Novel Methods to Detect Small Leaks over Large Areas

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Presentation Outline

- Overview
- Data-Driven Detection Methods
  - Physics-Driven Methods VS Data-Driven Methods
  - Key Ideas
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- Accomplishments to Date
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- Synergy Opportunities
- Project Summary

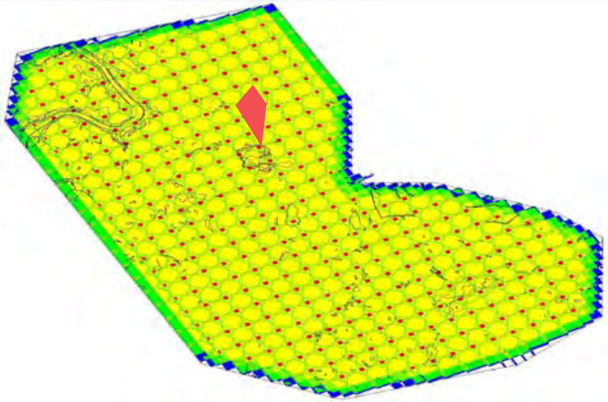
Overview
Novel Methods to Detect Small Leaks over Large Areas

Ultimate Goal

"Detect a leak of 100 g/s (brine or CO_2) within 100 days over an area of 100 km^2 for 10-year amortized cost of $100k/year."

Challenges

- **Small** and **useful** events buried in noisy and **large-scale** datasets
- **Efficient** method is required to allow early detection
- **Financially effective** method



Hypothesis and Potential Solutions

Hypothesis

- **Hypothesis:** There is useful information existing in the data, which is not used by current methods

Solutions

- Data-Driven/Machine-Learning Methods
- Test Data
  - **Simulations** (fluid & flow (LLNL) → Seismic Velocity (NETL) → Seismic Data (LANL))
  - Field data
- Multi-Physics Surface/Subsurface Measurements
  - **Seismic**
  - Pressure
  - Acoustic

Seismic Detection - Overview

- **Physics-Driven Methods** The governing physics equations are well understood and utilized to describe the underlying physics of the problems of interest.
- Seismic Monitoring

$$\boldsymbol{E}(\boldsymbol{m}) = \min_{m}\left\{\|\boldsymbol{d}-\boldsymbol{p}(\boldsymbol{m})\|_2^2+\boldsymbol{\lambda R}(\boldsymbol{m})\right\}$$

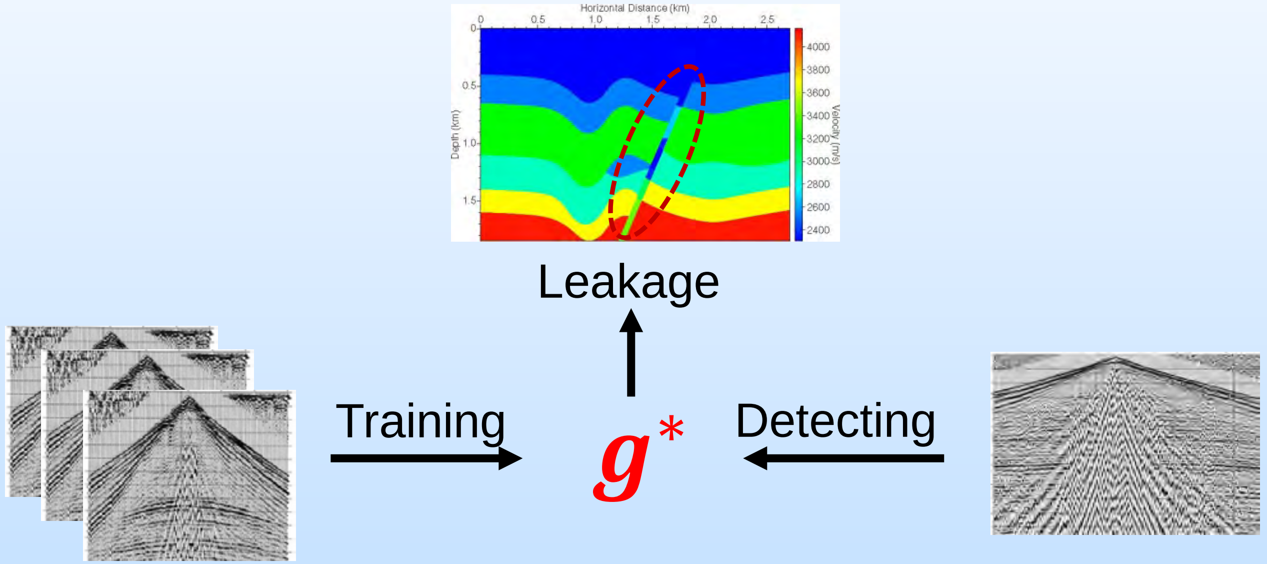
where m is the subsurface formation (rock + fluid), d is the seismic measurement, $p(\cdot)$ is the forward wave-propagation operator, and $R(\cdot)$ is the regularization operator.

