}^{N} \Pr (\tilde{\Theta} = \tilde{\theta}_j) \max_a \sum_{i=1}^{N} \Pr (\Theta = \theta_i | \tilde{\Theta} = \tilde{\theta}_j) v_a(\theta_i)
\]

Decision: stop/modify CCUS operations?

Average Outcome using no information

\[V_{\text{prior}}\]

Average Outcome with Current Information

Average Outcome with Additional imperfect Information

\[V_{\text{imperfect}}\]

Pr( Well Degraded | “Degradation” interpreted)

Lower Expected Benefits ($)

\[V_{\text{prior}} = \max_a \sum_{i=1}^{N} \Pr (\Theta = \theta_i) v_a (\theta_i)\]

VOI_{imperfect}

Higher Expected Benefits ($)

Wellbore

Reservoir

Shallow Aquifer

TDS PLUME

Cap Rock

2000

1500

500
## CCUS Scales of Uncertainty: Spatial & temporal

<table>
<thead>
<tr>
<th>Known wellbore</th>
<th>Direct Sensors in the well</th>
<th>Indirect Remote sensing</th>
<th>Direct sensors</th>
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</thead>
<tbody>
<tr>
<td>Relevant</td>
<td>Early times: Less relevant</td>
<td>Relevant</td>
<td>Relevant</td>
<td>Potentially more relevant as leak spreads through time</td>
</tr>
<tr>
<td>Unknown wellbore</td>
<td>N/A</td>
<td>Relevant</td>
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## Scales of Uncertainty: Spatial & temporal

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<td>N/A</td>
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</table>

- **Better resolution**
- **Larger coverage**

### Different Types of Bow

- **Recurve Bow**
  - Better resolution
  - Larger coverage

- **Compound Bow**
  - Better resolution
  - Larger coverage

- **Longbow**
  - Better resolution
  - Larger coverage

### Different Types & Conditions Surrounding the Target

- **Perfect**
- **Imperfect**
- **Prior**
- **Vimperfect**
Quantifying the Reliability of Measurements under different conditions

For the subsurface, this is difficult:
1. We rarely know the true target
2. Target is multidimensional
3. Repeat measurements unlikely

Numerical simulations:
Calculate the probability distribution to estimate the “reliability” of each data type for many different scenarios.
VOI in context of CCUS goals

- Include different possible target characteristics ($V_{\text{prior}}$)
  - High Plains Aquifer & varying leak rates
- Assess **reliability** of particular techniques to detect changes in subsurface
  - Electrical Resistivity: 3 survey geometries [ well sensors ]
- Economic consequences of decision
  - Simple Decision & Nominal economics
- VOI encompasses all three!

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<td>Unknown wellbore</td>
<td>N/A</td>
<td>Relevant</td>
</tr>
<tr>
<td></td>
<td>Less occurrence with time</td>
<td></td>
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</table>

**1. Electrical Resistivity**
• Leak from underlying reservoir through abandoned wellbore (long after injection period)

Concurrently varying:

• Sand: permeability, Correlation Length, Volume Fraction

• Clay: permeability, Correlation Length

• CO2 leak rate

• Brine leak rate

• Distance of injector to leaking wellbore

High Plains Aquifer Study: 713 Simulations

Trainor-Guitton et al., 2013
Electrical Resistivity

- Shallow target: aquifer depth 240 m
- 2 factors decreasing electrical resistivity: Drop in pH (dissolved CO\textsubscript{2}) & increase of TDS (brine)

1. Surface Electrode Coverage
   - Leaky Well: X=5000 m
   - 1,200 m

2. Added borehole electrodes
3. Middle of electrode coverage is 1500 m away from leak

Aquifer Grid
5x Vertical Exaggeration

Distance of first electrode to leaky well:
0 m (200 m upstream of well)

Middle of electrode coverage is 400 m away from leak

ER Grid

Other survey’s

Distance of other survey's 240m

Another Possible Well X=8000 m

10,000 m
Simulation #2

Leaky Well

Factor Change of Electrical Resistivity (50 years / 0 years):

Ionic Conductivity

\[ R = \frac{1}{C} = \sum C_i = \sum c_i z_i \lambda_i \]

- \( C_i \): conductivity (Siemens/m)
- \( c_i \): concentration (moles/cm\(^3\))
- \( z_i \): electrons/ion
- \( \lambda_i \): ionic/molar conductivities (cm\(^2\) / Ω mol); includes ionic mobility

species \( i \): H\(^+\) = 349.65, Na\(^+\) = 50.08, Cl\(^-\) = 76.31

(Hearst et al, 2000)
Electrical Resistivity Leak Diagnostic: MLR

- Forward model ER response for 713 simulations (OhmTomo, X. Yang)
  - At time = 0 and time = 50 years
  - 3% Gaussian noise added to data
- Metric to determine if ER detects conductive plume (Daily et al, 2004)

**Mean Log Ratio (MLR)**

\[
MLR(\text{time})_s = \frac{1}{n} \sum_{k=1}^{n} \log_{10}\left(\left|\frac{r_{k}^{\text{time}}}{r_{k}^{0}}\right|\right)
\]

