Critical Stress State

FWP-FE-112-19-FY19

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National Energy Technology Laboratory
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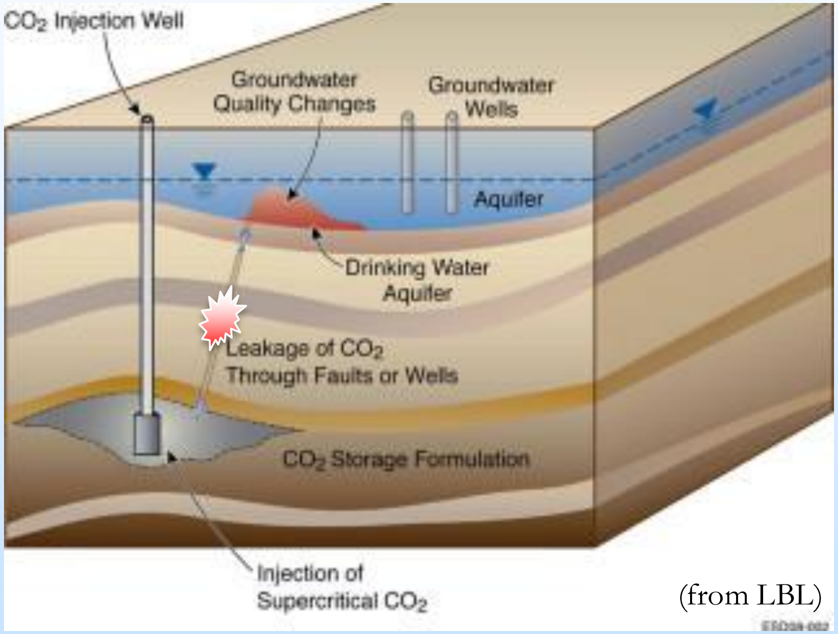
Project Overview

- Funding:
  - DOE Office of Fossil Energy
  - FWP FY19
- Project Participants
  - LANL
    - Ting Chen, Xiaofei Ma, Richard Alfaro, Andrew Delorey, Yan Qin, Jeremy Webster, Youzuo Lin, Avipsa Roy, Alex Eddy, Yue Wu, Zhongping Zhang, Tiantong Wang, Peter Roberts, Christine Gammans, Paul. Johnson, Velimir Vesselinov, Daniel O'Malley, Rajesh Pawar, George Guthrie
  - External partners (synergy)
    - CarbonSAFE – San Juan Basin project
    - U. Alberta, U. Oklahoma, U. Rochester

Objectives

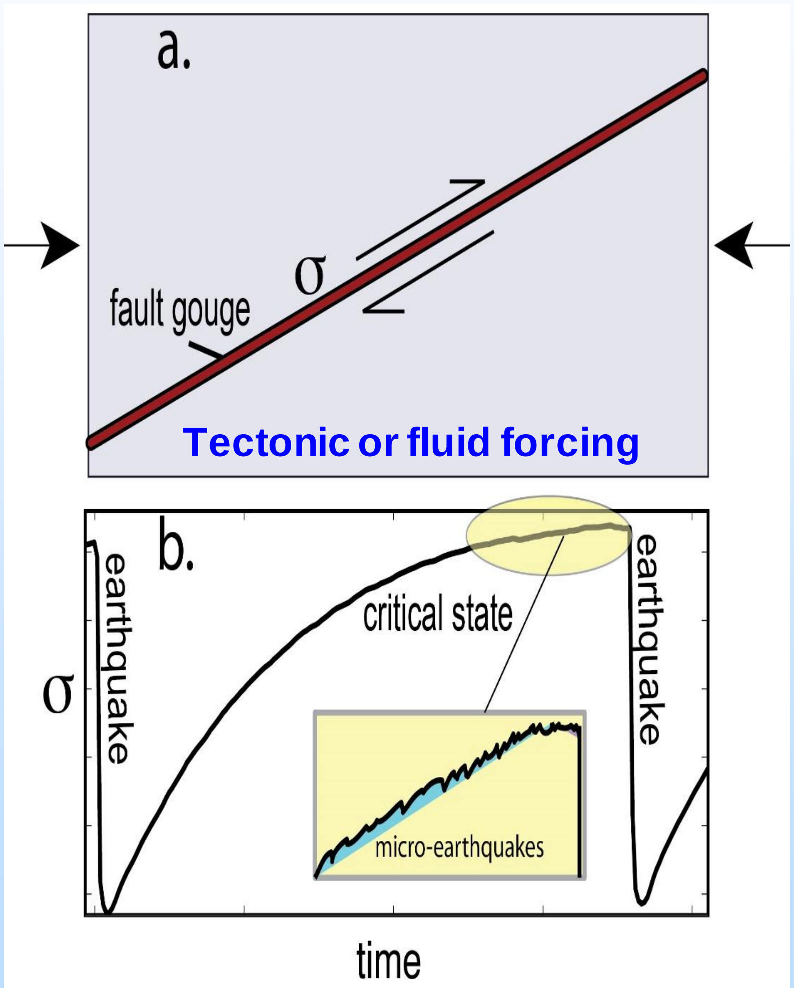
Improve the risk assessment of induced seismicity in carbon sequestration through monitoring of critical state of stress

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

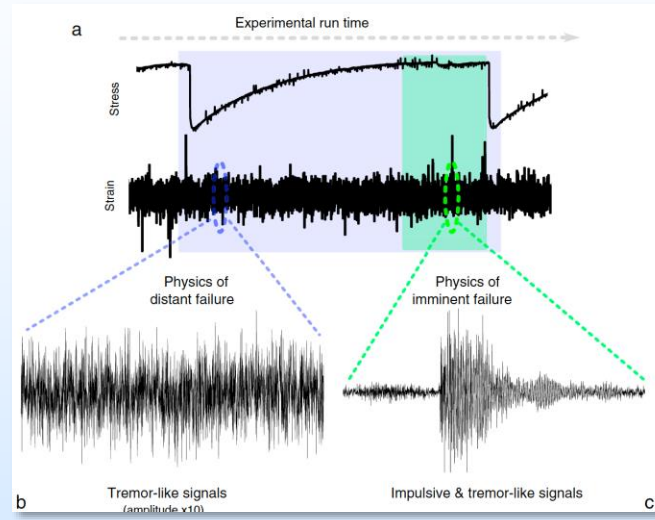


(from LBL)

Critical State of Stress

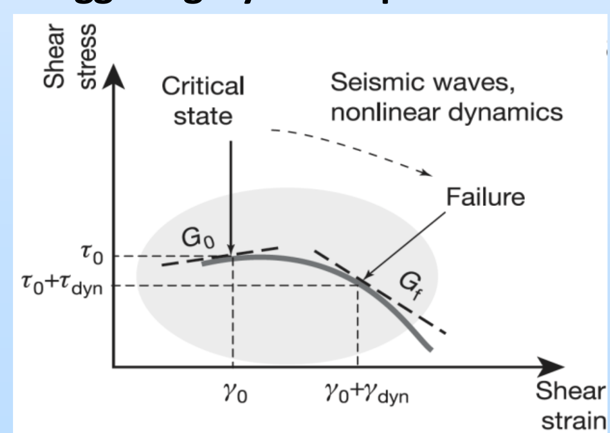


"Precursor" events occur prior to major slip events



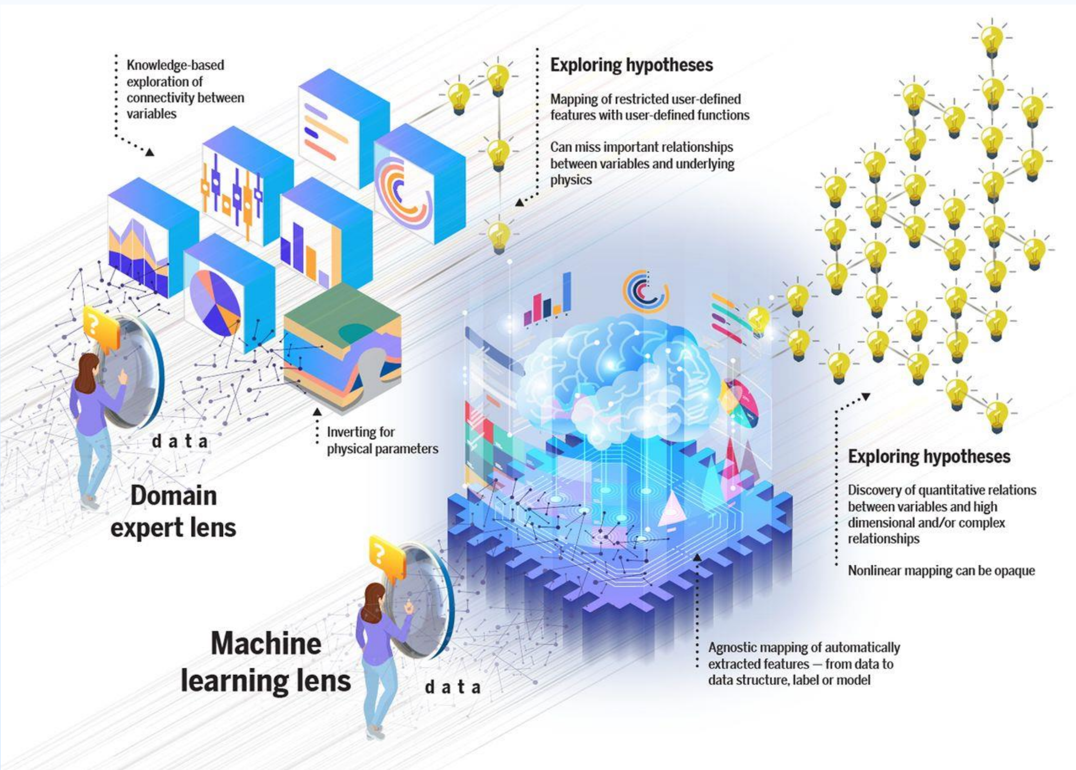
Rouet-LeDuc et al. (2017)

