# Monitoring for Small Leaks over Large Areas

Project Number (FE-890-18-FY19)

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**Los Alamos National Laboratory**

U.S. Department of Energy

National Energy Technology Laboratory

Addressing the Nation's Energy Needs Through Technology Innovation – 2019 Carbon Capture, Utilization, Storage, and Oil and Gas Technologies Integrated Review Meeting

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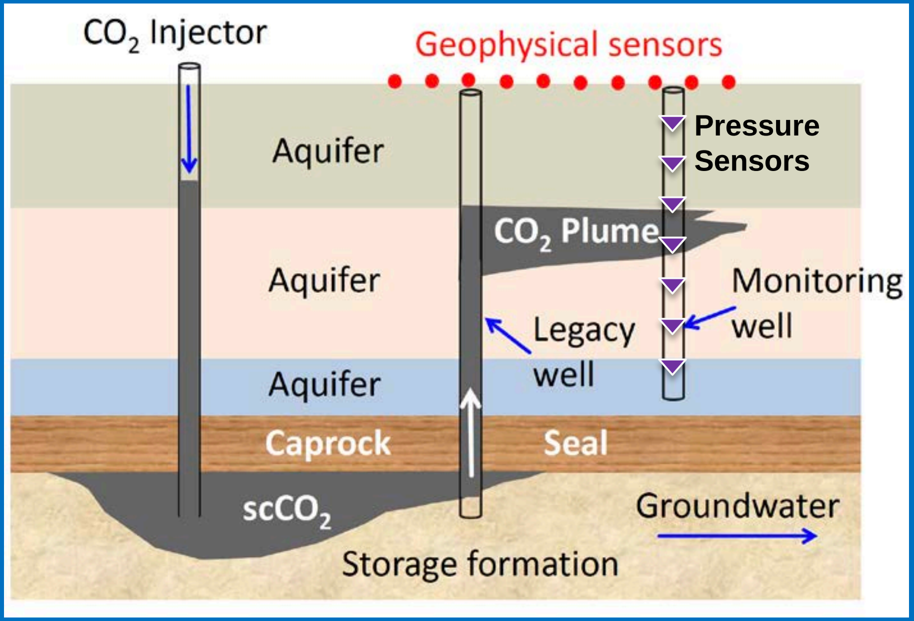
# Technical Objective

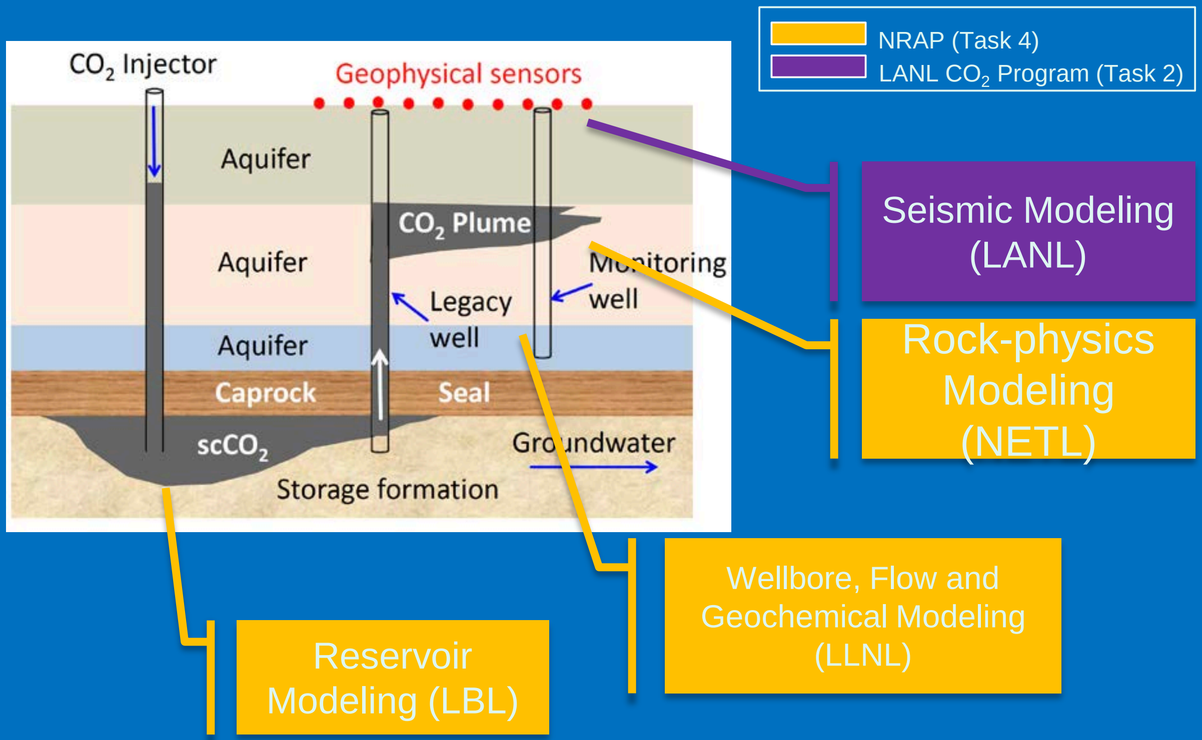
- Identify small signals in geophysical datasets to monitor for small leaks of $CO_2$ and/or brine over large areas economically
  - Detect leaks of 100 g/s within 100 d over an area of 100 $km^2$ for $100k/yr amortized over 10 years
    - Detectability: ~1 k ton (**$10^6$ kg**)
    - Economics: **$1M total**
  - Exploit machine learning algorithms for detection, which can lower both sensitivity (remove bias) and costs
    - Synthetic datasets for proof of principle to evaluate the presence of useful signals in seismic and pressure data