- CO_2 leaks will lead to subsurface formation change of δm

Detection of Formation Change → **Leak Monitoring**

Seismic Detection - Overview

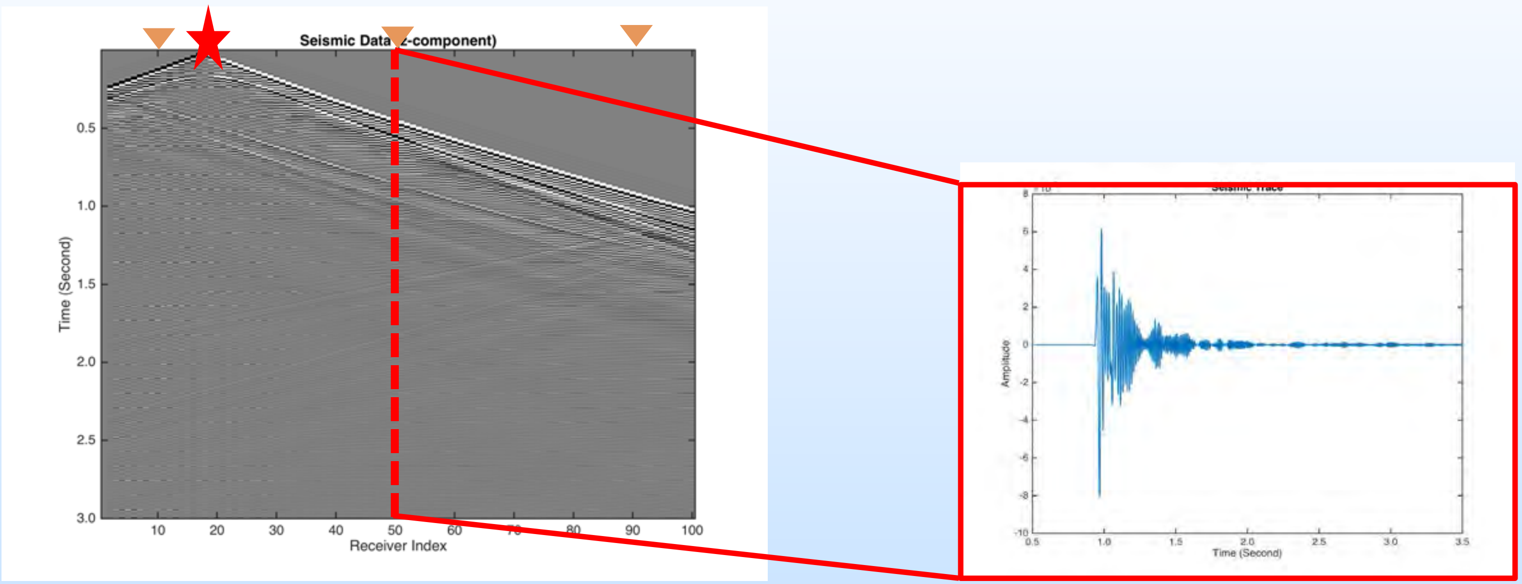
- **Data-Driven Methods** Machine-learning techniques are used to infer the intrinsic correspondence between seismic data and the leakage mass.