Triggering by stress perturbation

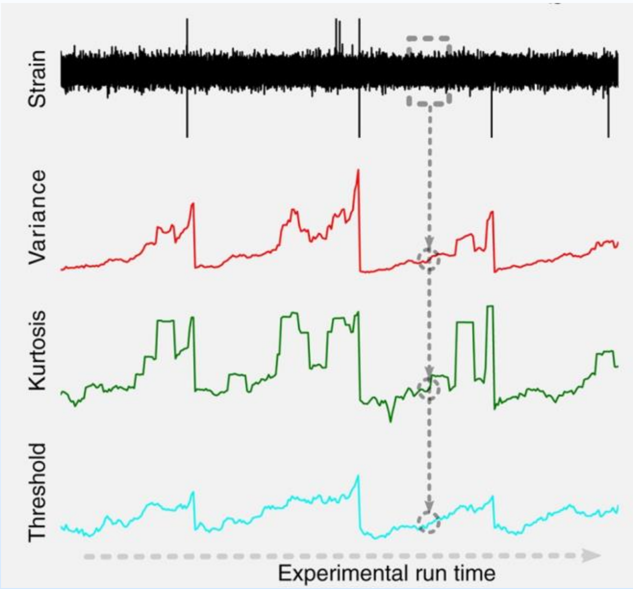


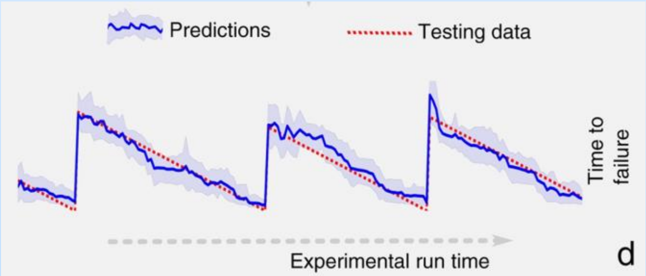
(Johnson & Xia, 2005)

Extract information from data with ML



(Bergen et al., 2019)





"noise" gives insight into fault physics

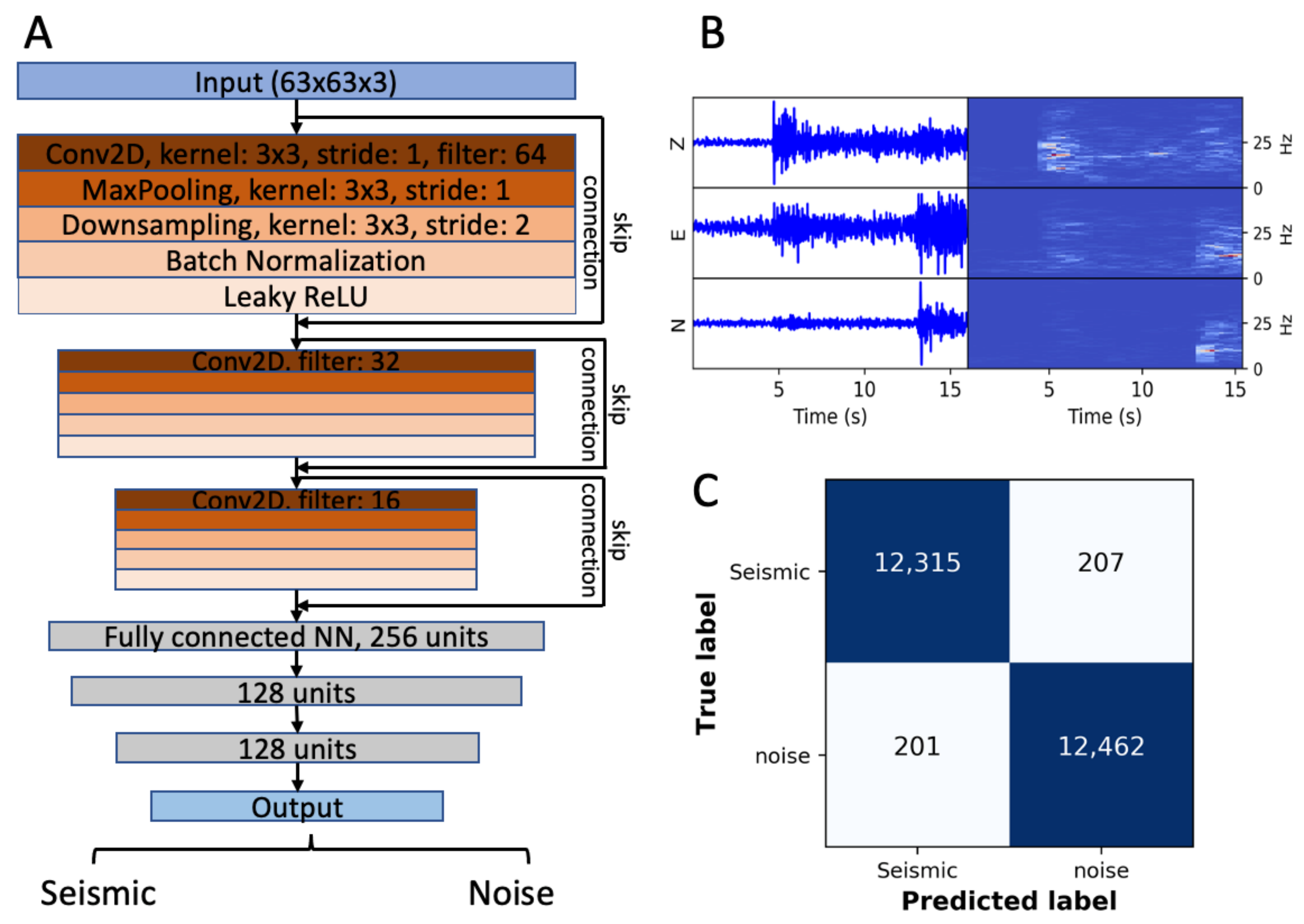
(Rouet-LeDuc et al., 2017)

Extract Small Seismic Signals

- Manual
  - Least false positive, but may miss small signals
  - High cost: takes hours for 1 well-trained person to process 1-day data from a 1C station
- Traditional algorithm
  - e.g., STA/LTA
  - High false positive (requires extra manual inspection); may miss small signals
- Cross-correlation based
  - Automatic
  - Can detect smaller signals
  - Computationally expensive, limited by templates
- Machine learning
  - Accurate (reduce the detection threshold)
  - Low cost (automatic, fast)

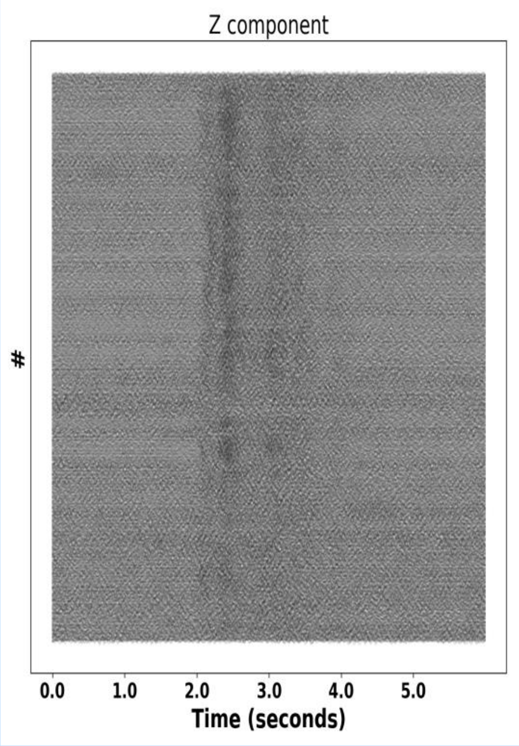
Machine Learning for Seismic Signal Detection

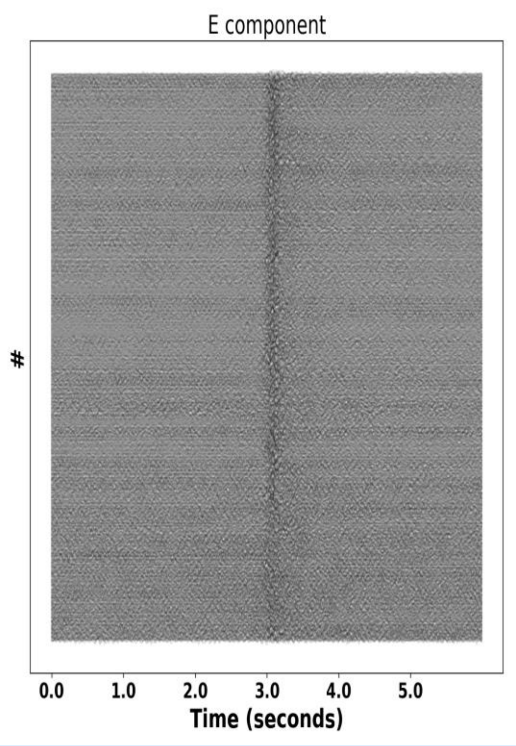
- Input: 3C spectrograms
- Training: ~ 1.1M samples
- Accuracy: 98.4%