# Project Background/Methodology

- Two geophysical datasets
  - Raw seismic and pressure
- Seismic
  - Advantages: based on 4D seismic; surface deployment; possibly passive; large spatial extent
  - Disadvantages: repeated source deployment necessary, indirect method (detects property changes resulting from leak)
- Pressure
  - Advantages: small number of low cost sensors, could also detect brine leaking before $CO_2$
  - Disadvantages: sensors must be placed in unit where leakage occurs

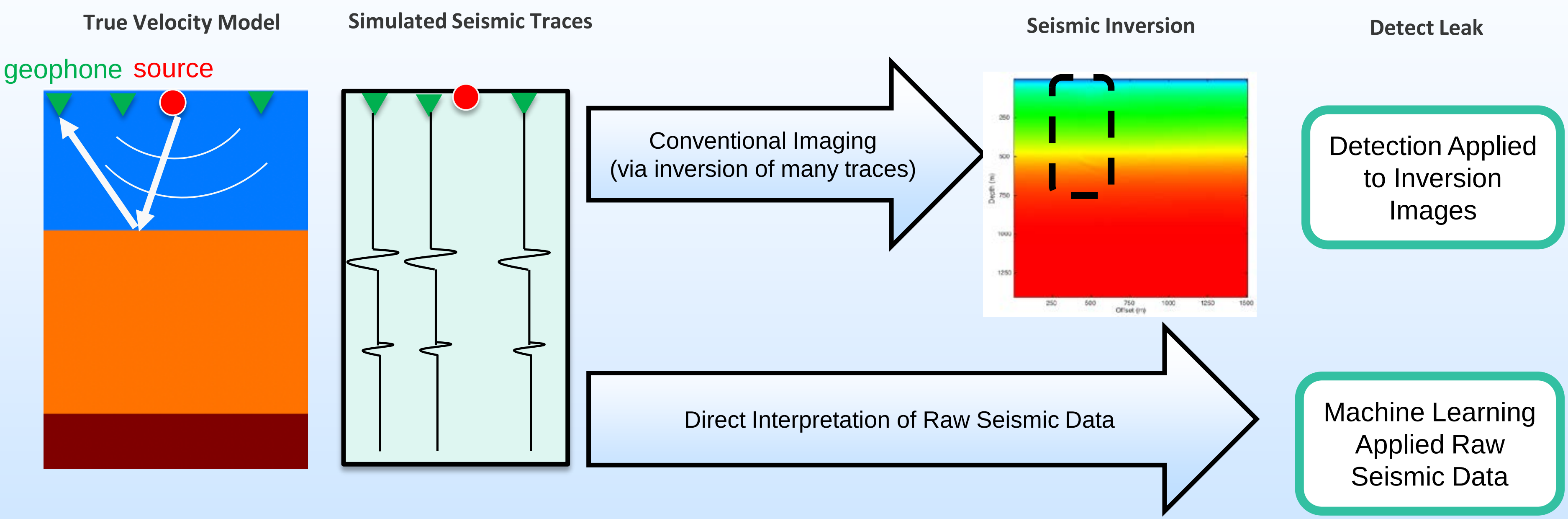


# Kimberlina Synthetic Data



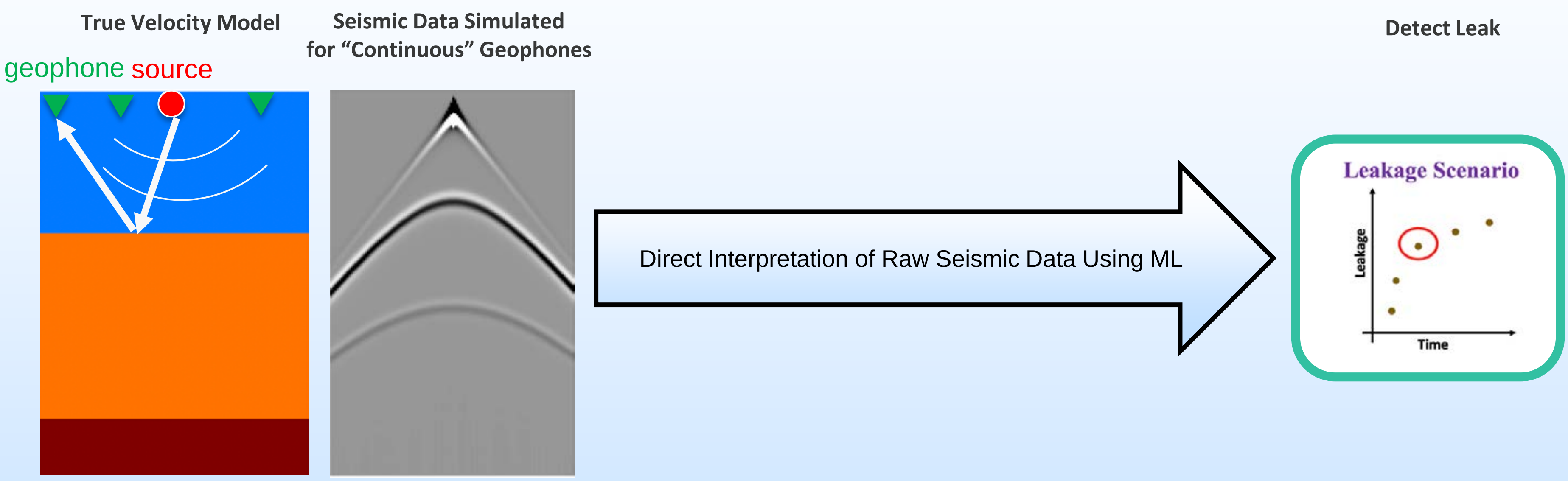

| Available Data |
|---|
| **Seismic** |
| **Pressure** |
| Magnetotellurics (MT) |
| ERT |
| Gravity |
| Total Dissolved Solids (TDS) |