Seismic Data $\xrightarrow{g^*}$ **Leakage Mass**

Seismic Detection – Key Ideas

- Characteristics of Reflection Seismic Data



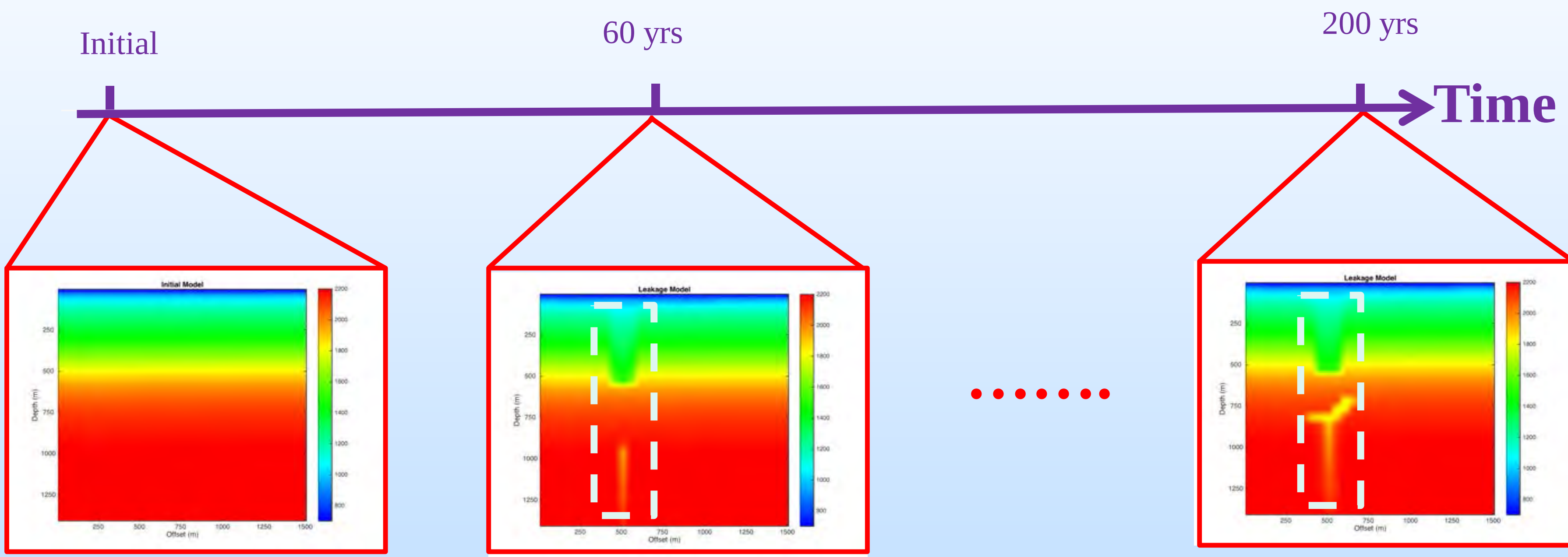
2D Seismogram

1D Time Series

- Seismic data contain both **spatial- and temporal** characteristics

Seismic Detection – Key Ideas

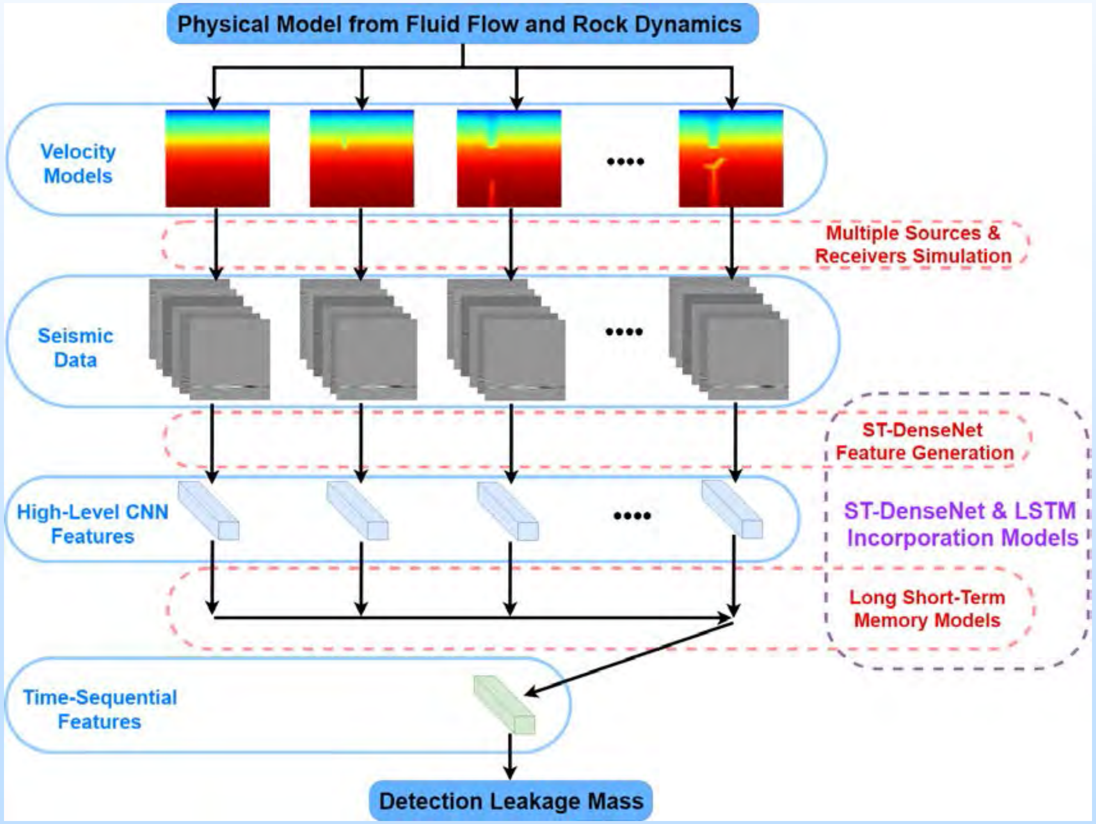
- CO_2 Leakage is **time-dependent accumulated sequential** procedure



- Previous measurements (if available) can be important for current detection

Seismic Detection - Diagram

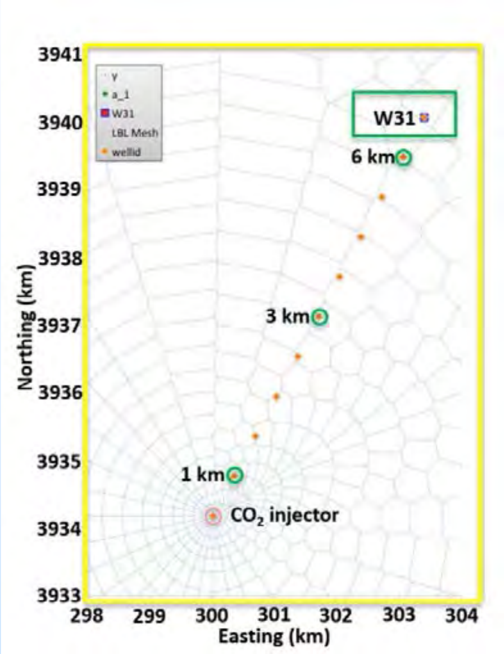
- Our **Spatial-Temporal DenseNet (ST-DenseNet)** for CO_2 Leakage Detection