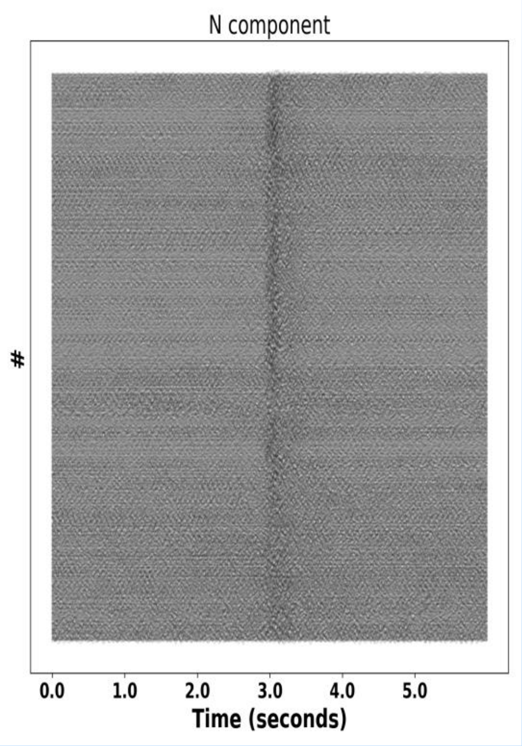


Detection Examples

- Continuous data recorded at one station
- Detected 10s times of more events compared with original catalog

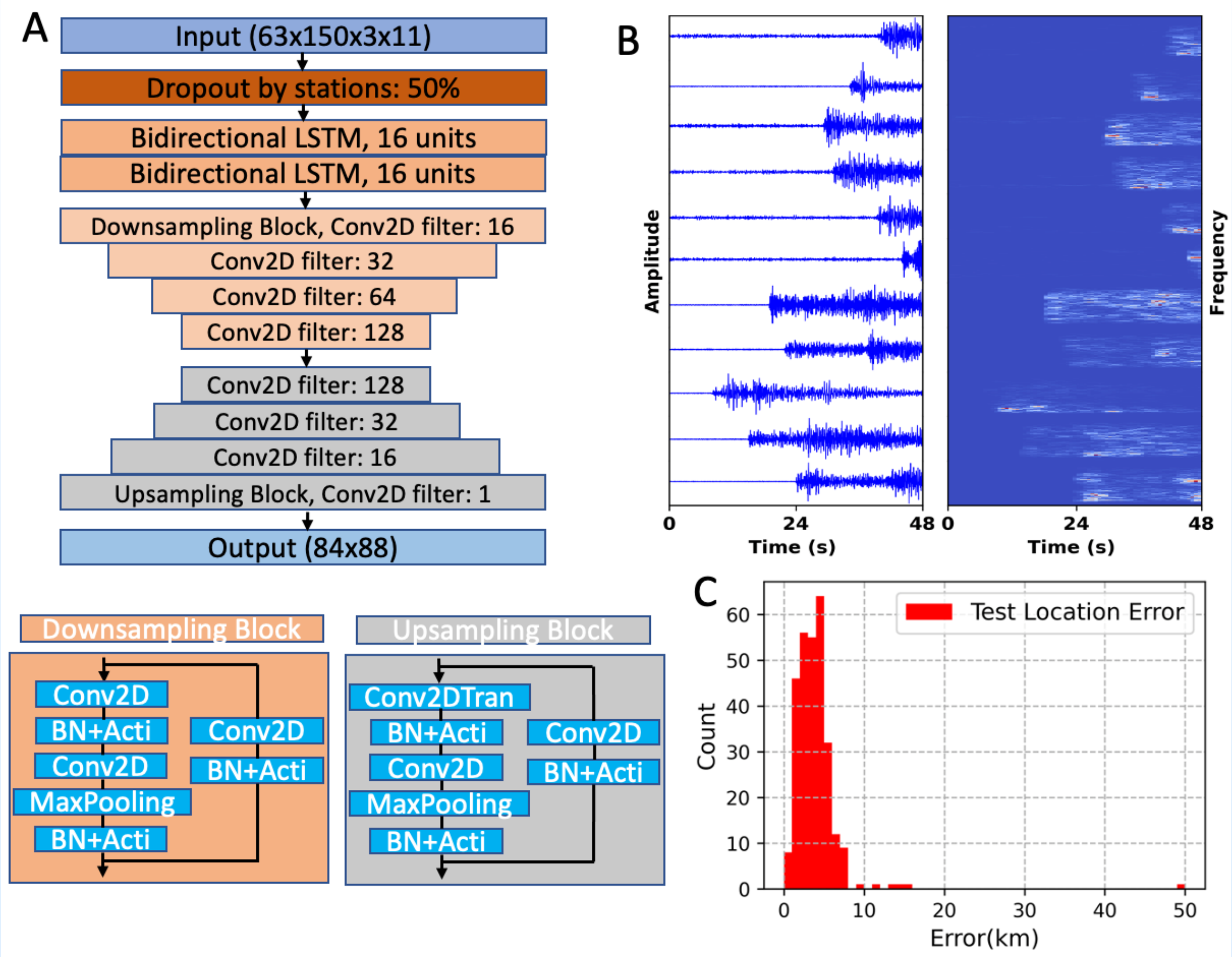






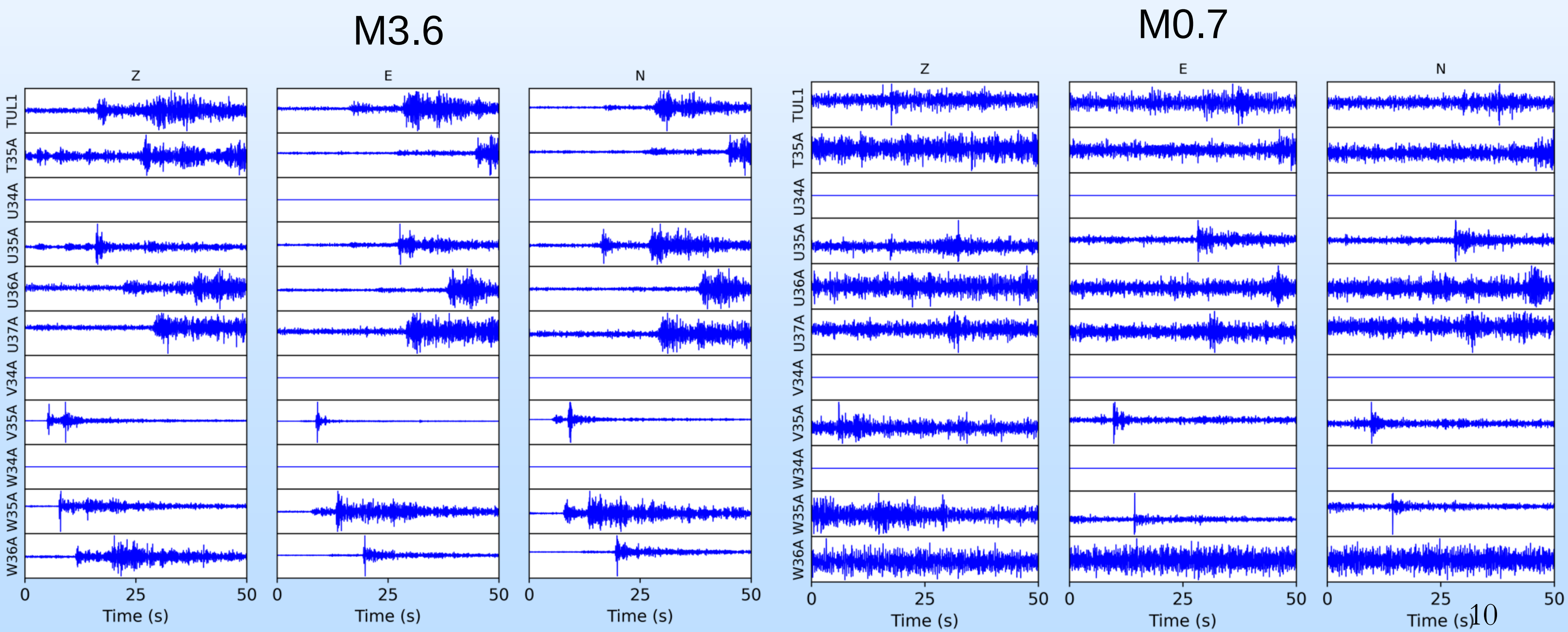
Machine Learning for Seismic Event Location

