Monitoring for Faults at a Critical State of Stress – Application to Carbon Storage

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Research Team

- LANL
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- External partners (leveraging with)
  - U. Alberta [Canada], Penn State, U. Tenn., USGS, ETH [Zurich], ENS [Paris]. U. Rochester, Georgia Tech

Presentation Outline

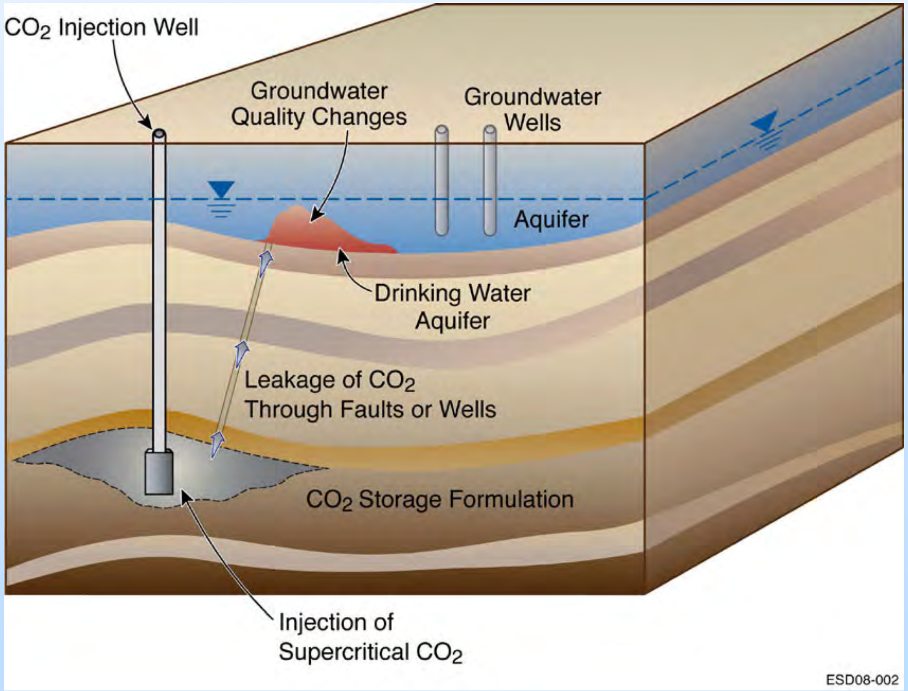
- Introduction
- Approach
- Method application
- Summary

Objectives

Monitoring for faults at a critical state of stress

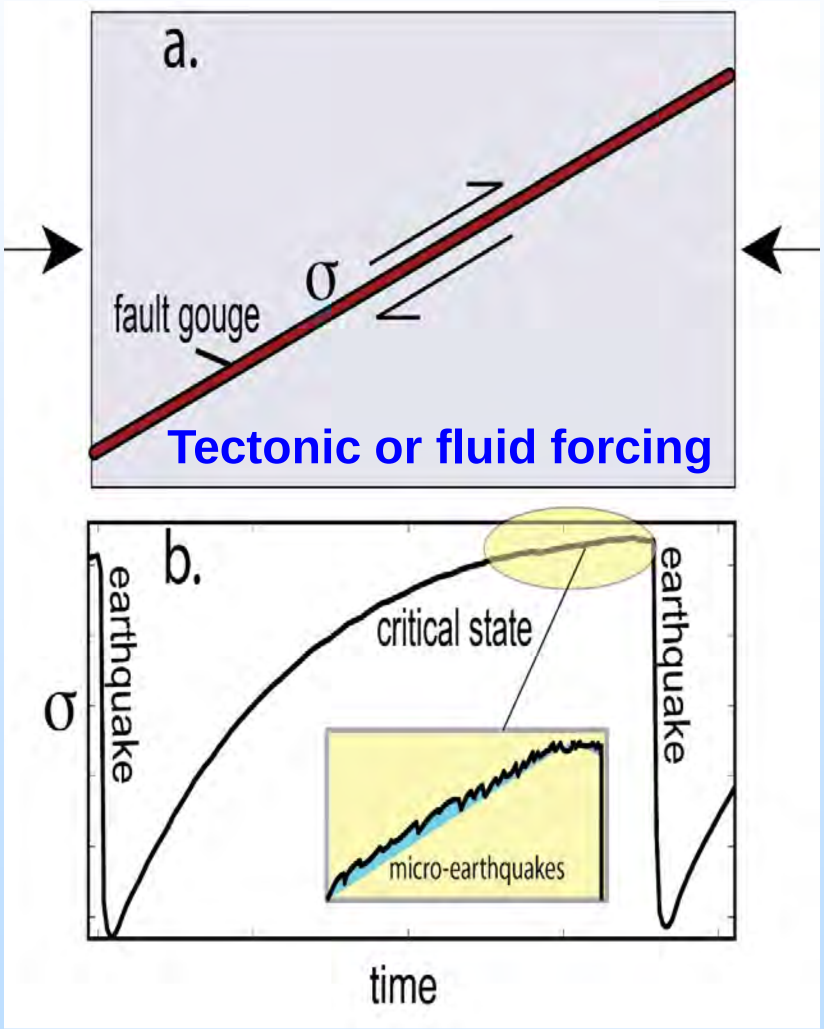
Goal: ensure safe and long-term CO2 storage