# Two Possible Pathways for Using Seismic Data to Detect a Leak




- Obtain seismic inversion is very expensive
- Critical leakage information can be lost after inversion

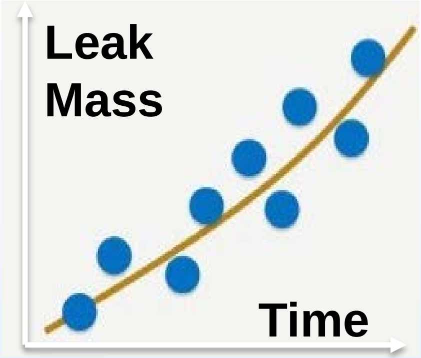
# Seismic (Non) Imaging Leak Detection



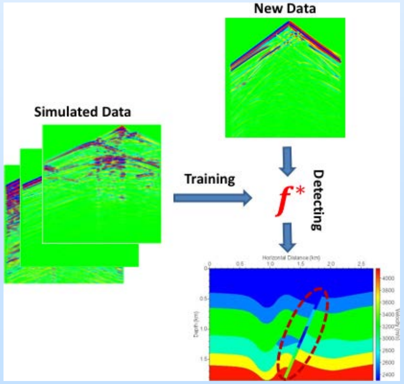

- Raw seismic data contains more information on leakage than is present in a derived seismic image—more sensitive; fewer stations.

# Relevant Machine Learning Tools

- **Supervised Machine Learning**
  - Machine attempts to learn the relationship between existing data and target. This learned relationship can be used to estimate target when new data is available.
- **ML Approaches**
  - Deep learning regression - how much leakage
- **Physics Informed ML**
  - Training data generated from governing physics
  - Results in more robust and generalized tools
- **Verification and Validation**
  - Validated through blind test data
  - Verified based on physics knowledge




**Regression**

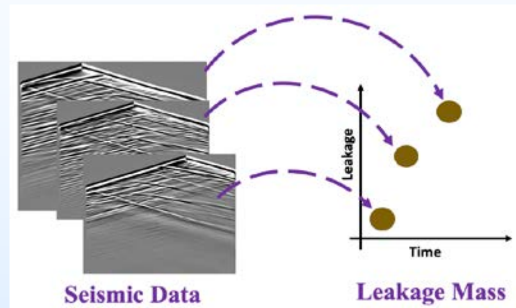



**Physics Informed ML**

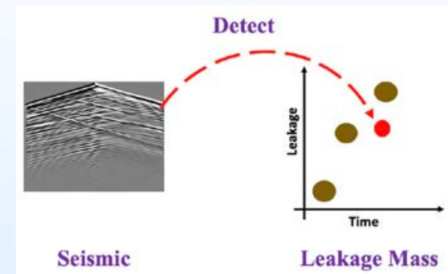
# A Closer Look:
# Non-Imaging Leakage Detection

**Non-Imaging detection technique [*Zheng. et al., 2019*]**

- Apply ML to infer the intrinsic correspondence between seismic data and the leakage
- Capable of detecting small changes in the subsurface with much less data (lower cost) than would be required for conventional imaging




**Training Stage**



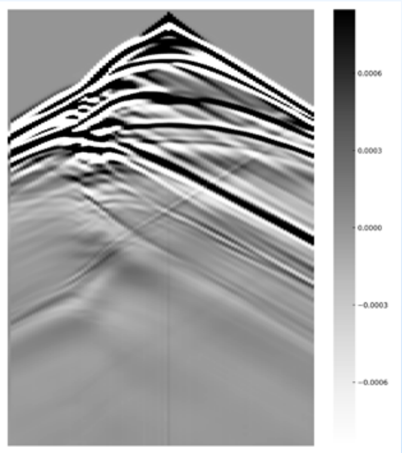

**Detection Stage**

**Raw Seismic** → **Leakage Mass**

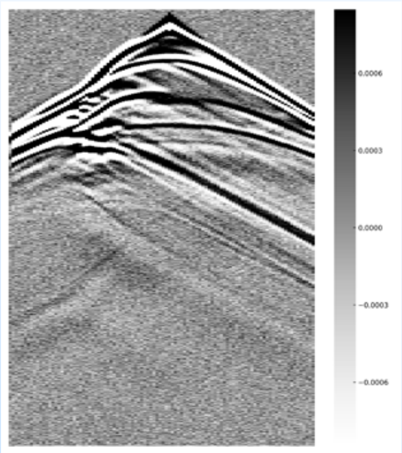

Zheng Zhou, Youzuo Lin, Zhongping Zhang, Yue Wu, Zan Wang, Robert Dilmore, and George Guthrie, "**A Data-Driven $CO_2$ Leakage Detection Using Seismic Data and Spatial-Temporal Densely Connected Convolutional Neural Networks**," International Journal of Greenhouse Gas Control, Vol. 90, 2019.

# Non-imaging Leakage Detection Results

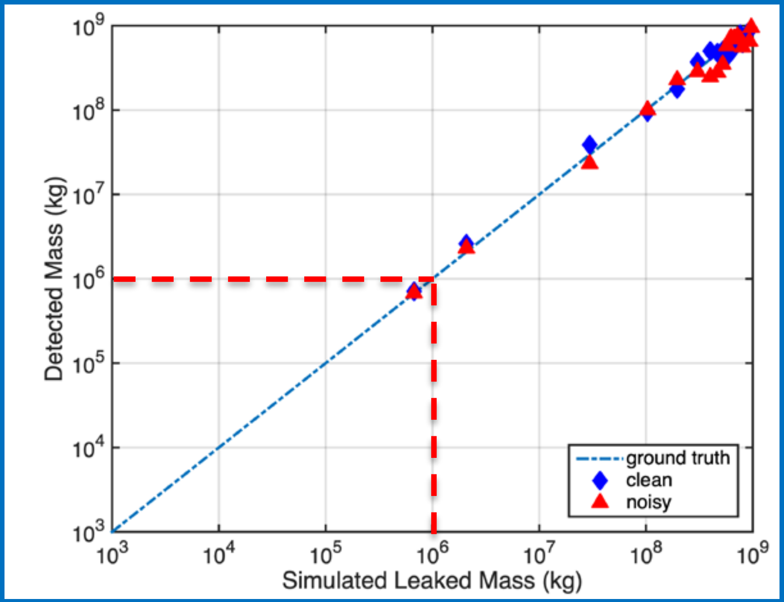
- **Scenario: Leak Detection Using Noisy Seismic Data**