- Time = 50 years
- Time = 0 years

\(n\): number of resistance measurements
\(r_{k}^{t}\): transfer resistance on year \(t\)
\(r_{k}^{0}\): transfer resistance on year 0

- **713 simulations represent wellbore leak events:**
  - 4.5% frequency (Watson & Bachu, 2009)
- **15,131 non-leak events:** generate synthetic MLR
  (from non-plume simulations which include noise)
Reliability of electrical resistivity (MLR) to detect existence of plume

Time = 50 years

Probability

MLR (ERT sensitivity)

Reliability: bigger plumes are easier for ER to see

TDS 500

TDS 1500

TDS 2000

\[ Pr(\tilde{\Theta} = \tilde{\Theta}_j | \Theta = \theta_i) \]

\[ Pr(\Theta = \theta_i | \tilde{\Theta} = \tilde{\Theta}_j) \]
Simulation 275

TDS=500: the longest plume (of 713 simulations)
TDS=2000: No plume
Simulation 746

Leaky well

TDS=1500: 16th (of 713) longest plume
TDS=2000: No plume
**VOI** imperfect for Surface Electrodes

\[
V_{\text{imperfect}} = \sum_{j=1}^{N} \Pr(\bar{\theta} = \tilde{\theta}_j) \max_a \sum_{i=1}^{N} \Pr(\theta = \theta_i | \bar{\theta} = \tilde{\theta}_j) v_a(\theta_i)
\]

<table>
<thead>
<tr>
<th>Decision Actions (a)</th>
<th>$\theta = \text{No Leak}$</th>
<th>$\theta = \text{Leak}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Do Nothing</td>
<td>$0$</td>
<td>-$100M</td>
</tr>
<tr>
<td>Use Aquifer</td>
<td>$100M$</td>
<td>-$500M</td>
</tr>
</tbody>
</table>

Probability

\[
\Pr(\theta_{1500} = \text{Leak} | \bar{\theta} = 0.04) = 0.75
\]

\[
\Pr(\theta_{1500} = \text{No Leak} | \bar{\theta} = 0.04) = 0.25
\]

Reliability is influencing VOI: bigger plumes are easier for ER to see

<table>
<thead>
<tr>
<th>Avg. size plume</th>
<th>MCL</th>
<th>Value$_{\text{prior}}$</th>
<th>Value$_{\text{imperfect}}$</th>
<th>VOI$_{\text{imperfect}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>16,032</td>
<td>500</td>
<td>$73M$</td>
<td>$82.25$</td>
<td>$9.25M$</td>
</tr>
<tr>
<td>5,856</td>
<td>1500</td>
<td>$73M$</td>
<td>$81.75$</td>
<td>$8.75M$</td>
</tr>
<tr>
<td>4,825</td>
<td>2000</td>
<td>$73M$</td>
<td>$80.5$</td>
<td>$7.50M$</td>
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</tbody>
</table>
Different Electrical Resistivity Surveys

2. “Ideal” Surface-to-Borehole (250 m away from leaky well)
3. Offset Surface

Leaky Well
X=5000 m

Surface Electrode Coverage
1,200 m

Middle of electrode coverage is 1500 m away from leak

Distance of first electrode to leaky well: 900 m

Another Possible Well
X=8000 m
VOI imperfect for other ERT geometries

$$V_{\text{imperfect}} = \sum_{j=1}^{N} \Pr (\vec{\Theta} = \vec{\Theta}_j) \max \sum_{i=1}^{N} \Pr (\Theta = \Theta_i | \vec{\Theta} = \vec{\Theta}_j) v_a(\Theta_i)$$

<table>
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<tr>
<th>MCL (ppm)</th>
<th>VOI SURFACE ELECTRODES</th>
<th>VOI BOREHOLE ELECTRODES</th>
<th>VOI 1500m further away from leak</th>
</tr>
</thead>
<tbody>
<tr>
<td>500</td>
<td>$9.25M</td>
<td>$13.8M</td>
<td>$1.5M</td>
</tr>
</tbody>
</table>

Basecase: 200m from leak

With Borehole electrodes

1500m from leak
Summary & Concluding Remarks

- VOI$_{II}$ behaves as expected when comparing acquisition geometries and distance to leak
  - $VOI_{surface-borehole} > VOI_{surface} > VOI_{FARsurface}$

- Reliability captures the indirect measurement
  - Plume is a geochemical indicator
  - Electrical resistivity is a geophysical attribute

- Other VOI-CCUS studies included comparing pressure signals to geochemical changes
  - Pressure will arrive faster than other physical indications (e.g. TDS and pH)
  - Timely leak diagnosis and mitigation action (should be part of $Va$ of decision outcomes)

- VOI: ties the reliability of the information to its ability to change decisions that affect economic and/or environmental impact.
Extra slides
Simulations & signals based on High Plains Aquifer

Model parameters based on regional model

All major US aquifers: 1 to 2.6 monitoring wells per km²

Carroll et al. (2014)