- Pre-injection characterization
  - Identify faults of concern in the region
- During-injection monitoring
  - Avoid induced seismicity



(from LBL)

Critical State of Stress

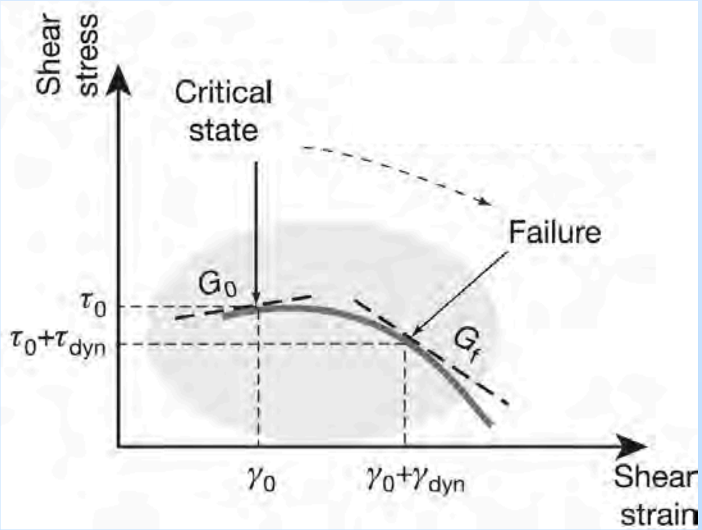


- All brittle failure experiments exhibit precursors
- All shear experiments exhibit precursors
- Many avalanches exhibit precursors
- Many earthquakes exhibit precursors (but not all!)

We posit that all slip events exhibit precursors but that we cannot always record or identify them.

Approach

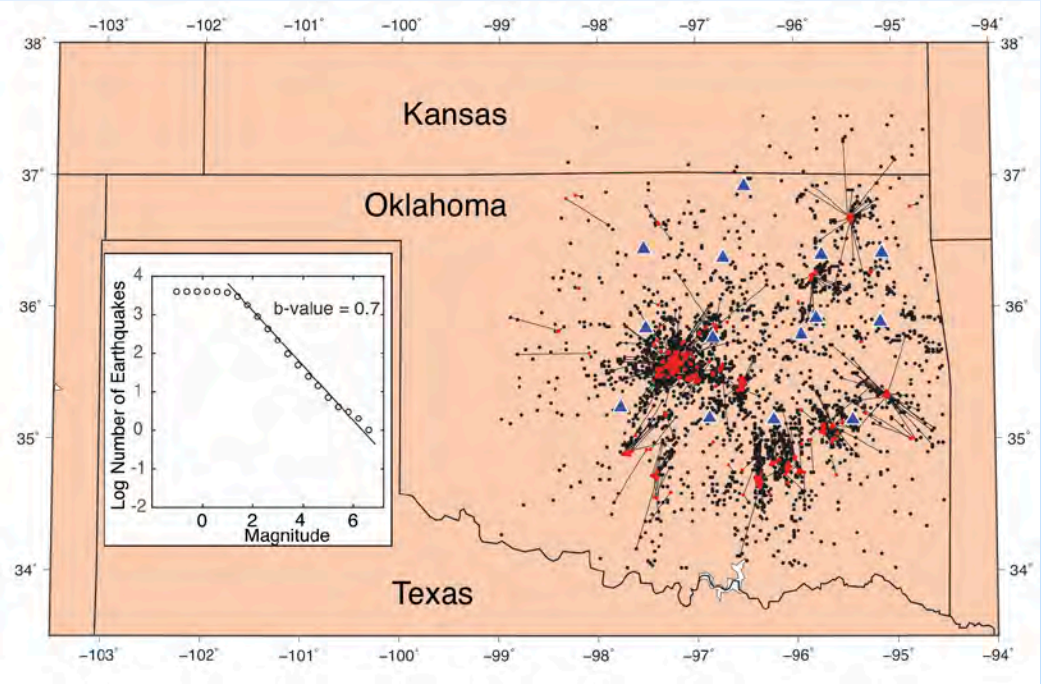
- Detect small seismic signals
  - Abundant small events provide a robust path for testing our hypothesis
  - previously unidentified, new signals
- Analyze the relationship to critical state
  - Response to small stress perturbation (e.g., triggering by solid Earth tide)

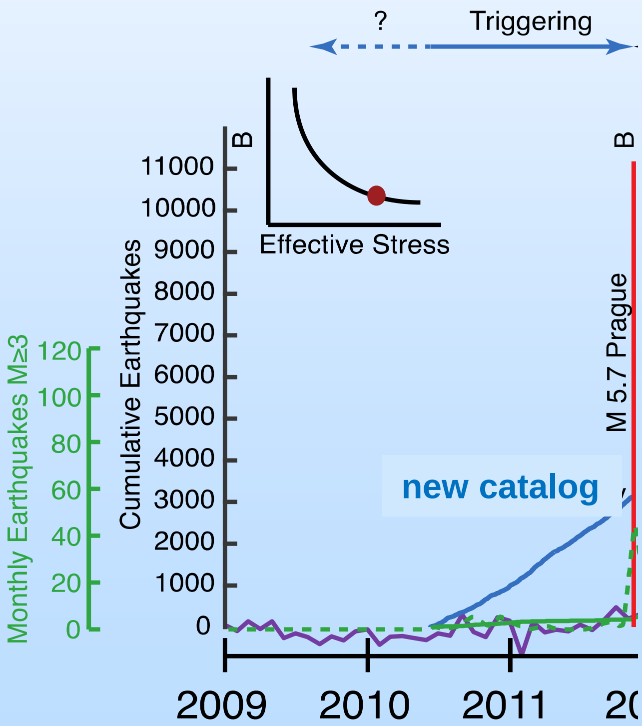


(Johnson & Xia, 2005)