Clean



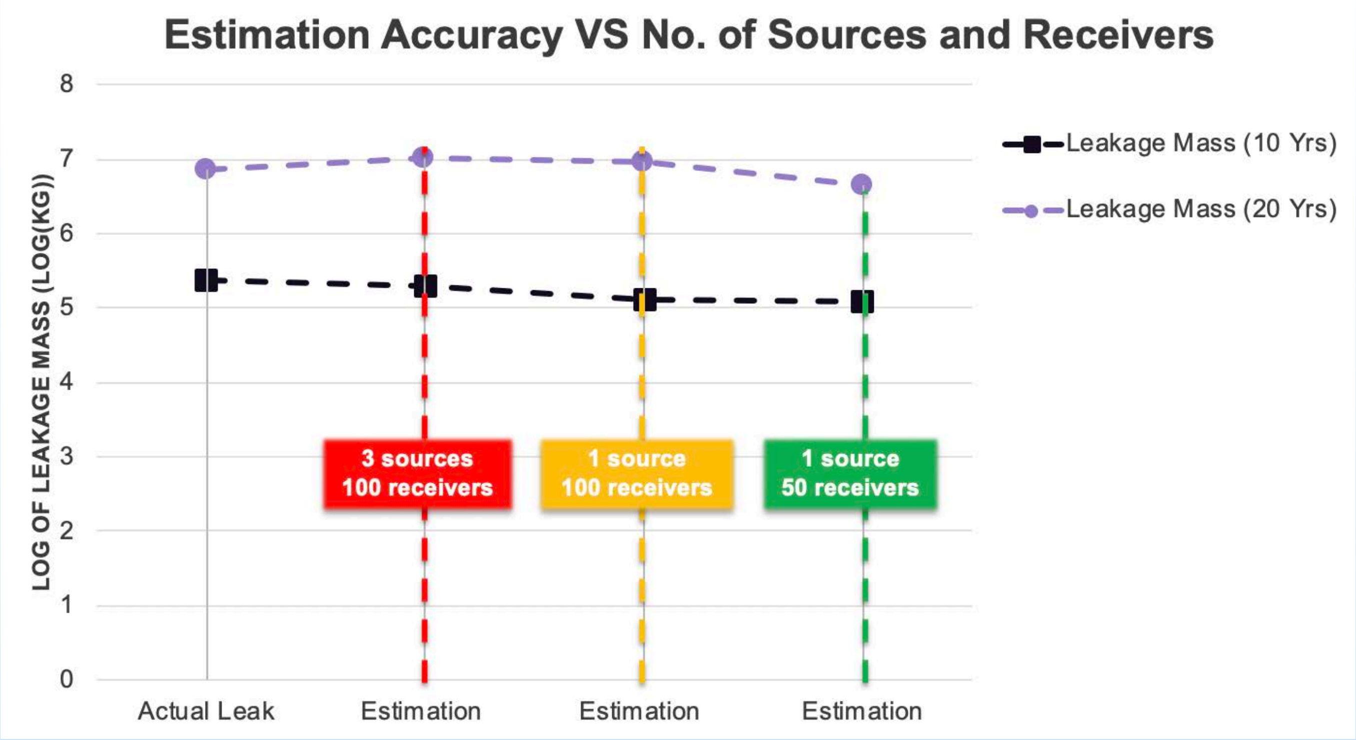
Noisy




Leakage Detection

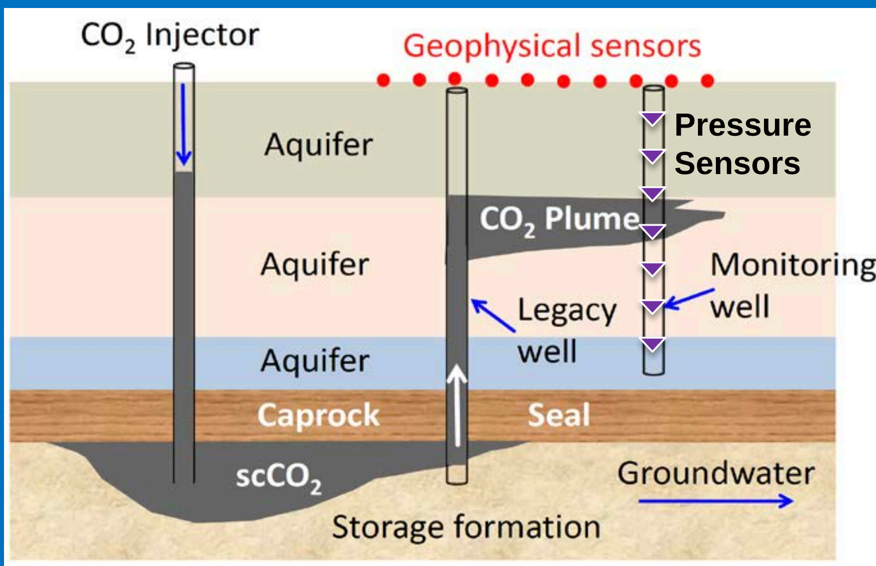
- It is possible to use ML techniques to detect small $CO_2$ leakage using synthetic seismic data with noise.