Schematic Illustration of Our Detection Method

Seismic Detection – Model and Test

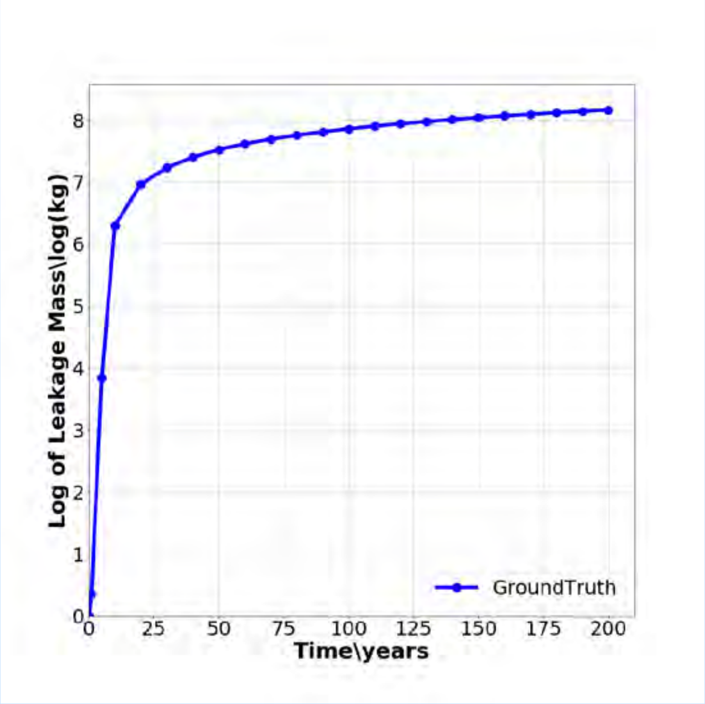
- Kimberlina Model
  - The simulations were generated from Kimberlina model with wellbore leakage dataset
  - This dataset contains multi-phase flow models of wellbore leakage from legacy wells located at 1, 3, and 6 km away from the CO_2 injector
  - Reflection seismic data are generated (3 sources and 100 receivers)
  - Total number of leakage simulations: 2,927 (133 groundwater simulations, 23 time steps, and 1 initial model)
- Test Scenarios
  - Scenario 1: Random CO_2 Leakage Test
  - Scenario 2: Sequential CO_2 Leakage Test
  - Scenario 3 & 4: Robustness Test (Noisy Test and Cross-Location Test)
  - Scenario 5: Brine Leakage Test



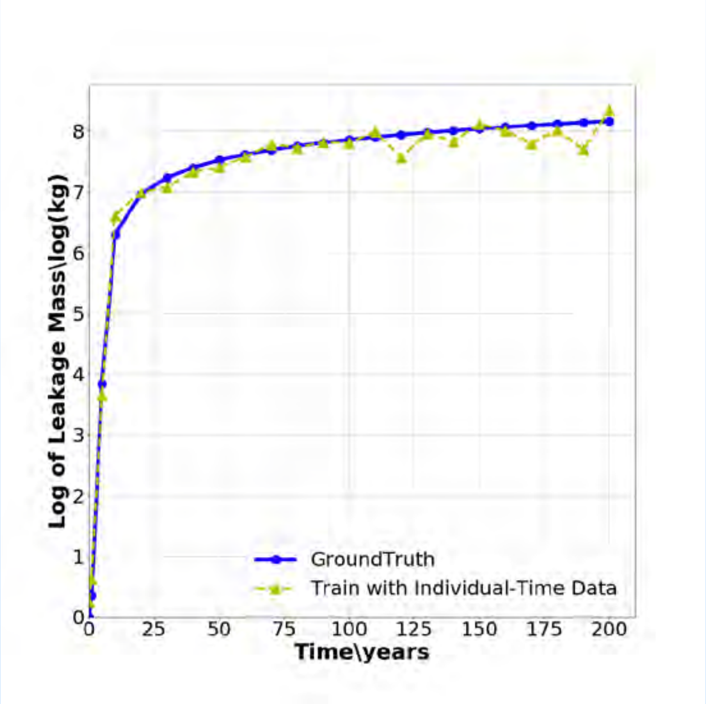
Kimberlina Site Map
(Image Courtesy of Buscheck et al. 2017.)