Define leak according to EPA “no impact”

\[ i = \text{Leak} \quad \text{if} \quad TDS(t) > 1300\text{mg/L} \]
\[ pH(t) < 6.625 \]
Objective: Evaluate efficacy of above zone pressure & geochemical monitoring as a leak diagnostic

- Determine the detection likelihoods:

\[
\Pr\left( P > 0.3 \text{ PSI} \mid i = \text{Leak} \right) = \Pr \left( TDS > 1300 \mid i = \text{Leak} \right) = \Pr \left( \text{pH} < 6.625 \mid i = \text{Leak} \right)
\]

- Pressure change (↑)

- TDS (total dissolved solids) change (↑)

- pH (-log H+ concentration) (↓)
“Success” of signals depends on many parameters. We consider these 3:

1. Distance between source leak & monitoring wells
2. Leakage rates of CO₂ and brine
3. Heterogeneity of aquifer flow properties

From the detection likelihoods, what kind of spatial and time scales can we recommend for PISC (post-injection site care)?
We assume the monitoring well could be anywhere within the simulation grid.
**Sampling & Simulation Workflow**

**Concurrently varying:**
- Correlation lengths
  - sand facies
  - clay facies
- Sand percentage
- Time-varying leakage rates
  - $\text{CO}_2$
  - brine

**Generate 500 permeability / porosity models**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Minimum</th>
<th>Maximum</th>
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<tbody>
<tr>
<td>Horizontal correlation length</td>
<td>200 m</td>
<td>2500 m</td>
</tr>
<tr>
<td>Vertical correlation length</td>
<td>5 m</td>
<td>25 m</td>
</tr>
<tr>
<td>Sand volume fraction</td>
<td>0.35</td>
<td>0.65</td>
</tr>
</tbody>
</table>

facies permeability:
- Sand $= \log_{10} (-11) \text{ m}^2$
- Clay flow barriers $= \log_{10} (-18) \text{ m}^2$

2 vertical slices: example aquifer model

- $z = 222\text{m}$
- $z = 122\text{m}$
Sampling & Simulation Workflow

**Concurrently varying:**

- Correlation lengths
  - sand facies
  - clay facies
- Sand percentage
- Time-varying leakage rates
  - CO$_2$
  - brine

Generate
- 500 permeability /porosity models

Generate
- 500 leakage rates

- Leakage rates from reservoir & well models

Graphs showing cumulative CO$_2$ and brine emissions over time.
Pressure signal that traverses simulation grid is an order magnitude smaller than detecting limits.

Relative pressure change (from neighboring time step) at time = 75 days is within 0.1 - 0.3 PSI, which is the accuracy range of typical pressure transducers used in aquifers <=240m deep.
Sampling & Simulation Workflow

Concurrently varying:

- Correlation lengths
  - sand facies
  - clay facies
- Sand percentage
- Time-varying leakage rates
  - CO₂
  - brine

Generate 500 leakage rates

Generate 500 permeability/porosity models

Simulation of leaking well into bottom of groundwater aquifer
  - Two-phase flow: gas and liquid
  - Allows for phase transition of CO₂

Calculate ΔPSI, TDS & pH for all time steps from time=0, for all grid locations

374 simulations successfully completed.

Calculate detection likelihood:
Pr (signal | leak)
Detection Likelihoods $\text{Pr}(\text{signal} | \text{leak})$

### Pressure

![Graph showing detection likelihoods for pressure across different time periods.]

### TDS

![Graph showing detection likelihoods for TDS across different time periods.]

### pH

![Graph showing detection likelihoods for pH across different time periods.]

The graphs illustrate the probability of detection likelihoods for pressure, TDS, and pH over various time periods. Each graph includes data points for different time durations, such as 8 days, 30 days, 50 days, 70 days, 95 days, 140 days, 300 days, and 730 days. The x-axis represents distance in meters, and the y-axis represents probability. The graphs are designed to help understand the likelihood of detecting signals in the presence of leaks under different conditions.
Detection Likelihoods: Assume monitoring well above the leak

Pressure

TDS

pH
Detection Likelihoods: top 25% cumulative CO₂ leakage

Pressure

TDS

pH
Objective: Assess pressure & geochemical signals as a monitoring method for early CO₂/brine leak detection

Pressure is the most timely & spatially extensive signal
- Well density of 1 well / km² is not adequate to ensure that a non-signal equates to no leakage

Heterogeneity
- Pressure signal builds behind flow barriers
- TDS & pH signals stronger beyond the flow barriers

Detection likelihoods for highest leak simulations: higher but still produce “false negatives”

Future work:
- Use data set for modeling geophysical surveys
- VOI metric to compare the efficacy of different monitoring techniques
Part 1

Fault / Not Fault Labels

For All 2D slices:

183 2D slices

Part 2

Migration Images: “Features”

Receiver Type ➔

Source Type ↓

Example slice:

X=175

Vibe Motion

Part 3

Geophone

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<th>“F”</th>
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<tbody>
<tr>
<td>NF</td>
<td>86.35</td>
<td>0.26</td>
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<td>F</td>
<td>13.65</td>
<td>99.74</td>
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DAS

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<td>8.58</td>
<td>99.79</td>
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<td>0.16</td>
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