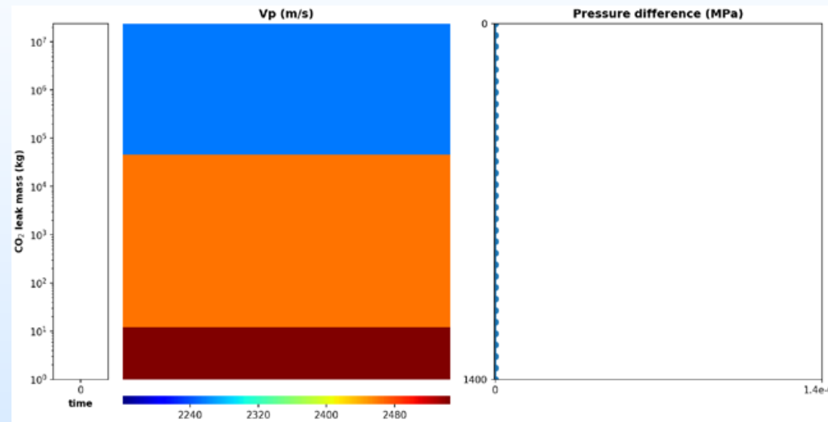
# Non-imaging Leakage Detection Results




- Potential to significantly reduce number of sensors.

# Kimberlina Dataset, Pressure

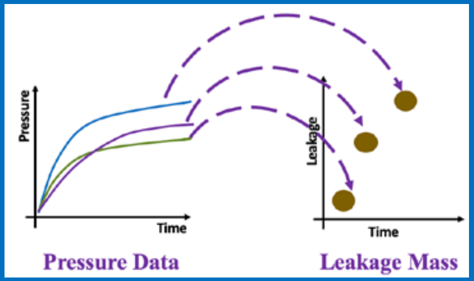



- There are signatures in the pressure data containing leakage information that we need to extract