Seismic Detection - Result

- Scenario 1: Random Leakage Monitoring



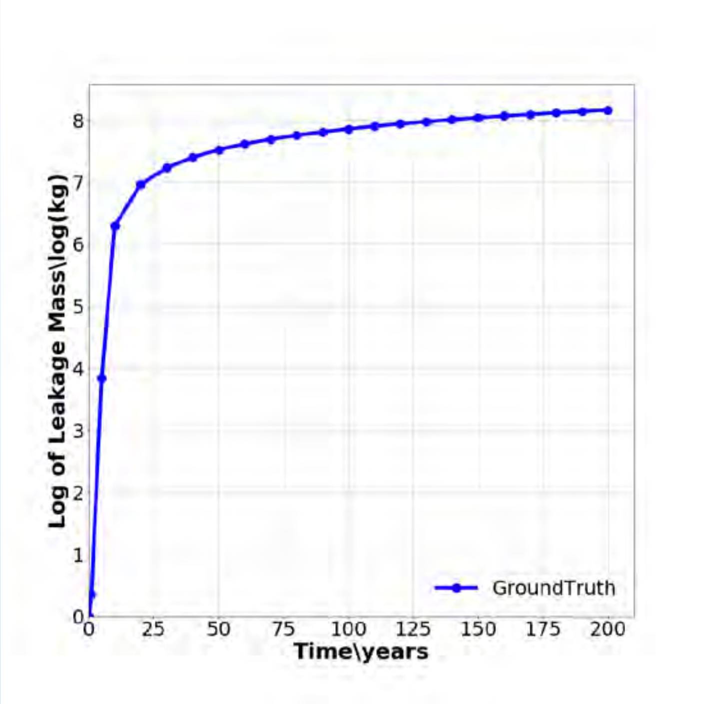
Ground Truth



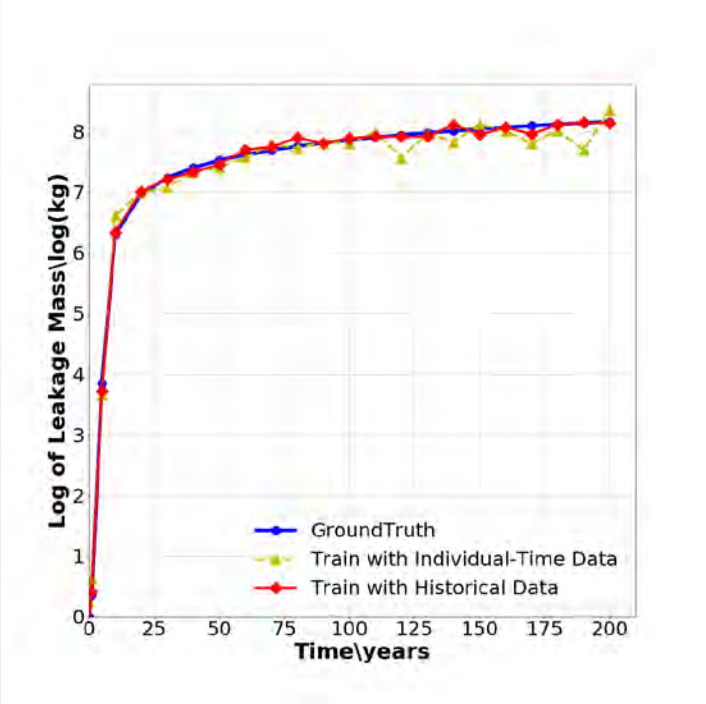
Detection

Seismic Detection - Result

- Scenario 2: Sequential Leakage Monitoring



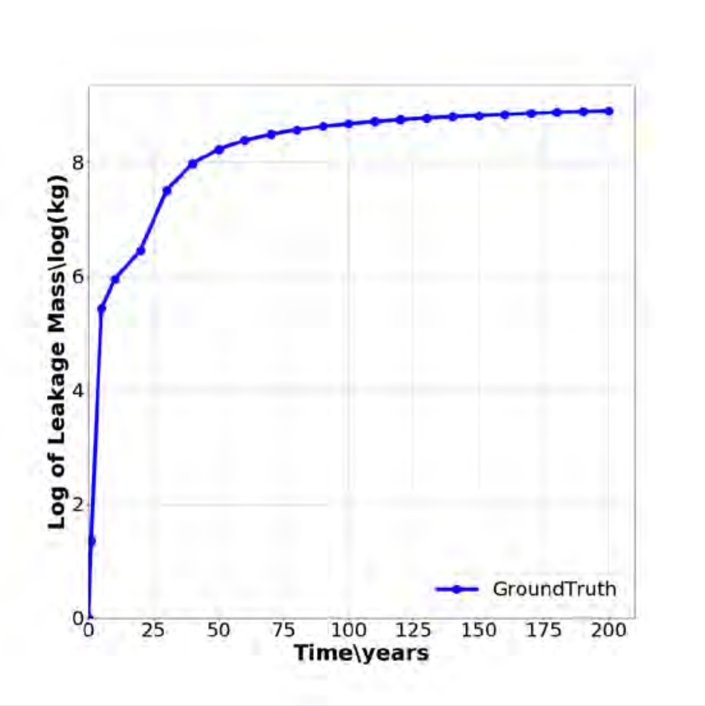
Ground Truth



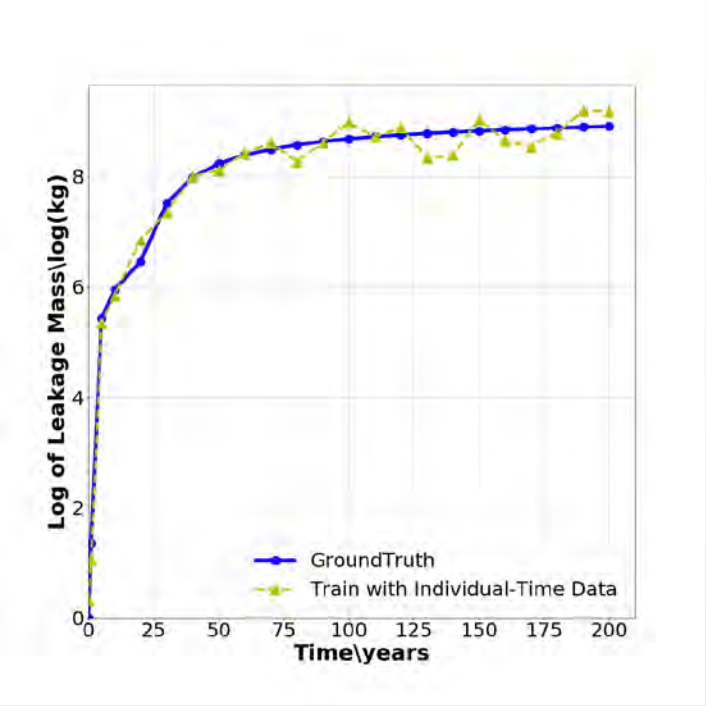
Detection

Seismic Detection - Result

- Scenario 3: Monitoring Using Noisy Data
  - 30 db additive Gaussian noise is imposed