Small Signals Reveal Fault State

- Oklahoma
  - With comprehensive new catalog (include many more small events), tidal triggering was detected before the M5.7 Prague earthquake, indicating a potential critical state



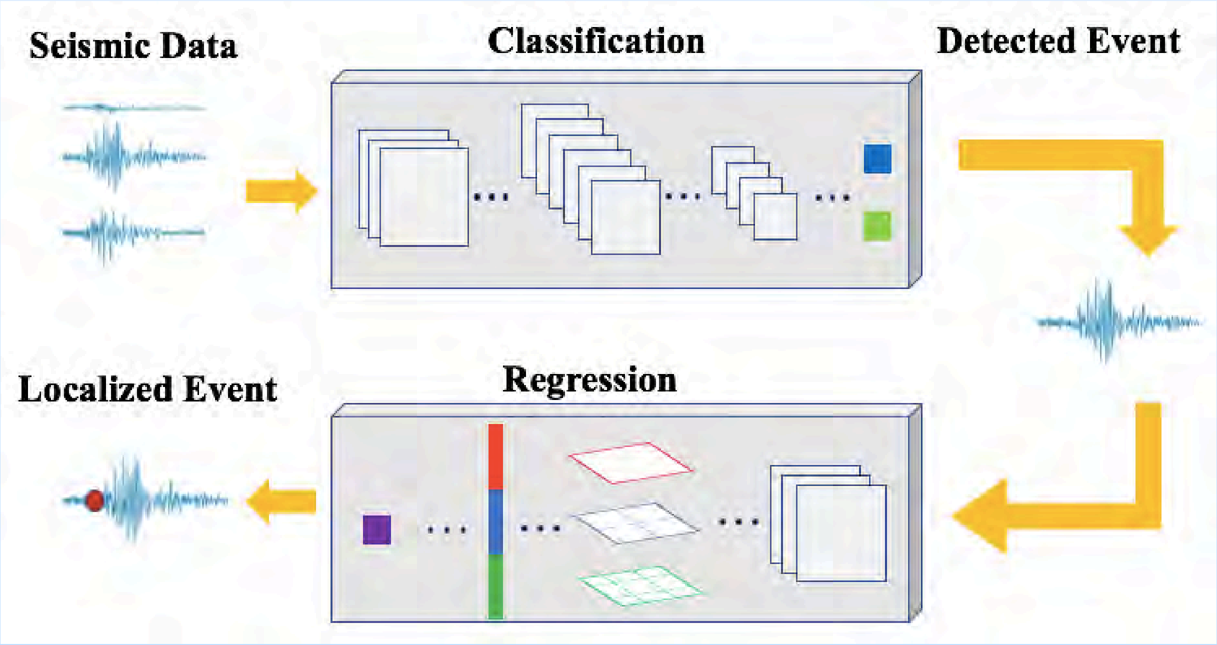


Methods to Detect Small Signals

- Inter-station waveform coherence
  - Multiple stations
  - Regional scale
  - High cost
- Machine-learning based algorithms
  - Accurate (reduce the detection threshold)
  - Low cost (automatic, fast)
  - Flexible
    - Single station, single component
    - Single station, multiple components
    - Multiple stations, multiple components