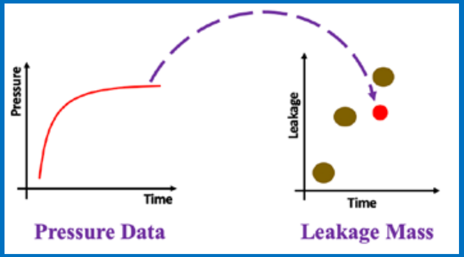
# Leakage Detection Using Pressure Data

## ML: Pressure Data →Leakage Mass



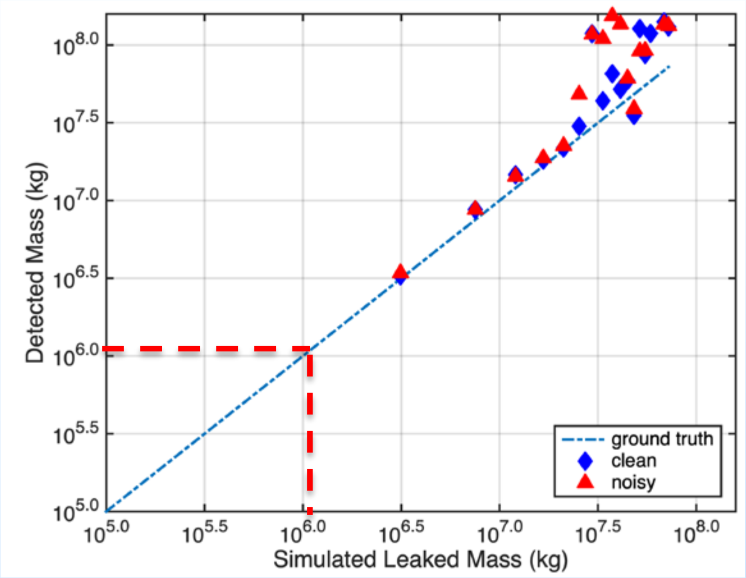

Training Stage

- Learn leakage signature from pressure data and map it to leakage mass



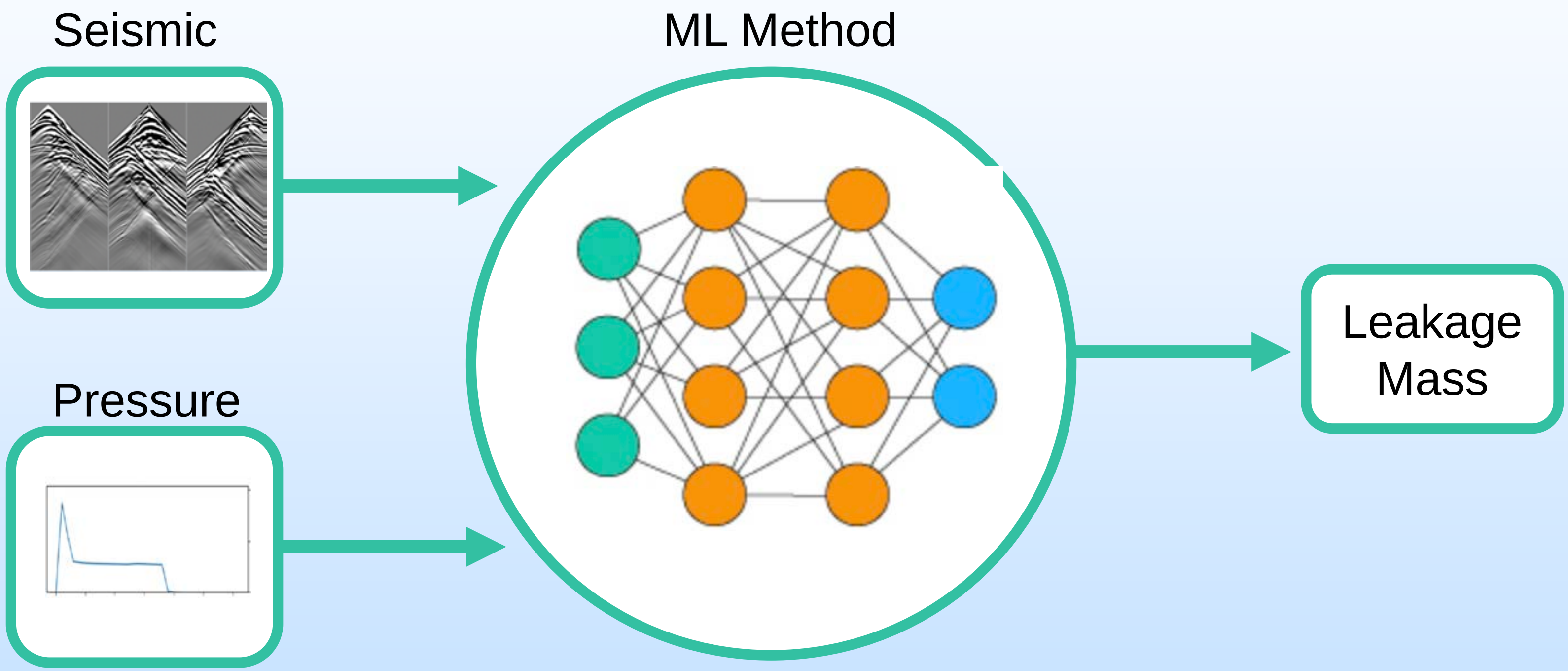

Detection Stage

- Detect leakage and mass directly from pressure data



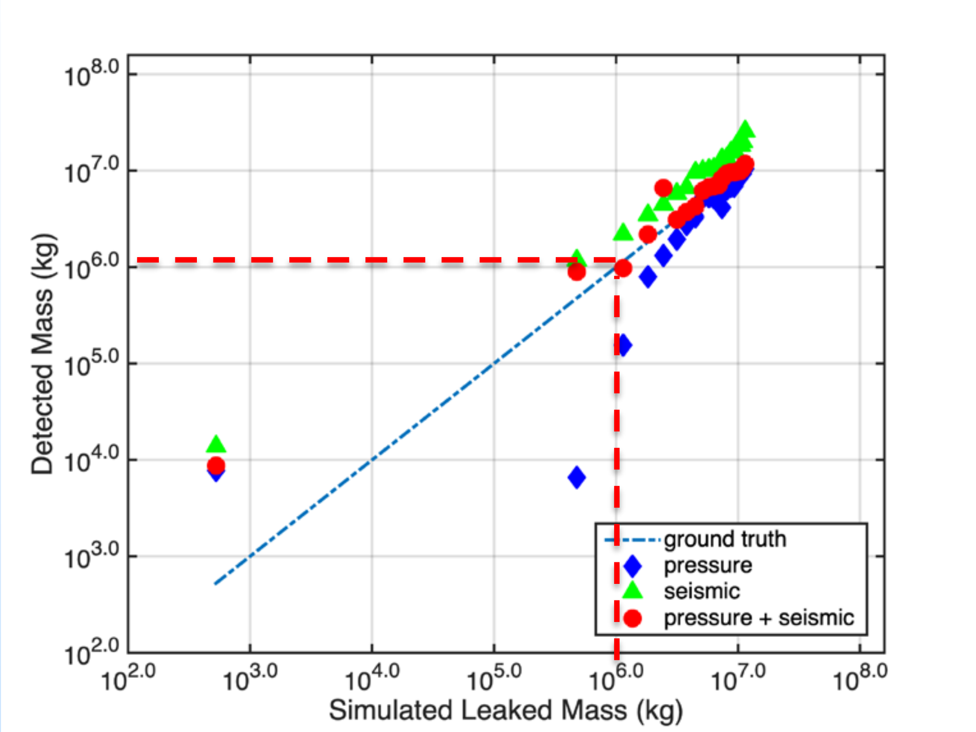

- It is possible to use ML techniques to detect small $CO_2$ leakage using synthetic pressure data with noise.

# Multi-physics Detection Method




Rafael Pires de Lima and Youzuo Lin, "Geophysical data integration and machine learning for multi-target leakage estimation in geologic carbon sequestration", SEG Technical Program Expanded Abstracts: 2333-2337, 2019.

# Multi-physics Detection Results




- A combination of seismic and pressure data may improve detection accuracy

Rafael Pires de Lima and Youzuo Lin, "Geophysical data integration and machine learning for multi-target leakage estimation in geologic carbon sequestration", SEG Technical Program Expanded Abstracts: 2333-2337, 2019.

# Accomplishments to Date

- Non-imaging Leak Detection [1, 2, 3]
  - Results: good detection capability with limited number of sources and receivers on the surface
    - Possible to use ML techniques to detect small $CO_2$ leakage using seismic and pressure data
    - Some robustness study (noise, survey)
    - May apply to other geophysical data

- Multi-Physics Leak Detection [4]
  - Results: A combination of seismic and pressure data may improve detection accuracy

- **Relevant Publications**


**[1].** Zheng Zhou, et. al, "A Data-Driven $CO_2$ Leakage Detection Using Seismic Data and Spatial-Temporal Densely Connected Convolutional Neural Networks," International Journal of Greenhouse Gas Control, Vol. 90, 2019.

**[2].** Rafael Pires de Lima, et. al "Transforming seismic data into pseudo-RGB images to predict $CO_2$ leakage using pre-learned convolutional neural networks weights", in the Proceeding of SEG Technical Program: 2368-2372, 2019.

**[3].** Zheng Zhou, et. al, "Spatial-Temporal Densely Connected Convolutional Networks: An Application to CO2 Leakage Detection", in the Proceeding of SEG Technical Program: 2136-2140, 2018.