Ground Truth



Detection

Seismic Detection - Result

- Scenario 3: Monitoring Using Noisy Data
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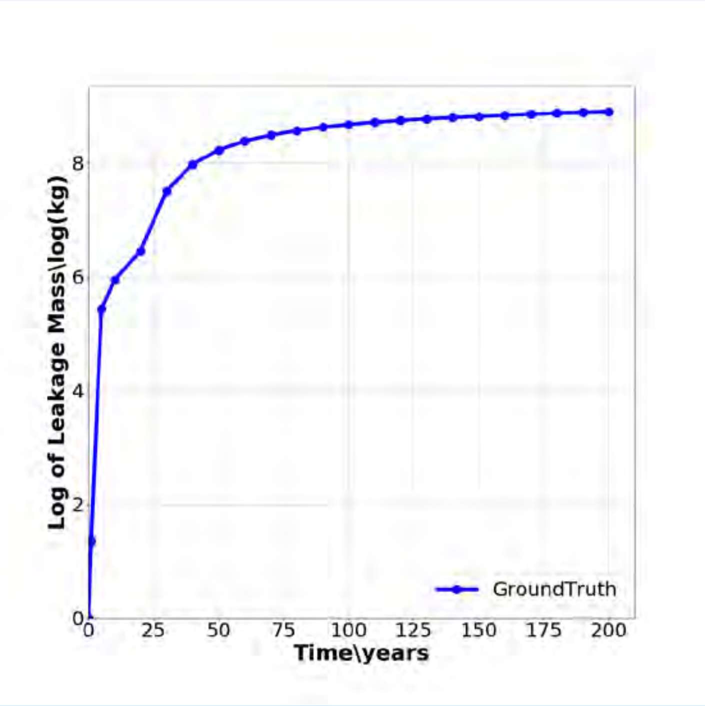
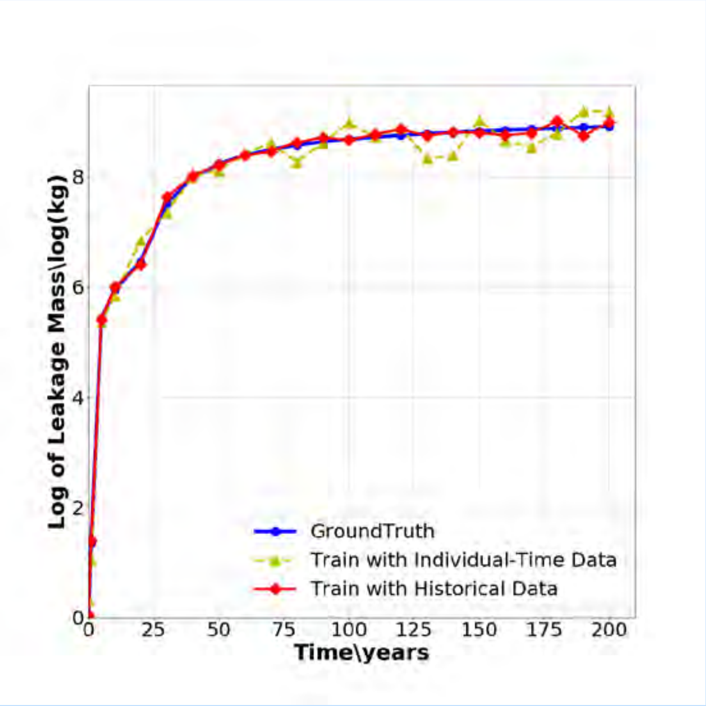


Ground Truth

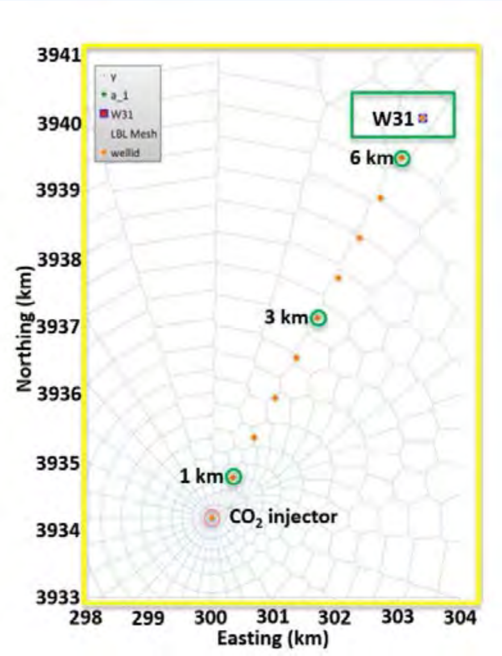


Detection

Seismic Detection - Result

- Scenario 4: Cross-Location
  - Train model on 2 locations and test on 3rd location

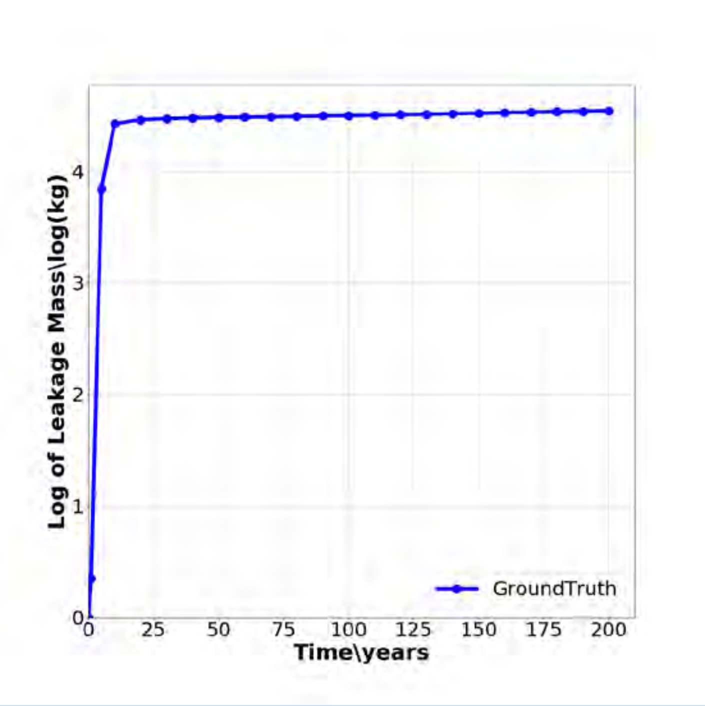
	1 km	3 km	6 km	Overall
ST-DenseNet	79.3%	82.3%	82.6%	81.2%