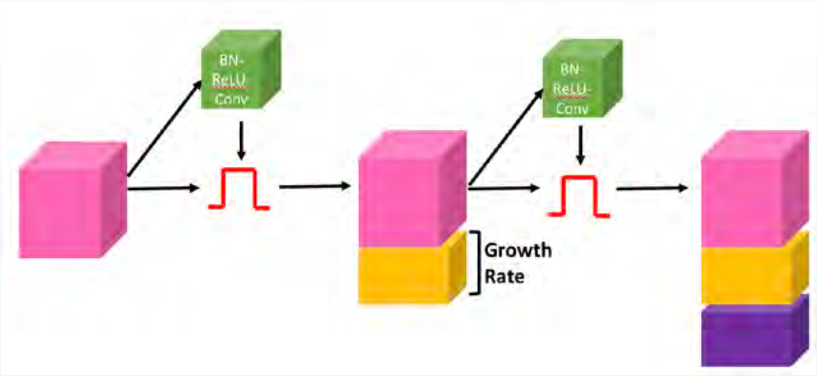
Machine Learning Detection

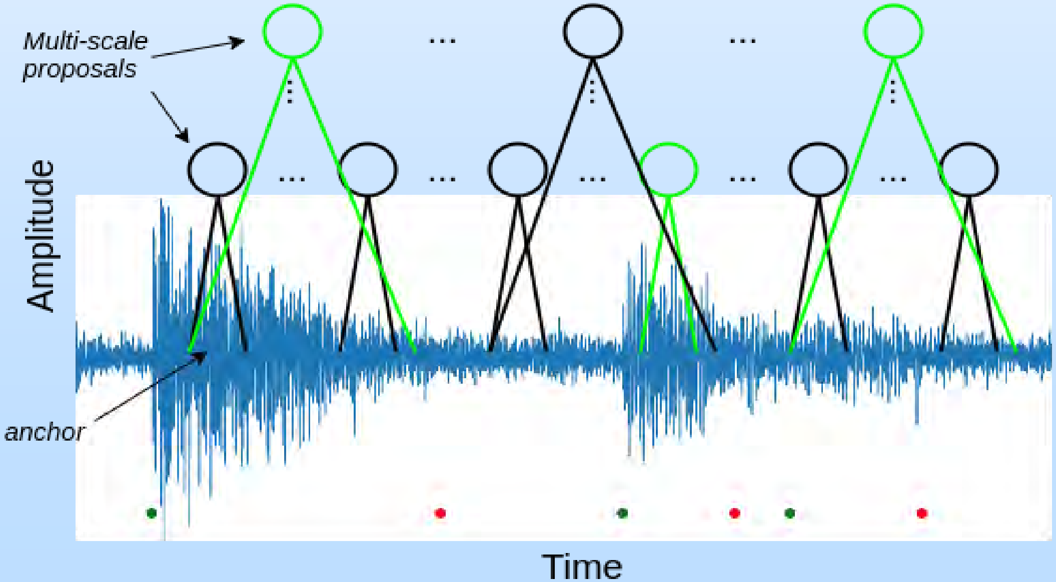
- Two-phase detection
  - Classification: determine whether the given time segment includes an earthquake
  - Regression: locate the earthquake arrival time



Machine Learning Detection

- End-to-End
  - No preprocessing
- Densely Connected Convolutional Neural Network (DenseNet)
  - Less parameters, reduce cost
- Multi-scale
  - Detect events of different size





Application to Field Data

- Dataset 1: central Oklahoma
  - Training set: ~3000

normal

- Dataset 2: northern Oklahoma
  - Small training set: ~ 500

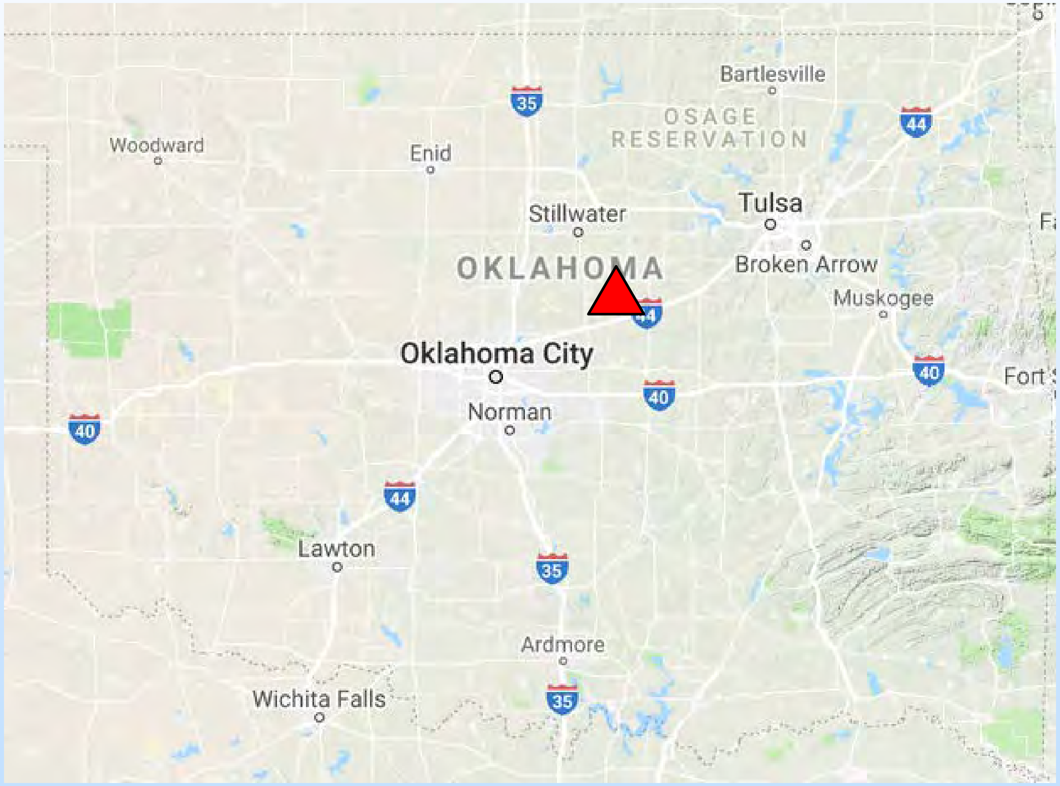
challenging

- Dataset 3: Decatur, Illinois
  - Small training set: ~ 100
  - Low SNR

highly challenging

Application – Dataset 1

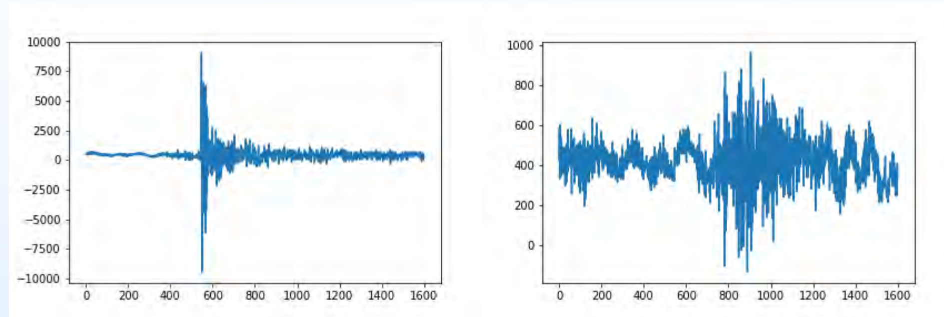
- Central Oklahoma (water injection)
- One station in US Array (2010-2011)
- Broadband seismometer
- Vertical component
- Earthquake catalog:
  - 3319 events
  - 1 < M < 5
  - Inter-station waveform coherence



