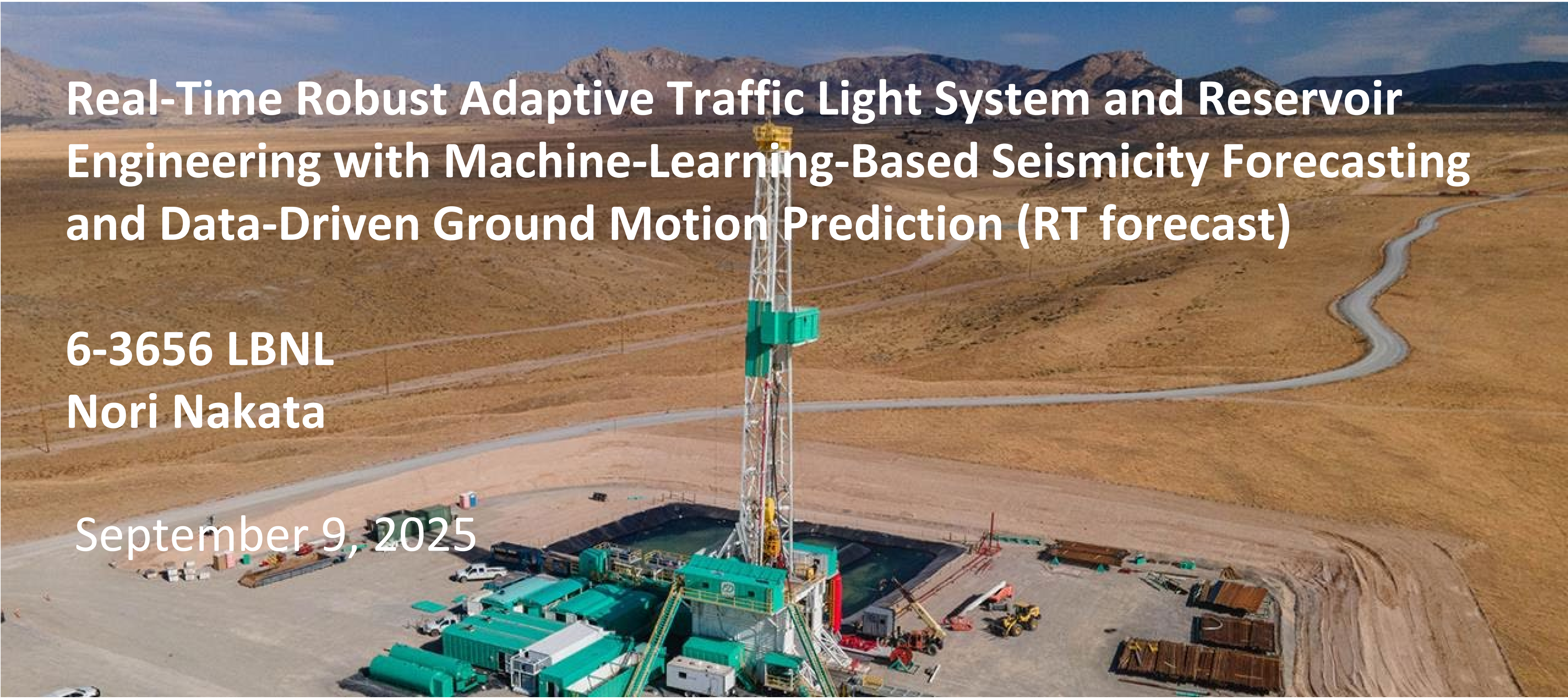
Utah FORGE– 2025 Annual R&D Workshop



Real-Time Robust Adaptive Traffic Light System and Reservoir Engineering with Machine-Learning-Based Seismicity Forecasting and Data-Driven Ground Motion Prediction (RT forecast)

6-3656 LBNL

Nori Nakata

September 9, 2025

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Real-Time Robust Adaptive Traffic Light System and Reservoir Engineering with Machine-Learning-Based Seismicity Forecasting and Data-Driven Ground Motion Prediction (RT forecast) / 6-3656

- Principal Investigator: Nori Nakata
- Organization: LBNL
- Presenter(s) Name (in addition to the PI): Matej Peč (MIT), Aditi Krishnapriyan (UC Berkeley)

- Total Project Funding: $1,006,981
- Project Start and End Date: 7/1/24 – 6/30/27
- Date of Presentation: 9/9/2025

This presentation does not contain any proprietary, confidential, or restricted information.