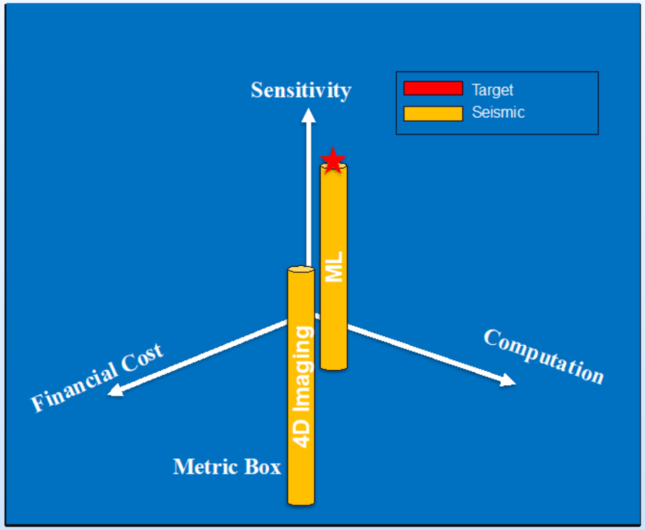
**[4].** Rafael Pires de Lima and Youzuo Lin, "Geophysical data integration and machine learning for multi-target leakage estimation in geologic carbon sequestration", SEG Technical Program Expanded Abstracts: 2333-2337, 2019.

# Economics

**Ultimate Goal**

**Detect leaks of 100 g/s within 100 d over an area of 100 km$^2$ for $100k/yr amortized over 10 years -> $1M total**

- **Seismic (Non) Imaging**
  - 3D seismic survey: ~$3M (based on 2017 estimated cost)
  - Based on synthetic: 1/10 sources and sensors in both x and y dimensions
    - Based on ML sensitivity compared to number of source/receiver pairs required for imaging
    - ~50k/survey (1/100 sensors and sources increased for repeated mobilization)
    - ~18 surveys (one every 200 days)
    - **$900k over 10 years**
- **Pressure**
  - **The pressure monitoring costs about $30K** (includes instrument and deployment plus data retrieval) for deep reservoirs. It will cost much less for much shallower data collection such as ground water aquifer ~ $5K.



# Lessons Learned

– Our results show that raw geophysical data (seismic and pressure) contain signature about $CO_2$ leakage. This information can be critical in detecting small leakage.
– PIML can extract those small signatures effectively and efficiently.
– Incorporation of both seismic and pressure data may improve accuracy of leakage detection.

# Synergy Opportunities

- Working with NRAP
- Working with NETL
- LANL institutional and LDRD projects
- Field Data (open for collaboration)

# Project Summary

- Data-driven approaches yield promising detection results.
- Physics information should be both taken into account when using data-driven approaches.
- A combination of different geophysical data may improve accuracy.


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.