- Input: multi-station spectrograms
- Training: ~ 10K samples
- Accuracy: ~ 4km



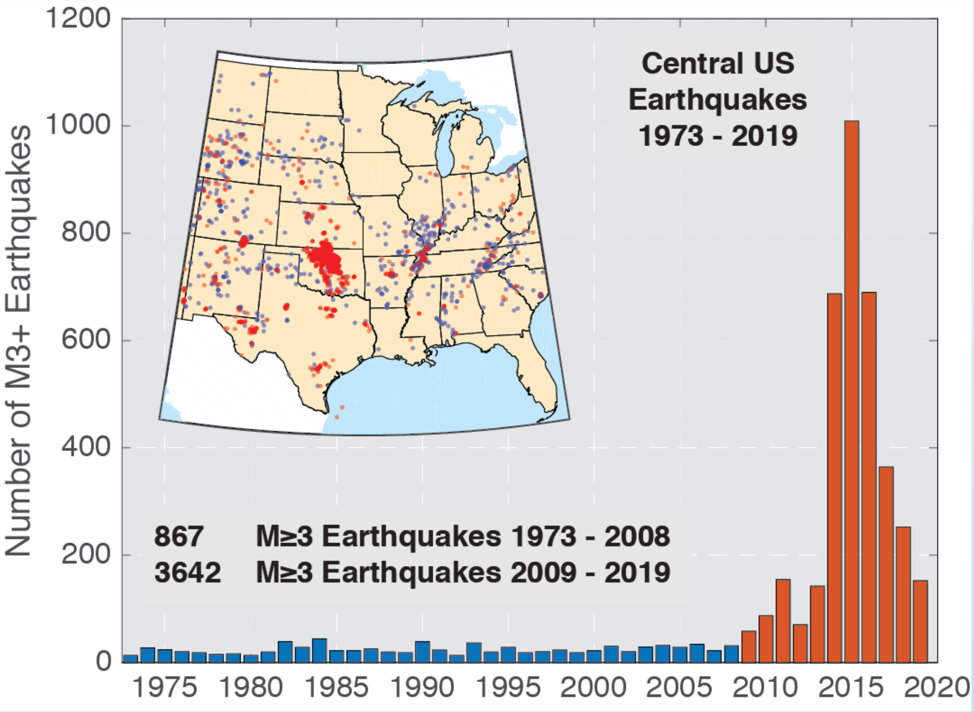
Location Examples

- Signals from multiple stations
- Similar waveform patterns across the station network result in similar locations

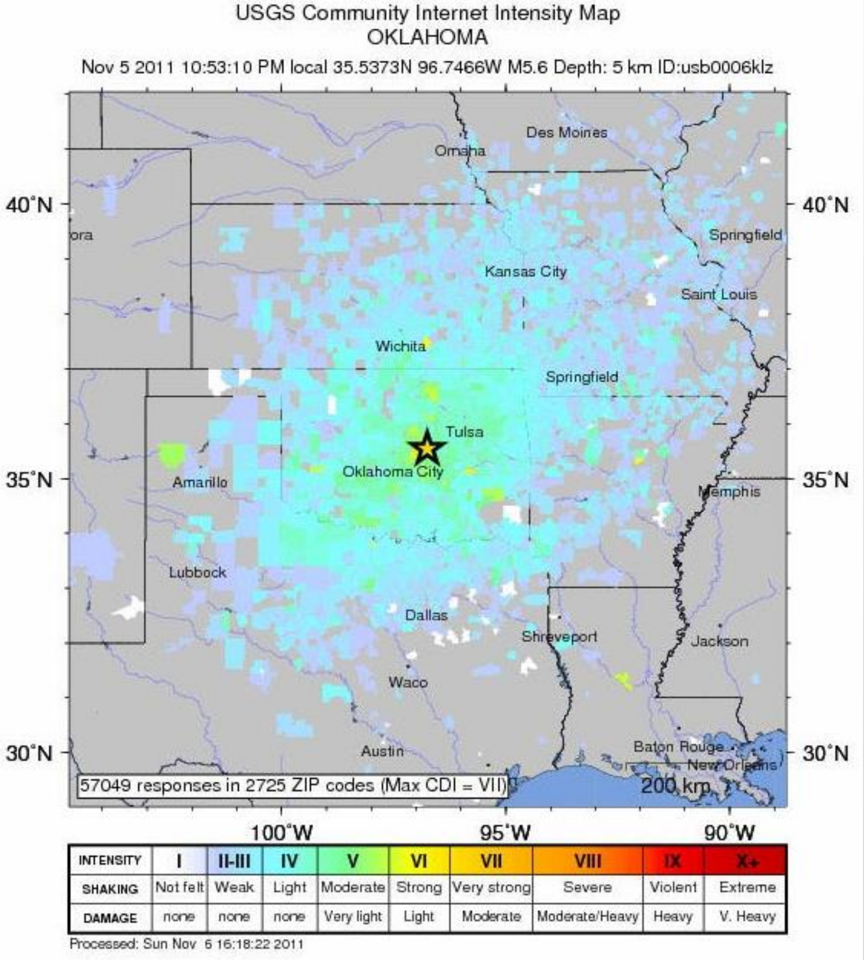


Application to Oklahoma

Induced by wastewater injection



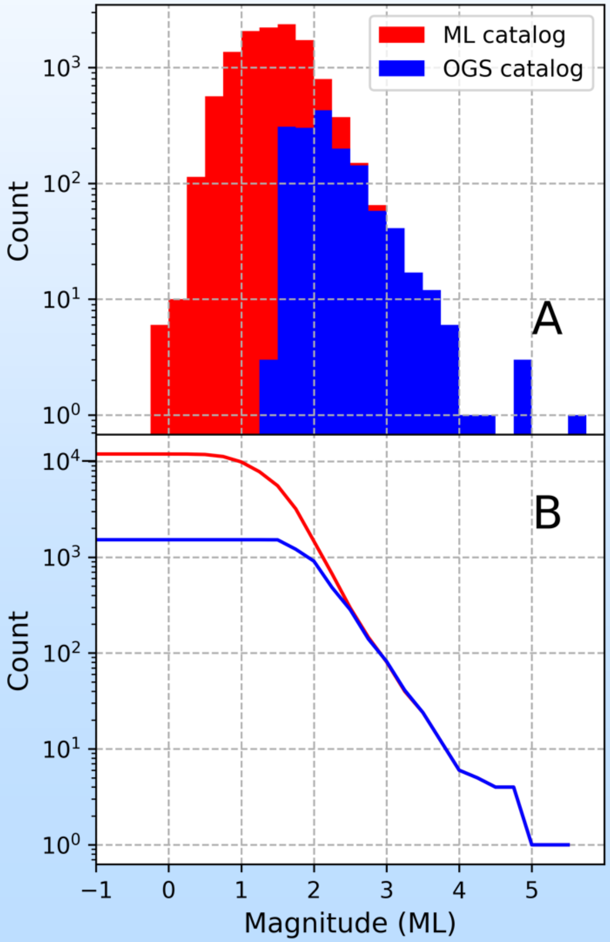
2011 Nov 5, M5.7 Prague event

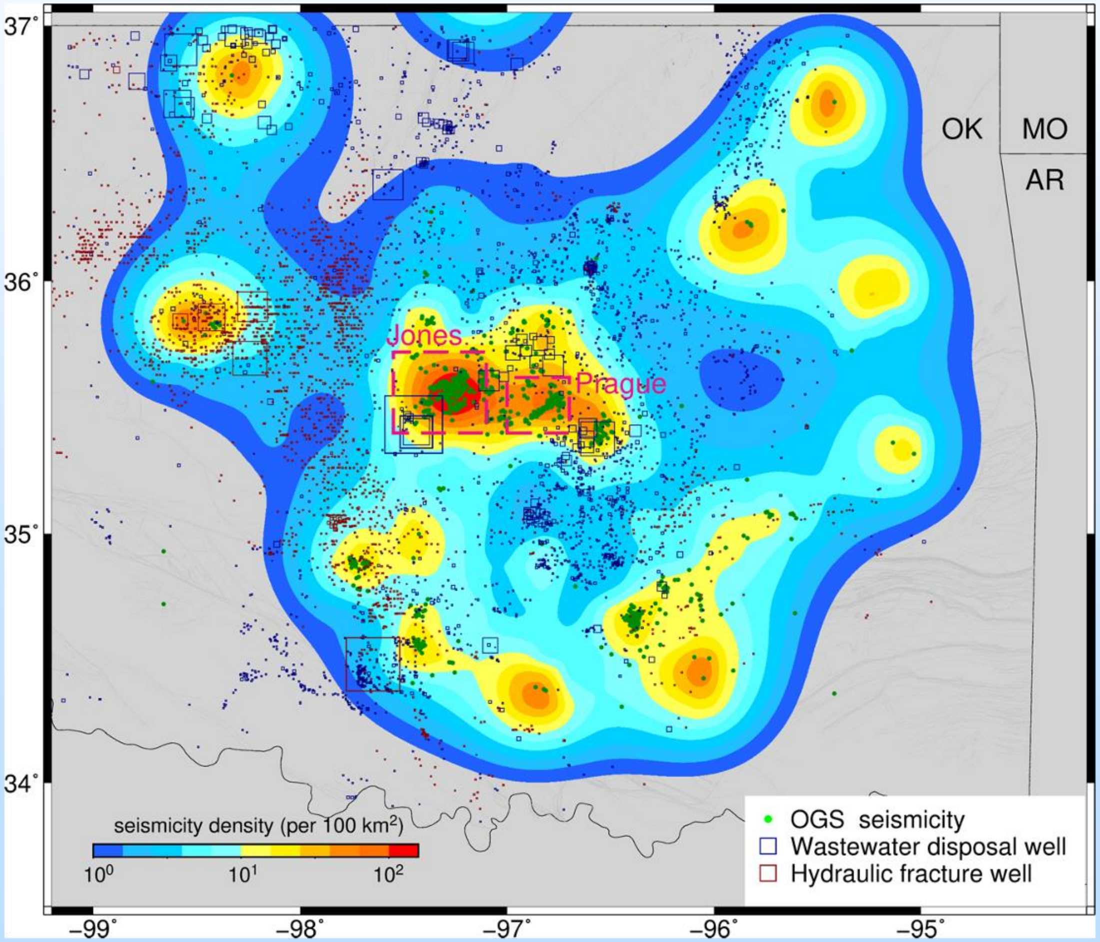


(from USGS)