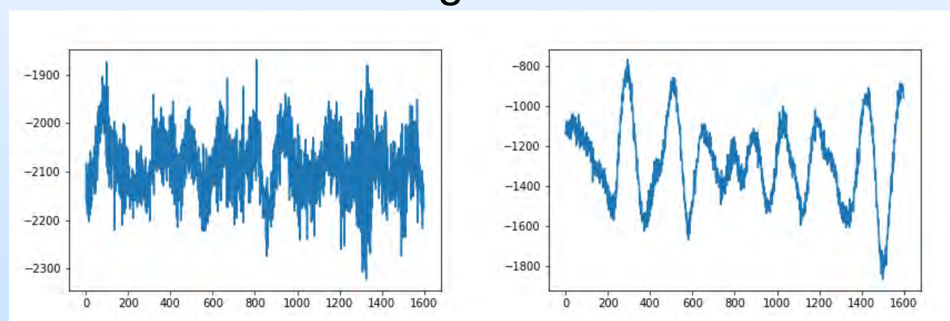
Application – Dataset 1

- Training set:
  - the first 19 months
  - Event: 2651
  - Noise: 2651
- Test set:
  - the rest 3 months
  - Event: 668
- Accuracy:
  - 90.2%

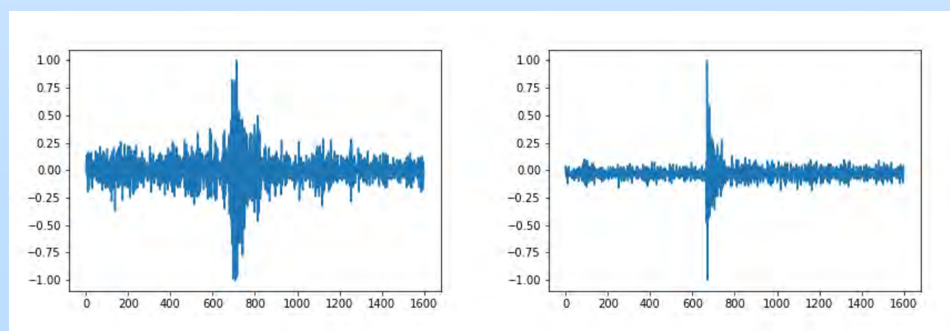
Training: event



Training: noise

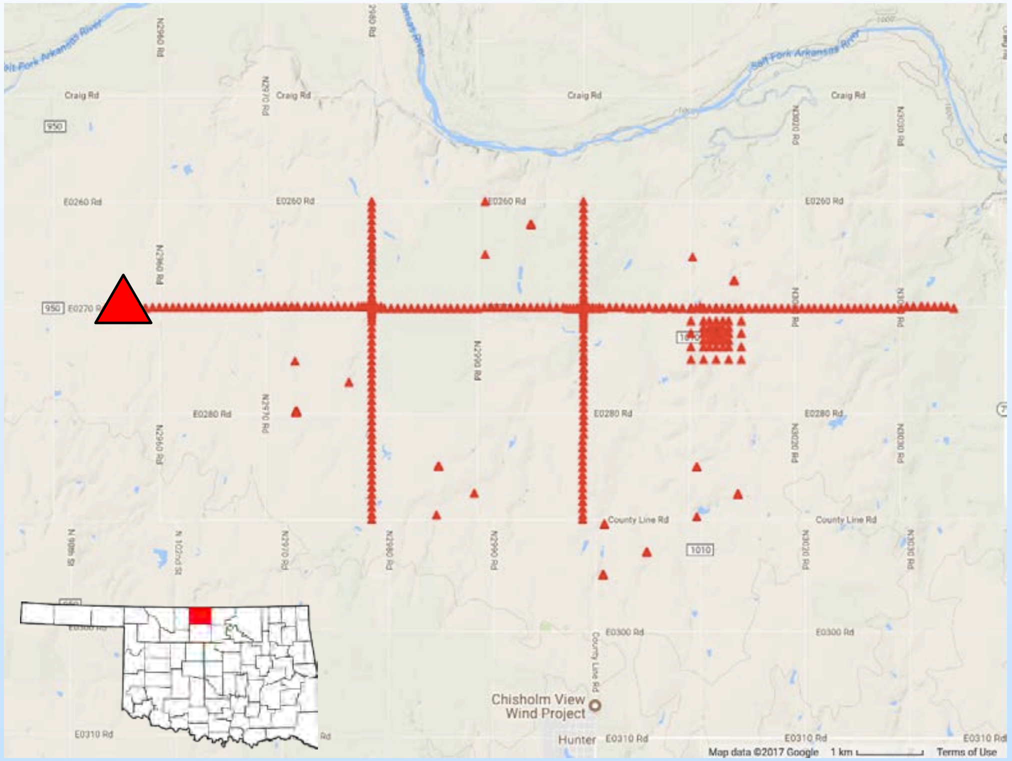


Detect: extra event



Application – Dataset 2

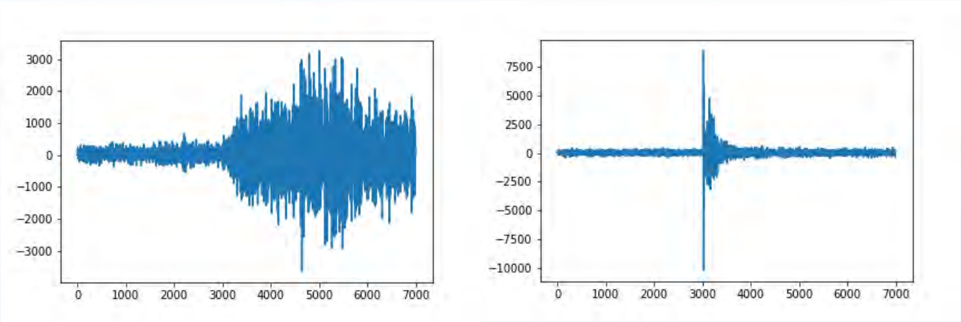
- Northern Oklahoma (water injection)
- One station in IRIS wavefield experiment (June-July, 2016)
- Geophone
- Vertical component
- Earthquake catalog
  - 509 events
  - Oklahoma Geological Survey (2<M<4)
  - Manual phase pick (M<2)



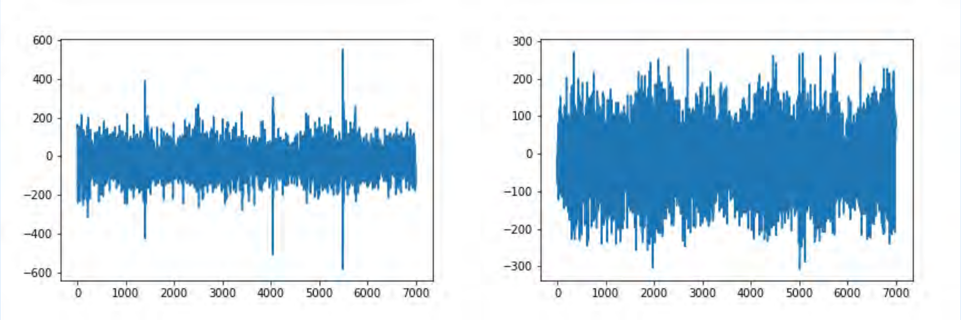
Application – Dataset 2

- Training set:
  - the first 10 days
  - Event: 382
  - Noise: 1146
- Test set:
  - the rest 5 days
  - Event: 127
- Accuracy:
  - 80%