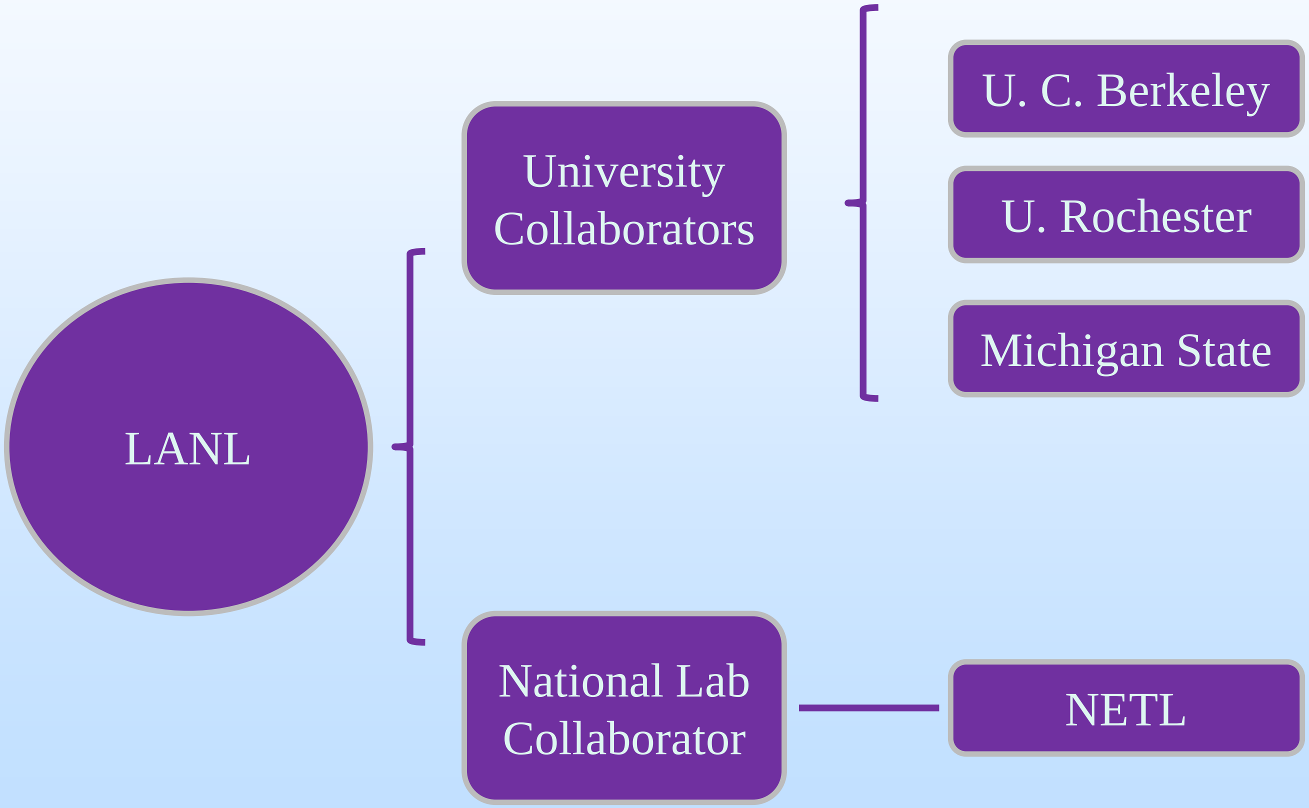
# Project Overview

## 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

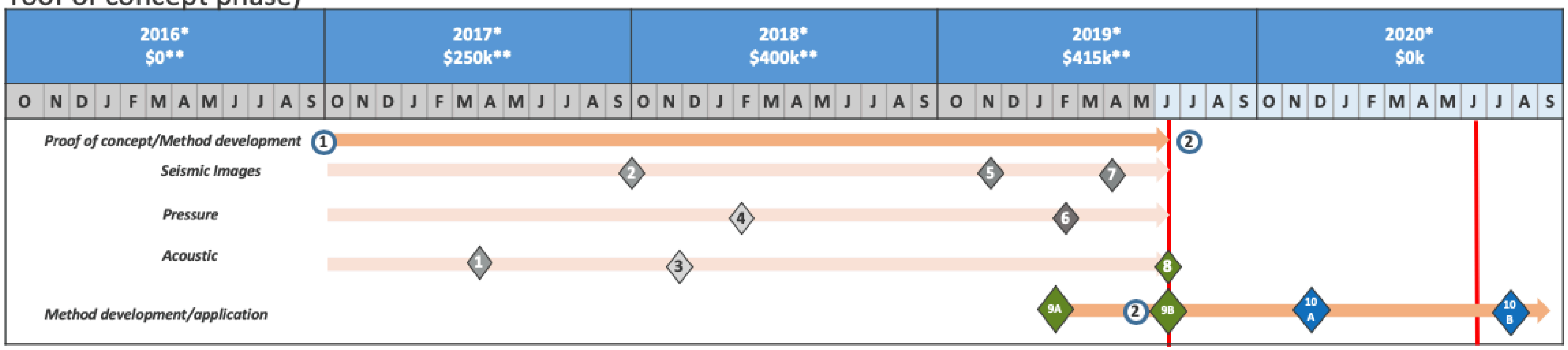


# Gantt Chart

## Task 2: Project Timeline Overview

NATIONAL ENERGY TECHNOLOGY LABORATORY

**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. <u>Seismic Images:</u> Development/testing of machine-learning (ML) method for extracting <u>large-leak</u> signal from synthetic data
3. <u>Acoustic:</u> Development/testing of ML method for extracting <u>large-leak</u> signal from acoustic
4. <u>Pressure:</u> Development/testing of ML method for extracting <u>large-leak</u> signal from pressure data
5. <u>Seismic Images:</u> Testing of ML potential to extract <u>large-leak</u> signal from <u>noisy</u> synthetic seismic images
6. <u>Pressure:</u> Testing of ML method for extracting <u>small-leak</u> signal from <u>noisy</u> pressure data
7. <u>Seismic Images:</u> Testing of ML potential to extract <u>small-leak</u> signal from synthetic seismic images
8. <u>Acoustic:</u> Testing of ML method for extracting <u>small-leak</u> signal from <u>noisy</u> acoustic data

9a. Develop requirements for Method Development/Application
9b. Develop multi-data ML integration method
10. Initial testing on real data sites (a, b, c…)

### Chart Key

\# TRL Score | Go / No-Go Timeframe | Project Completion | Milestone | Complete | FY19 | FY20

### Go / No-Go

1. Determine which method(s) should be used to detect a leak of 100 g/s over an area of 100 km² for 10-year amortized cost of $100k/year
2. *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

# Bibliography


- [1]. Youzuo Lin, Daniel O'Malley, Velimir V. Vesselinov, George Guthrie, and David Coblentz,"Randomization in Characterizing the Subsurface," SIAM News, Volume 51, Issue 1, Jan 2018
- [2]. Yue Wu, Youzuo Lin, Zheng Zhou, David Chas Bolton, Ji Liu, Paul Johnson, "Cascaded Contextual Region-based Convolutional Neural Network for Event Detection from Time Series Signals: A Seismic Application," in IEEE Transactions on Geoscience and Remote Sensing. (Accepted)
- [3]. Youzuo Lin, Shusen Wang, Jayaraman Thiagarajan, George Guthrie, and David Coblentz, "Efficient Data-Driven Geologic Feature Detection from Pre-Stack Seismic Measurements using Randomized Machine-Learning Algorithm," in arXiv, 2017. (Under Reviewing in Geophysical Journal International).
- [4]. Yue Wu, Zheng Zhou, Andrew Delorey, Ting, Chen, Youzuo Lin, "DeepDetect: A Deep Densely Connected Neural Network to Detect Seismic Events", SIAM Conference on Data Mining Workshop, 2018.
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- [6]. Zheng Zhou, Youzuo Lin, Yue Wu, Zan Wang, Robert Dilmore, George Guthrie, "Spatial-Temporal Densely Connected Convolutional Networks: An Application to CO2 Leakage Detection," Proceeding of Society of Exploration Geophysics (SEG), 2018 (Accepted).
- [7]. Zheng Zhou, Youzuo Lin, Yue Wu, Zan Wang, Robert Dilmore, George Guthrie, "Spatial-Temporal Densely Connected Convolutional Networks: An Application to CO2 Leakage Detection," Geophysical Journal International (GJI), 2018 (In Preparation).
- [8]. Youzuo Lin, Shusen Wang, Jayaraman Thiagarajan, George Guthrie, and David Coblentz, "Towards Real-Time Geologic Feature Detection from Seismic Measurements using a Randomized Machine-Learning Algorithm," Proceeding of Society of Exploration Geophysics (SEG), PP2143—2148, 2017.