Event Detections in Oklahoma

- 2010/10 – 2012/02
- ML located 21,107 events, > 10 times more than OGS catalog (1519 events)

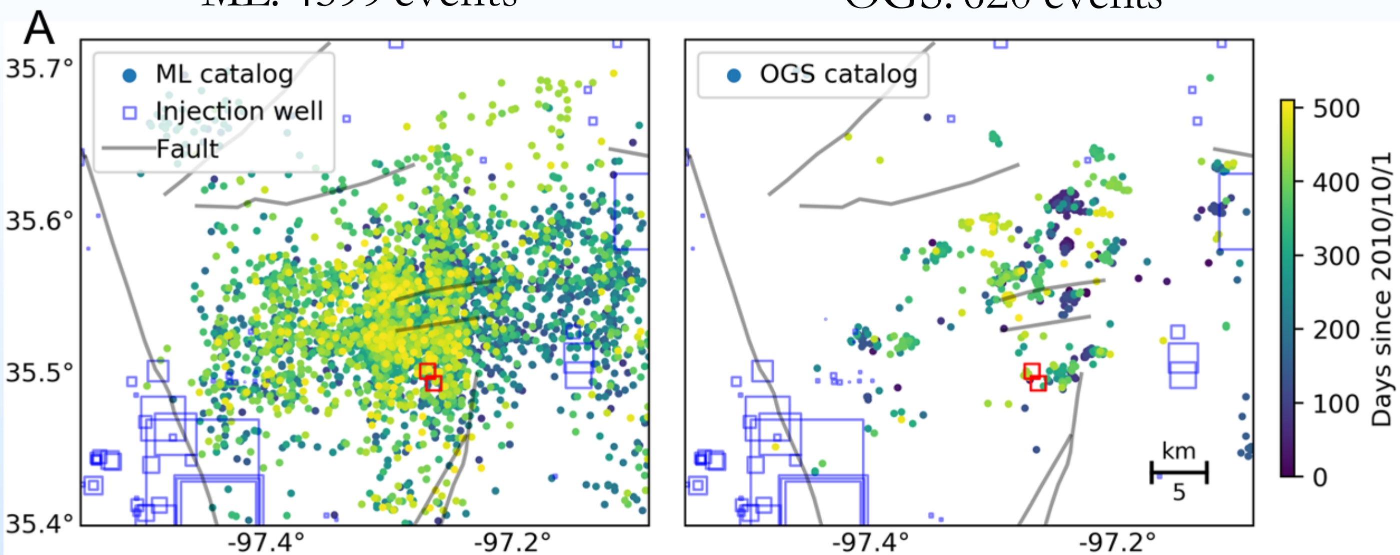




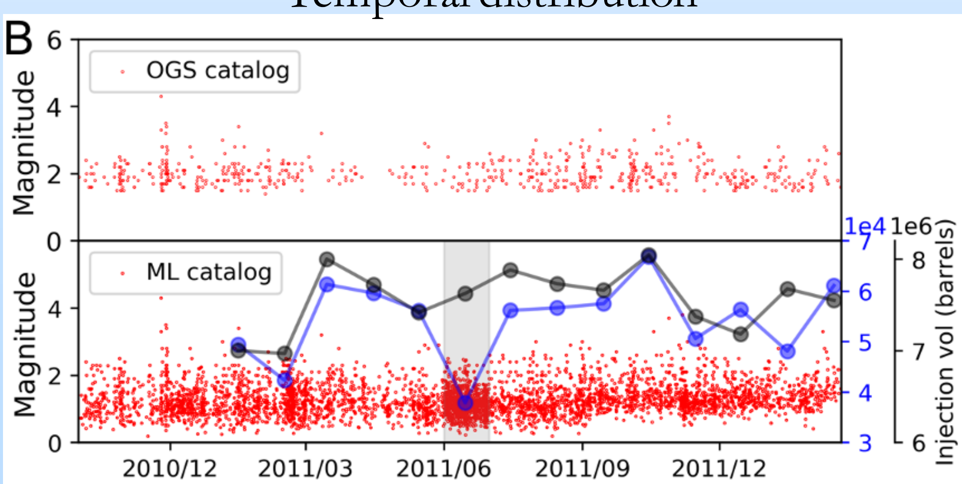
Seismicity in Jones, OK

ML: 4599 events

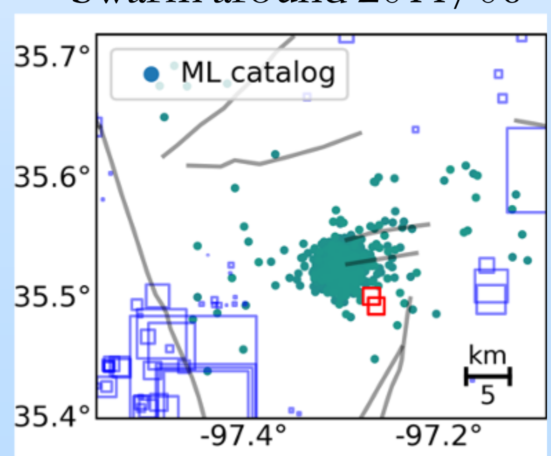
OGS: 620 events



Temporal distribution

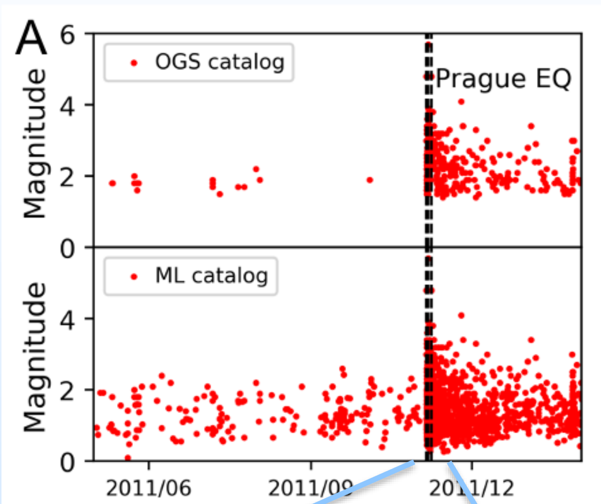


Swarm around 2011/06

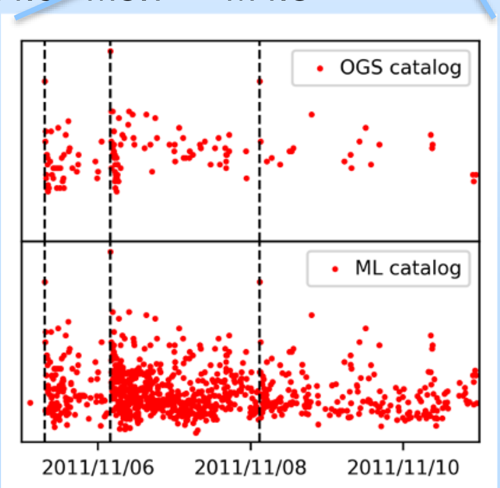


Seismicity in Prague, OK

Temporal distribution