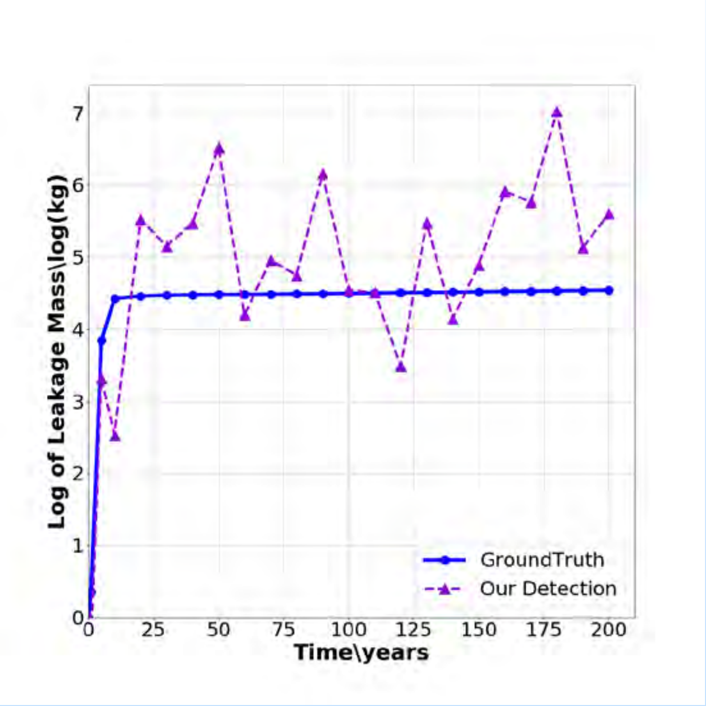
Kimberlina Site Map
(Image Courtesy of Buscheck et al. 2017.)

Seismic Detection - Result

- Scenario 5: Brine Leak Mass Detection



Ground Truth



Detection

Accomplishments to Date

– **ST-DenseNet:** Our team developed a deep neural network based leakage monitoring method to capture CO_2 leakage mass. [**Zhou et al. 2018**, **Zhou et al. 2018 (2)**]

Lessons Learned

- 👍 Our results show that seismic data contain information about CO_2 gas leakage. Our work is primarily on large leakage, but we have seen information about small leak, which is our future focus.
- 👍 Incorporation of historical seismic data can be significant in improving detection accuracy.
- 👍 Robustness tests (noisy and cross location) are important and challenging.
- 👎 Our results show that seismic yields unsatisfactory detection accuracy for brine leakage.

Synergy Opportunities

- Work with NRAP
- Work with NETL
- LANL institutional and LDRD projects

Project Summary

– Data-driven approaches yield promising detection results.
– Spatial- and temporal information should be both taken into account when using data-driven approaches.
– Results show that historical data can improve effectiveness in data-driven approaches.


Thank you

Appendix

– These slides will not be discussed during the presentation, but are mandatory.

Benefit to the Program

- Our techniques can detect small leaks out of large noisy data.
- Our techniques can extract useful information from different types of data sets.
- All these techniques will be critical to early detection of CO_2 leakage.