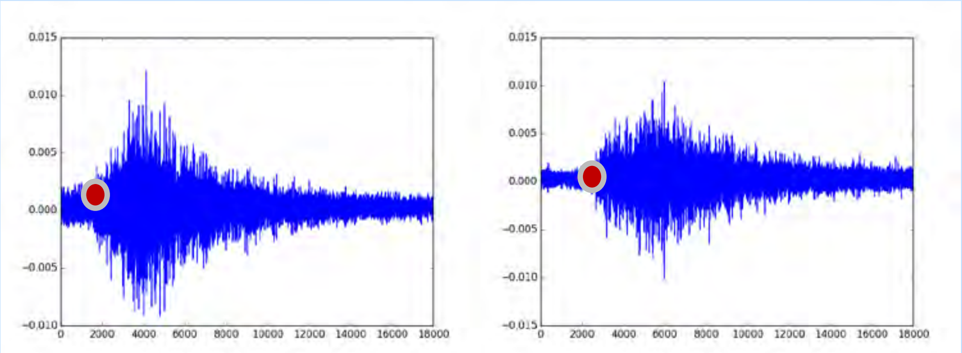
Training: event



Training: noise

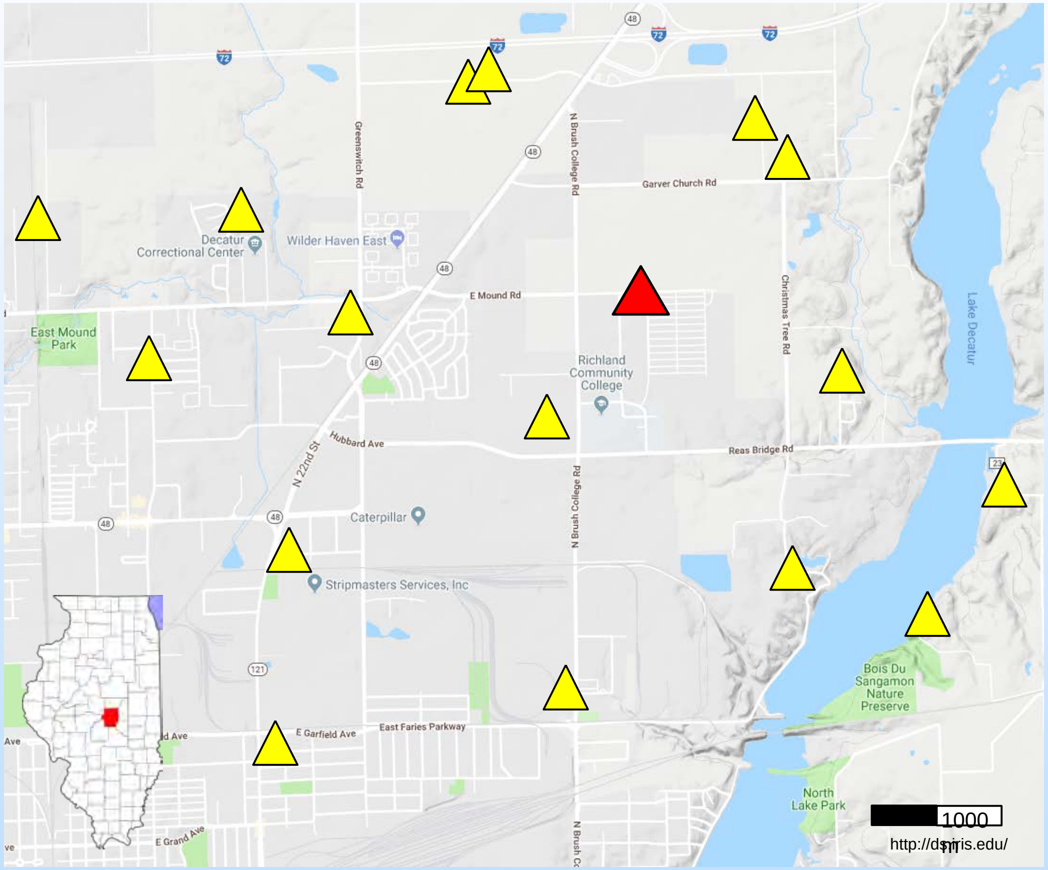


Detect: extra event



Application – Dataset 3

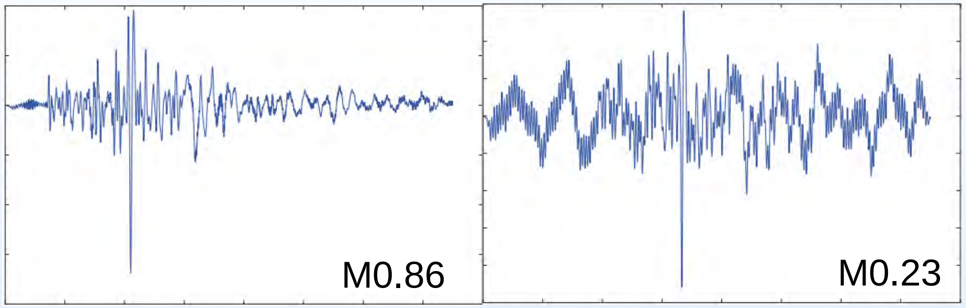
- Decatur, Illinois (CO_2 injection)
- One station from USGS seismic array (2013-)
- Borehole geophone (~150 m deep)
- Vertical component
- Earthquake Catalog:
  - 136 (2013-2015)
  - -1.1 < M < 1.3
  - Kaven et al., 2015



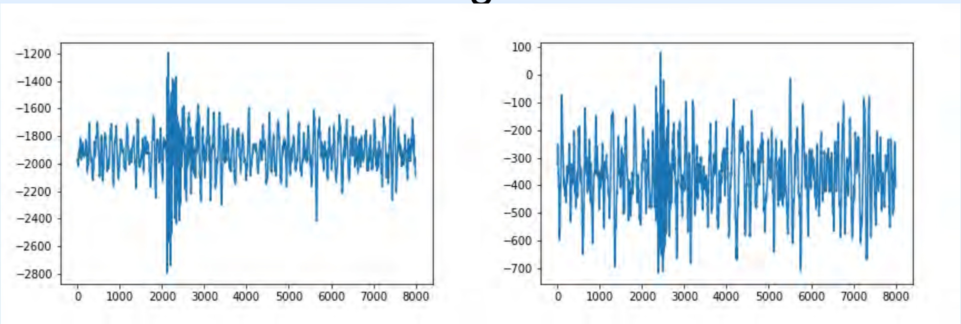
Application – Dataset 3

- Training set:
  - the first 10 months
  - Event: 264
  - Noise: 264
- Test set:
  - the rest 3 months
  - Event: 26
- Accuracy:
  - 72 %

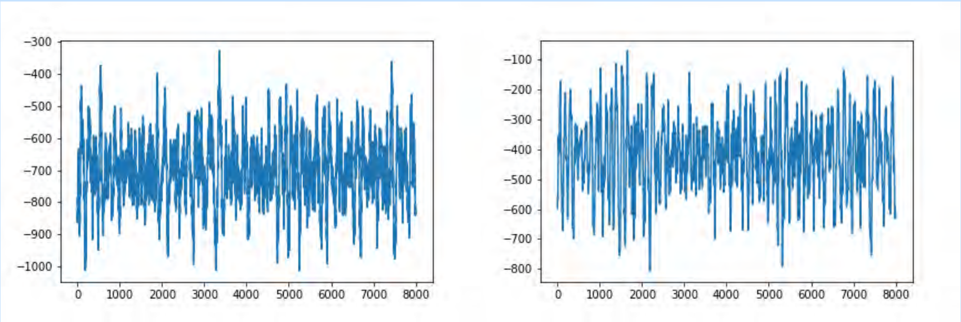
Example signal (Kaven et al., 2015)