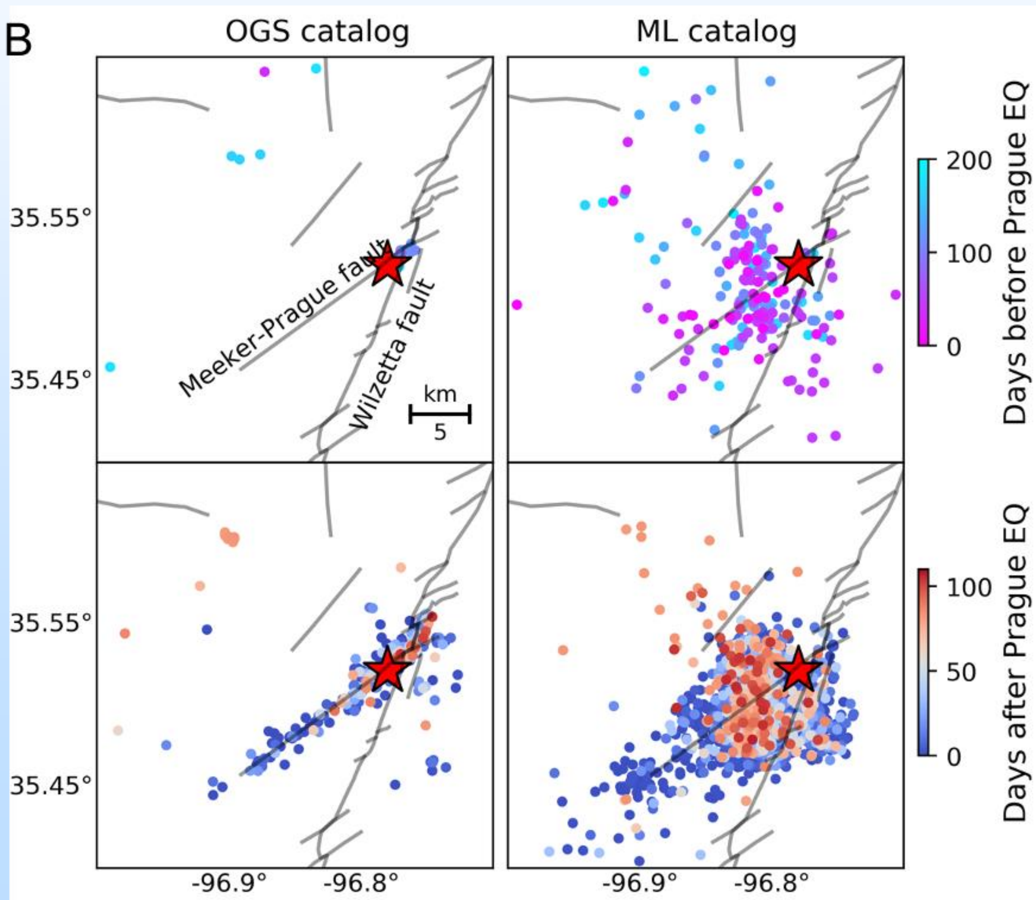


M4.8 M5.7 M4.8



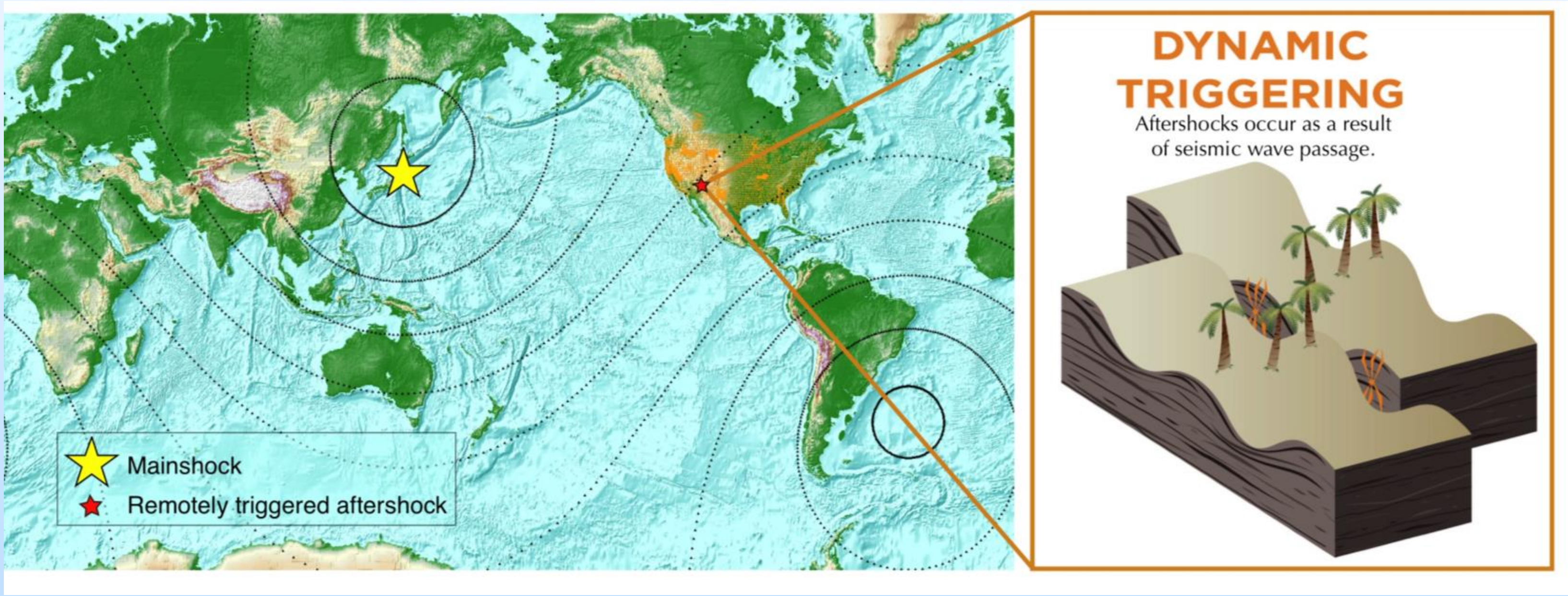
Spatial distribution

OGS: 785 events ML: 3532 events



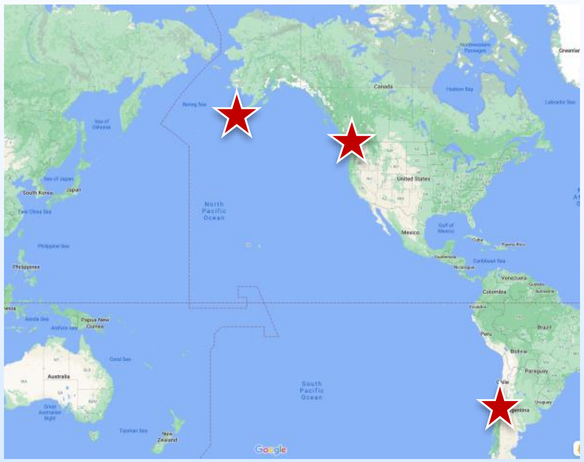
Infer Fault State from Seismicity – Dynamic Triggering

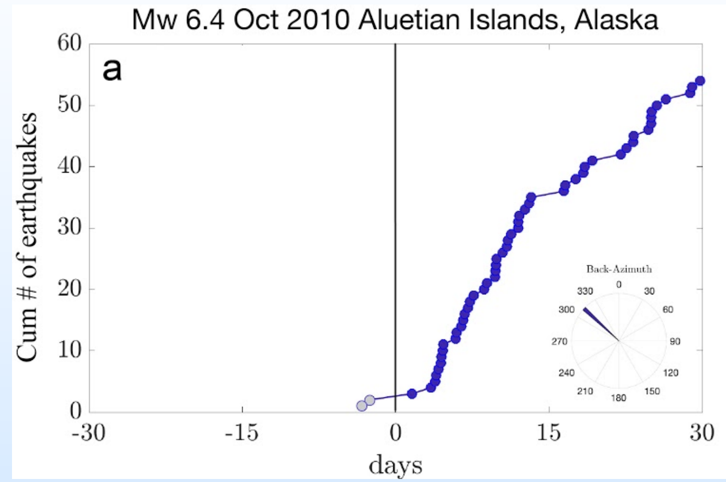
Dynamic stress*:* Generated by the passage of seismic waves (generally surface waves) from a distance earthquake

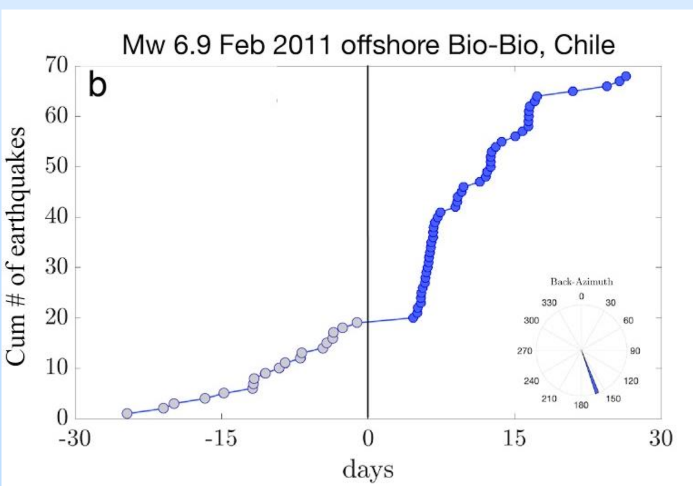


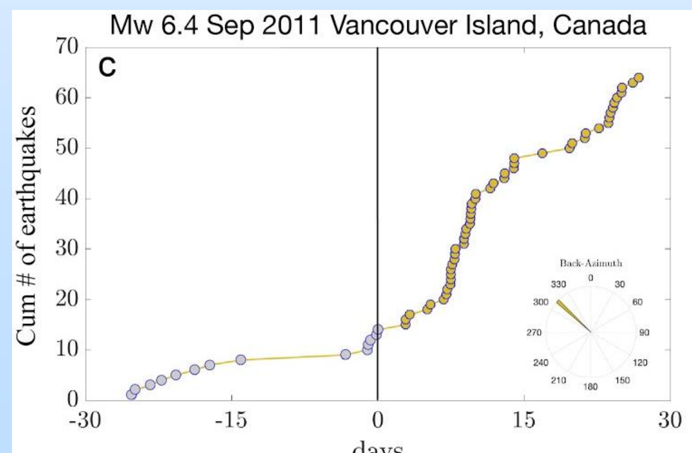
(Velasco et al., 2016)