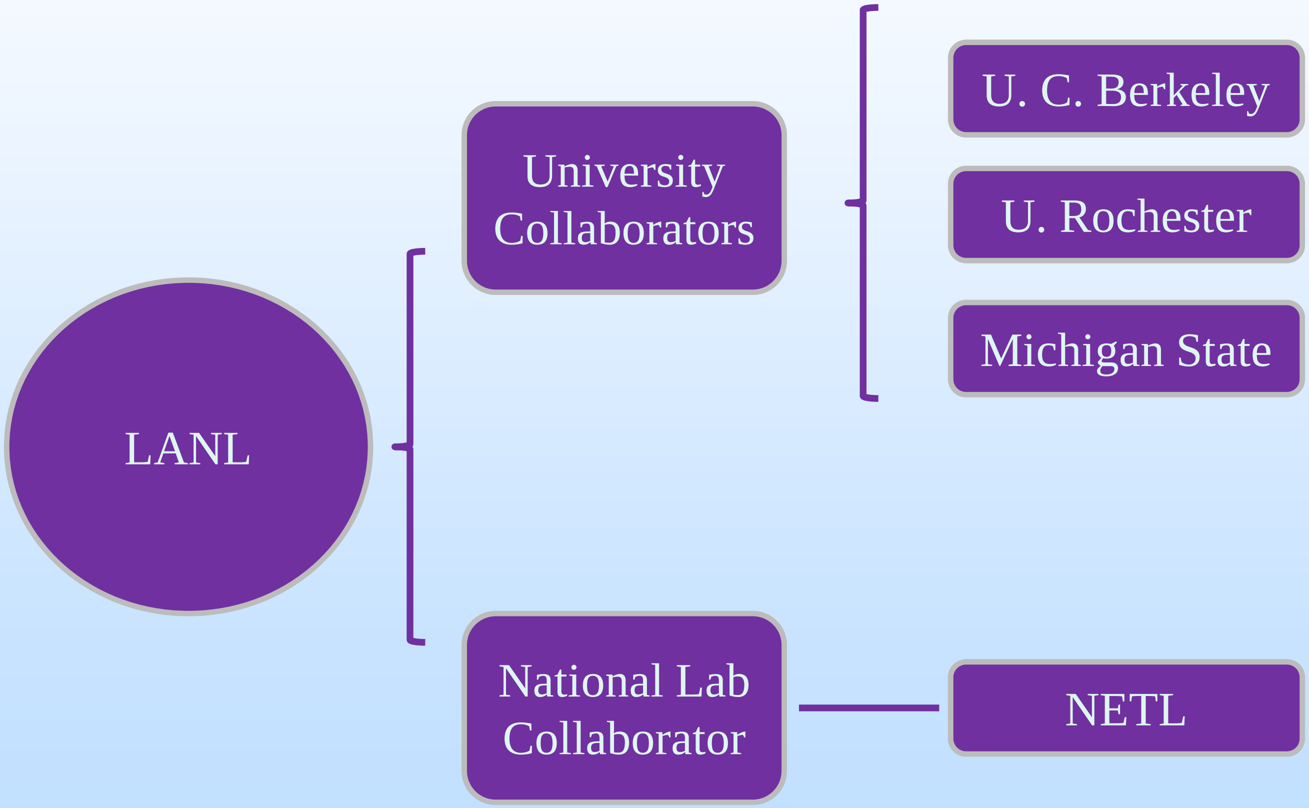
Project Overview

Goals and Objectives

- Task 2.1—Field-Scale Proof-of-Concept
  - “This task will leverage institutional investments by LANL that allowed acquisition of inexpensive seismoacoustic stations for development and testing of algorithms to search for small signals using large time series datasets.”

- Task 2.2—Strategic Plan for Detection of Atmospheric Leaks
  - “The objective of the sub-task is to develop a strategy for combining both surface and subsurface signals to detect leaks, but FY17 will focus on demonstrating individual components of the overall strategy.”

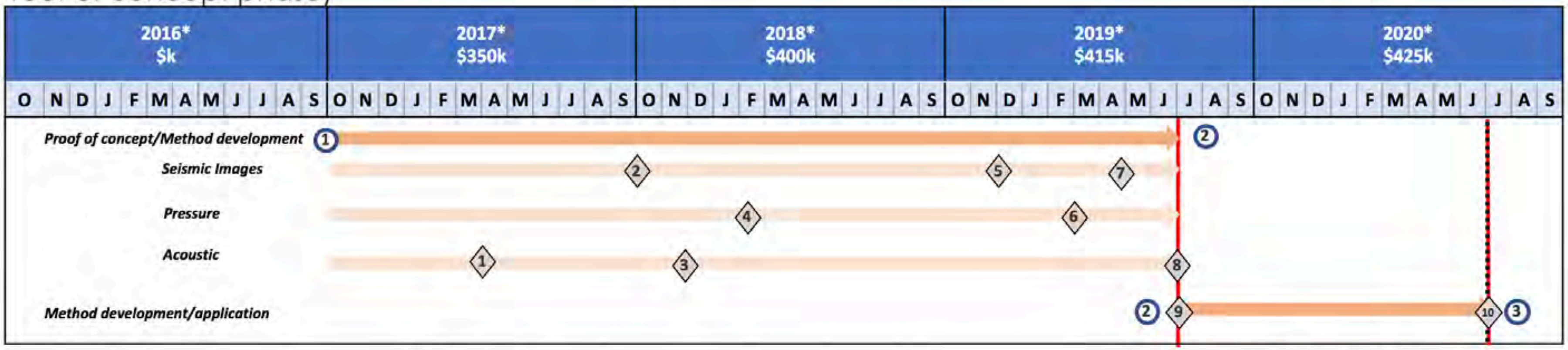
Organization Chart



Gantt Chart

Task 2: Project Timeline Overview

Monitoring for small leaks over large areas post-injection using conventional datasets
(Proof of concept phase)



Milestones

1. Collected field data set for testing extraction of small acoustics signals associated with fluid movement (leakage)
2. Seismic Images: Development/testing of machine-learning (ML) method for extracting large-leak signal from synthetic data
3. Acoustic: Development/testing of ML method for extracting large-leak signal from acoustic
4. Pressure: Development/testing of ML method for extracting large-leak signal from pressure data
5. Seismic Images: Testing of ML potential to extract large-leak signal from noisy synthetic seismic images
6. Pressure: Testing of ML method for extracting small-leak signal from noisy pressure data
7. Seismic Images: Testing of ML potential to extract small-leak signal from synthetic seismic images
8. Acoustic: Testing of ML method for extracting small-leak signal from noisy acoustic data
9. Develop multi-data ML integration method
10. Initial testing on real data

Chart Key

TRL Score | Go / No-Go Timeframe | Project Completion | Milestone

Go / No-Go

Initiate development of multi-data ML integration platform and test/demonstrate on field data? Decision based on proof-of-concept that analysis of conventional data (seismic ± pressure ± acoustic) could meet performance/cost goals

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