Training: event



Training: noise



Summary

- We have developed a machine learning algorithm to detect earthquakes using one-component record from one station
- This method can
  - differentiate earthquake signals from non-earthquake signals.
  - detect earthquakes of different length in times
  - estimate the first arrival times of the detected earthquakes
- We demonstrated the capability of this method by applying to different fluid-injection sites

Next steps

- Field application
  - Continue the large-volume data processing at different injection sites to extract small earthquake signals
  - Evaluate the results against other methods
  - Analyze the behavior of earthquake distributions in relation to stress perturbation
  - Economic evaluation of the monitoring approach
- Algorithm improvement
  - Extend the algorithm to single station, multi-component
  - Extend the algorithm to multi-station, multi-component

Synergy Opportunities

- Injection projects that have seismic monitoring system to collect passive seismic data

- Improve our event detection algorithm

- Feed back with seismic characterization and inferred fault state

Appendix

Benefit to the Program

- Program goals being addressed by this project
  - Improve the risk assessment of induced seismicity in carbon sequestration.
- Project benefits
  - The research project is developing new methodology to identify and monitor faults at a critical state of stress. If successful, the proof-of-concept work will demonstrate at field scale a transformational approach for both identifying potential faults of concern during site pre-characterization and monitoring a site during injection such that induced seismicity is minimized or even avoided.

Project Overview
Goals and Objectives

- Relationship to the program goals and objectives
  - The stress state of the fault is related to risk level of induced seismicity. Monitoring faults at critical state of stress enables advanced risk assessment of induced seismicity for carbon storage.

- Success criteria
  - New methodology for monitoring the stress state of faults
  - Successful application of the methodology to CO_2 storage field

Organization Chart

- LANL
  - Ting Chen, Youzuo Lin, Alex Eddy, Yue Wu, Zhongping Zhang, Peter Roberts, Christine Gammans, Andrew Delorey, Paul. Johnson, Velimir Vesselinov, Daniel O'Malley, Rajesh Pawar, George Guthrie

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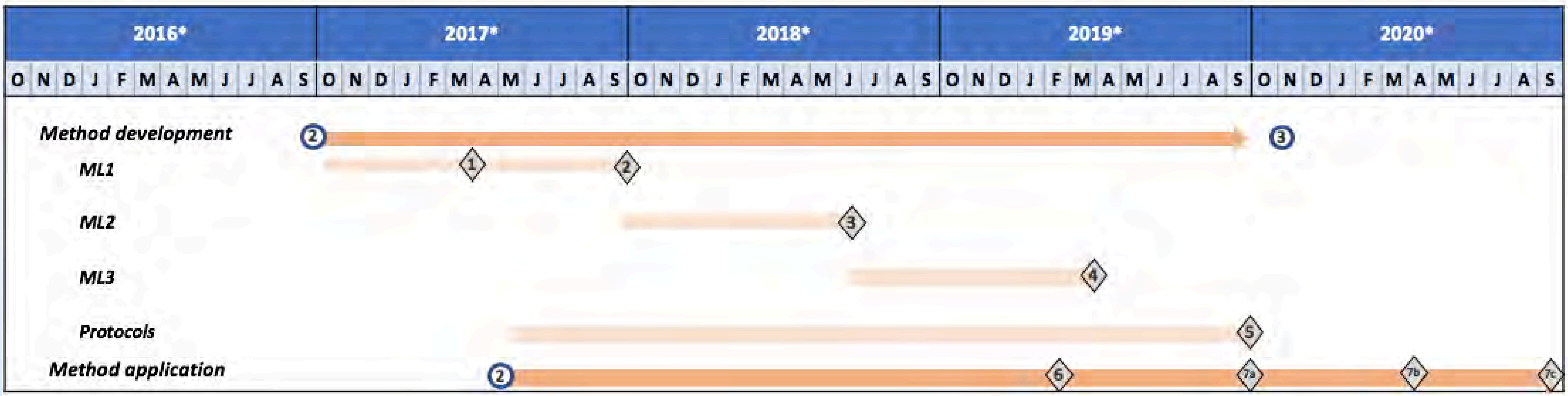
Gantt Chart



Prior work—IWC analysis of multi-station/multi-component data shows changes in small events using pre-2012 OK dataset

1. Develop/train machine-learning algorithm (ML-1) to extract events from single-component, single-station seismic data
2. Evaluate ability of ML-1 to extract small events relative to interstation waveform coherence (IWC) using pre-2012 OK dataset
3. Extend ML-1 to extract events from multi-component, single-station data (ML-2); test using pre-2012 OK dataset
4. Extend ML-2 to extract events from multi-component, multi-station data (ML-3); test using pre-2012 OK dataset
5. Protocols for use and application of ML algorithms as applied to seismic datasets at site- (ML-1; ML-2) or regional-scale (ML-3)
6. Apply ML protocol to OK data (2009–2016)
7. Apply ML protocol to seismic dataset(s) from other sites (a, b, c, …)

Bibliography

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- Wu, Y., Zhou, Z., Delorey, A., Chen, T., and Lin, Y., 2018, DeepDetect: A Deep Densely Connected Neural Network to Detect Seismic Events, Proceedings of SIAM Data Mining Conference

- Wu, Y., Zhou, Z., Chen, T., and Lin, Y., 2018, DeepDetect: Application of Deep Densely Connected Convolutional Neural Network to Earthquake Detection, SSA Annual Meeting, Miami, FL