Triggered seismicity before Prague event

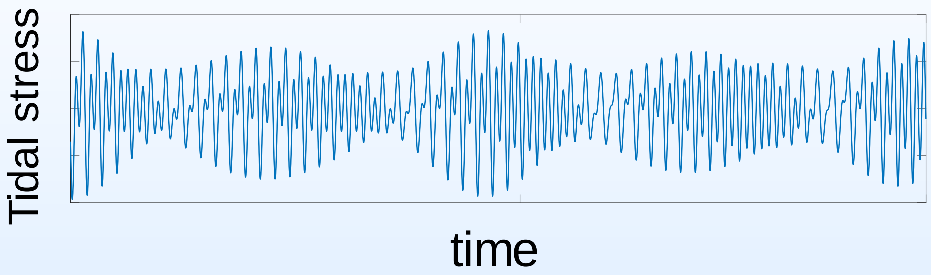


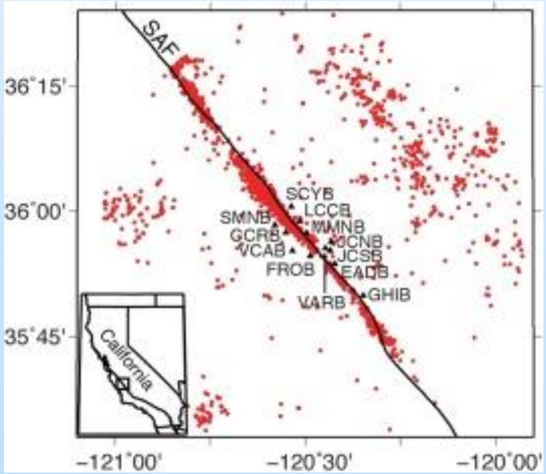


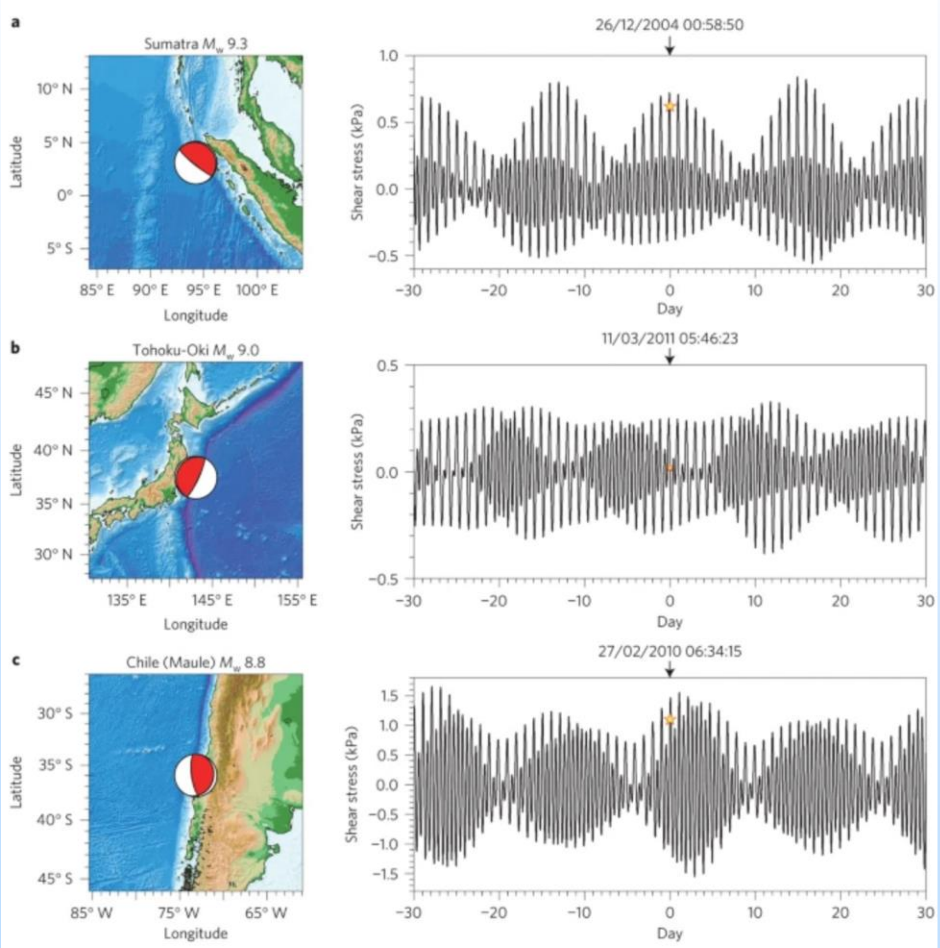




Infer Fault State from Seismicity – Tidal Triggering



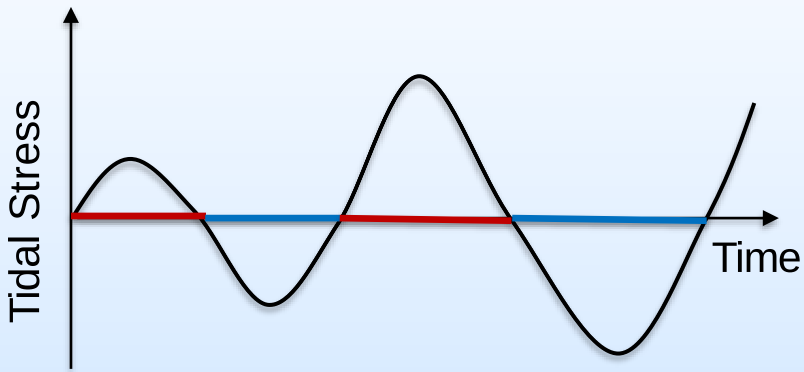


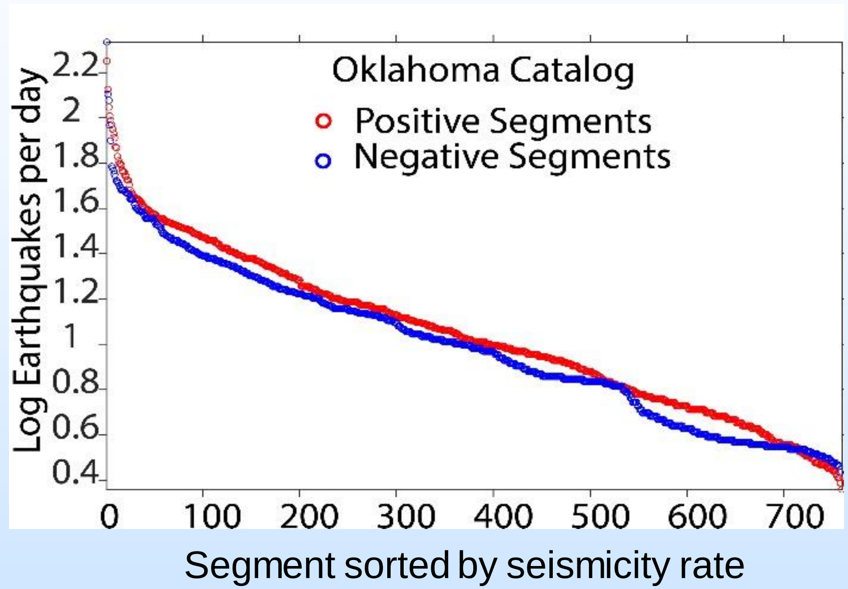


(Delorey et al, 2017)

(Ide et al, 2016)

Tidal Triggering in Oklahoma

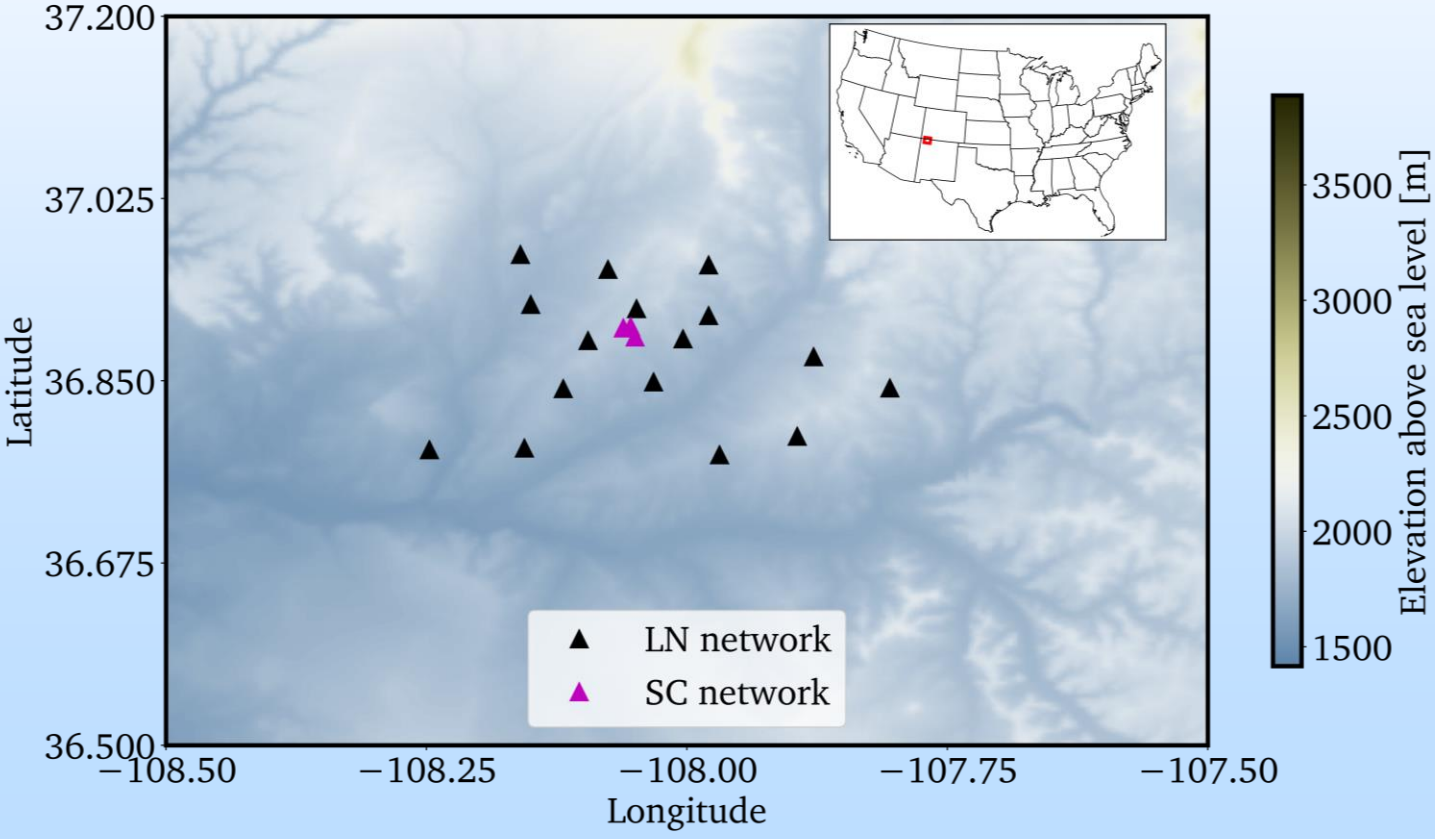




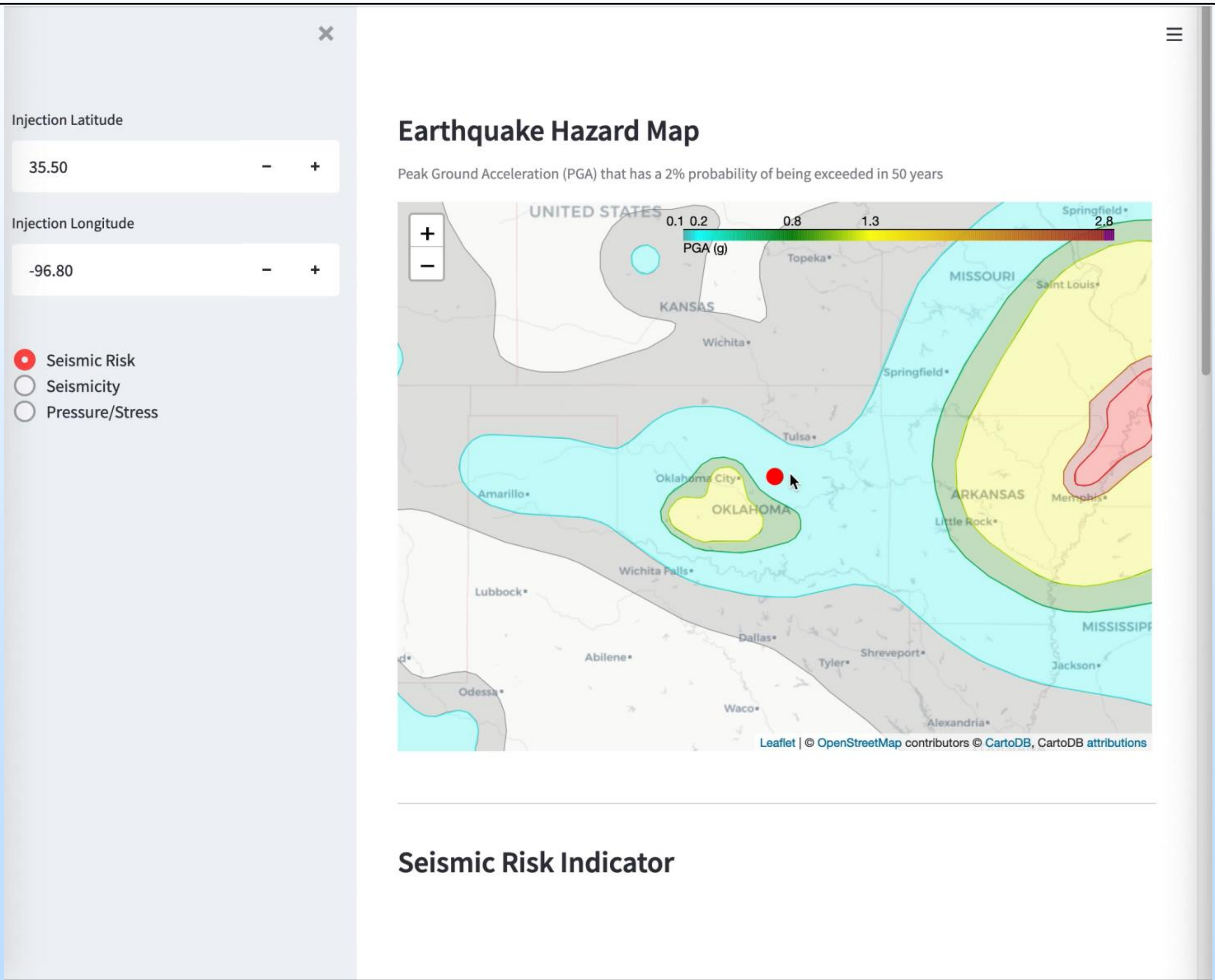
- Calculate tidal stress (Agnew, 2012)
- More earthquakes occur during positive deviation in shear stress
- Seismicity in Oklahoma is correlated with tidally induced fault shear stress
- Suggests high pore pressure in Oklahoma

Field Site Demonstration

- CarbonSAFE – San Juan Basin, New Mexico
- Station Deployment: from Jan/Feb 2022
  - 16 geophones
  - 3 broadband seismometers



Towards a Seismic Risk Tool



Summary

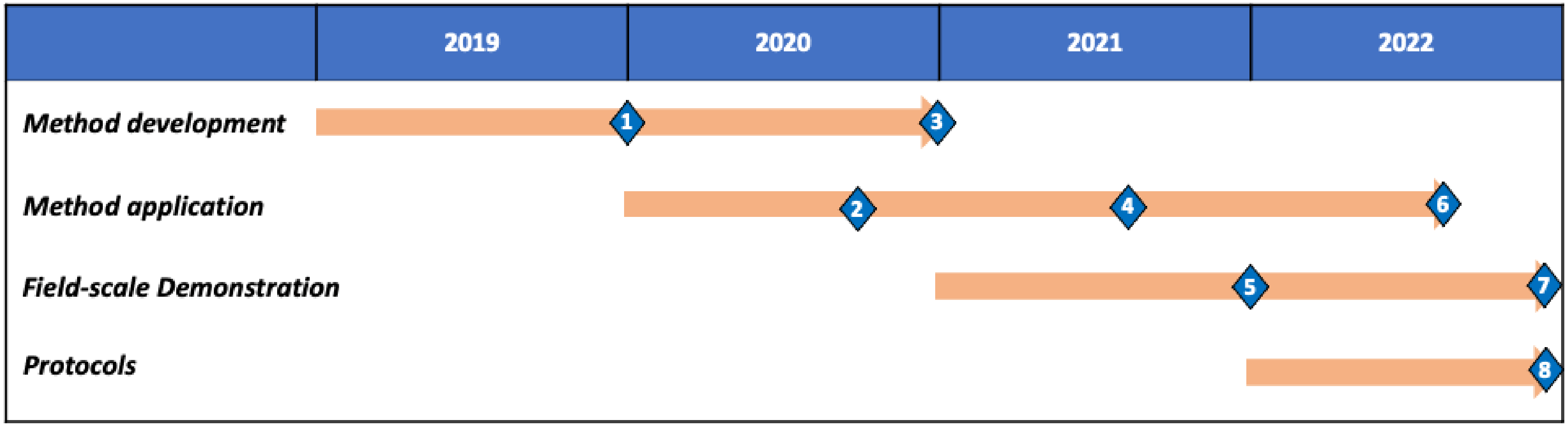
– We have developed machine learning algorithms to efficiently detect and locate small seismic events
  - extract seismic signals from noises
- We have demonstrated the capability of this method by applying it to field fluid-injection sites (Oklahoma)
  - Detected and located >10 times more events than original catalog
- Detected abundant small seismic events can provide important information on the fault state, e.g.:
  - Critical state of stress before the Prague event
  - High pore pressure in Oklahoma
- Ongoing: field site demonstration at San Juan Basin
- Future: seismic risk tool

Appendix

Organization Chart

- LANL
  - Ting Chen, Xiaofei Ma, Richard Alfaro, Yan Qin, Andrew Delorey, Youzuo Lin, Avipsa Roy, Alex Eddy, Yue Wu, Zhongping Zhang, Tiantong Wang, Peter Roberts, Christine Gammans, Paul. Johnson, Velimir Vesselinov, Daniel O'Malley, Rajesh Pawar, George Guthrie

Gantt Chart



Milestones

1. Develop machine-learning algorithm to extract events from multi-component seismic data
2. Application of developed machine-learning algorithm to detect seismic events from single station seismic data in Oklahoma
3. Develop machine-learning algorithm to locate events detected by multiple seismic stations
4. Application of developed machine-learning algorithm to locate seismic events detected on multiple stations in Oklahoma
5. Analysis of seismicity in Oklahoma to infer fault state
6. Verification of the developed method at a different site
7. Demonstration of the developed methods at field-scale CO_2 storage site
8. Protocols for use and application of the developed methods