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Objectives and Purpose

Development of near-real-time system for traffic light and reservoir engineering

- ML-based seismicity and ground motion forecasting
- data-driven approaches using various field and laboratory data
- near-real-time decision making for reservoir engineering and adaptive TLS methodology as part of Best Practice guidelines

Development of ML algorithms for seismicity and ground motion forecasting

- hard or soft constraints with physical and empirical equations
- the ML algorithms specifically for spatio-temporal evolution of seismic phenomena

Wet (pore-pressure-driven) vs. Dry (elastic loading and stress changes) earthquakes

- different physics may require different forecasting methods/parameters
- this condition can be related to fracture network, permeability and reservoir management

*Items **Not** in our scope in this project*

- Development of heavy data processing methods
- THMC modeling

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Methods/Approach

Field data analysis and application of ML-based R.T. forecasting

Lead: Nori Nakata


Nori Nakata


Zhengfa Bi


Ernest Majer

Spatio-temporal forecasting with physical and statistical equations

Lead: Aditi Krishnapriyan

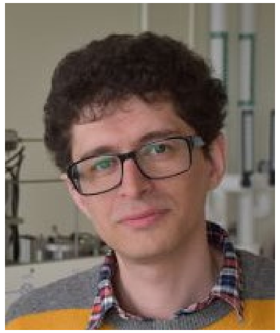

Aditi Krishnapriyan


Yiheng Du

Laboratory experiment at various P-T-H conditions

Lead: Matej Peč


Matej Peč


Hoagy O’Ghaffari


Ulrich Mok

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Technical Accomplishments and Progress

- Development of AI-ready datasets of induced seismicity at various geothermal and oil/gas fields
- Laboratory granite experiments (>10k AEs/test) provide labeled wet/dry data to train ML and reveal fluid–fracture interactions
- Development of a prototype ML forecasting models
  - induced seismicity forecasting
  - ground motion modeling
- Test the prototype models to geothermal data

Actual Milestone/Technical Accomplishment	Date Completed
Compile seismicity and injection/production data at Geothermal and oil/gas fields (M1.1, M1.2)	12/2024, 3/2025
Development of an initial prototype of ML forecasting models and apply it to geothermal datasets (M3, M4)	6/2025
Go/No-Go: Data compile & application of initial ML model	Met (6/2025)

No major variances from what we proposed.

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Technical Accomplishments and Progress

AI-ready data at geothermal and oil/gas fields.

Site	Year & operation	Type of field	Data duration	Number of earthquakes	Magnitude range	Injection volume	Number of wells	Other available datasets, notes
Utah FORGE	2019 stimulation	EGS	3 days	500	-2 - -0.10	649 bbl	1	well log, velocity model, wellhead pressure, tracer, etc.
	2022 stimulation	EGS	8 days	2500	-2 - 0.52	10315 bbl	1	
	2023 flow test	EGS	3 days	1000	-2 - 0.45	5400 bbl	2	
	2024 stimulation	EGS	15 days	3000	-2 - 2	18682 bbl	2	
	2024 flow test	EGS	30 days	1000s	-2	15 bbl / min	2	
Geysers	production	Geothermal production	50 years	360,000	0 - 5	10 G bbl	1153	
	EGS demonstration	EGS	1.5 years		0 - 2.87	758519 bbl	2	
Salton Sea	production	Geothermal production	40 years	60,000	0-5	2 G bbl	10's	Monthly injection data only
Coso	production	Geothermal production	40 years	170,000	0-5	3 G bbl	10's	Monthly injection data only
Newberry	2012 stimulation	EGS	4 weeks	175	0 - 2.3	261,905 bbl	1	well log, velocity model, wellhead pressure
	2014 stimulation	EGS	4 weeks	400	0-2.3	60,000 bbl	1	maximum 2850 psi
HFTS-1	2015 stimulation	hydraulic fracturing	7 weeks	128,405	-1.5-1.5	1.5 M bbl	11	434 stages, LF-LP-LD earthquakes core, well log
HFTS-1	2016-2018 EOR	Enhanced Oil Recovery		almost none	N/A	280 MMscf (gas)		
HFTS-2	2019-2020	hydraulic fracturing	4 months	30,000	-3-0	1833 bbl, 11,794 tons of proppant	12	52 stages
Oklahoma	2009-2018	Wastewater disposal	20 years	10,000	2 - 5.8	600M bbl	147	
Basalt rock	6 tests, CO2	laboratory AE	100-300 hours	~1,000s	small	N/A	N/A	stress/strain, permeability
Granite rock	ongoing	laboratory AE						

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Objectives and Purpose

- Can we **distinguish** between **seismic events triggered** by **increases of pore fluid pressure** vs. events triggered by **changing the reservoir stress state** due to loading?
- Understanding the source of micro-seismicity is important for **mitigating seismic risks.**

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Methods/Approach

- Collect **Acoustic Emissions (AEs)** during well controlled laboratory experiments **under varying boundary conditions**
- Basic idea:

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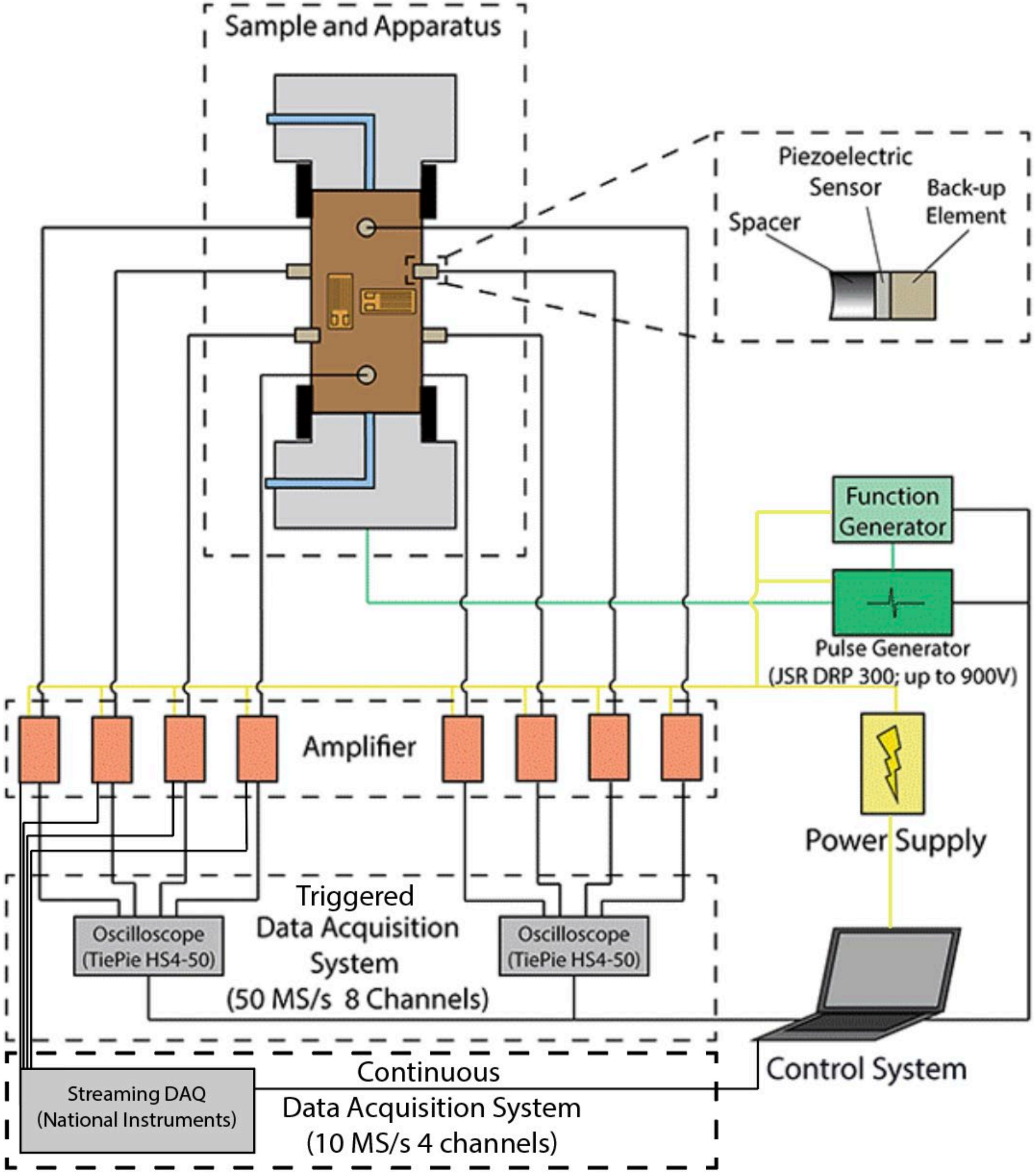
Methods/Approach

- High-pressure, high-temperature **tri-axial rock deformation experiments**
- NER Autolab 3000
  - ≈ **80 x 40 mm cores** of thermally cracked Barré granite
  - **T ≈ 80˚C, P_{eff}** = (P_c – P_p) **= 10 & 40 MPa**
  - P_c = 40 & 70, P_p =30 MPa (≈**0.5 – 2.5 km** depth)
- De-noised **triggered** & **continuous** DAQ system
  - Independent battery power supply
- **Multi-physics experiments** (measuring permeability, P-wave velocity, mechanical & AE data)



Modified after Xing et al. 2022, Solid Earth

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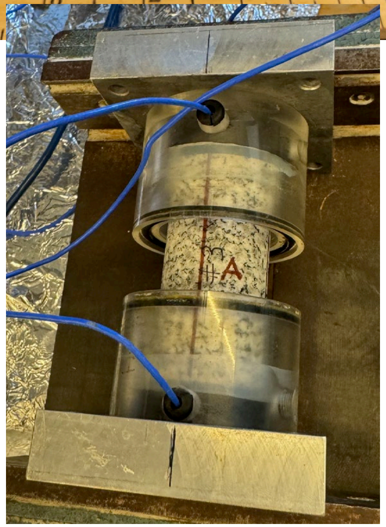
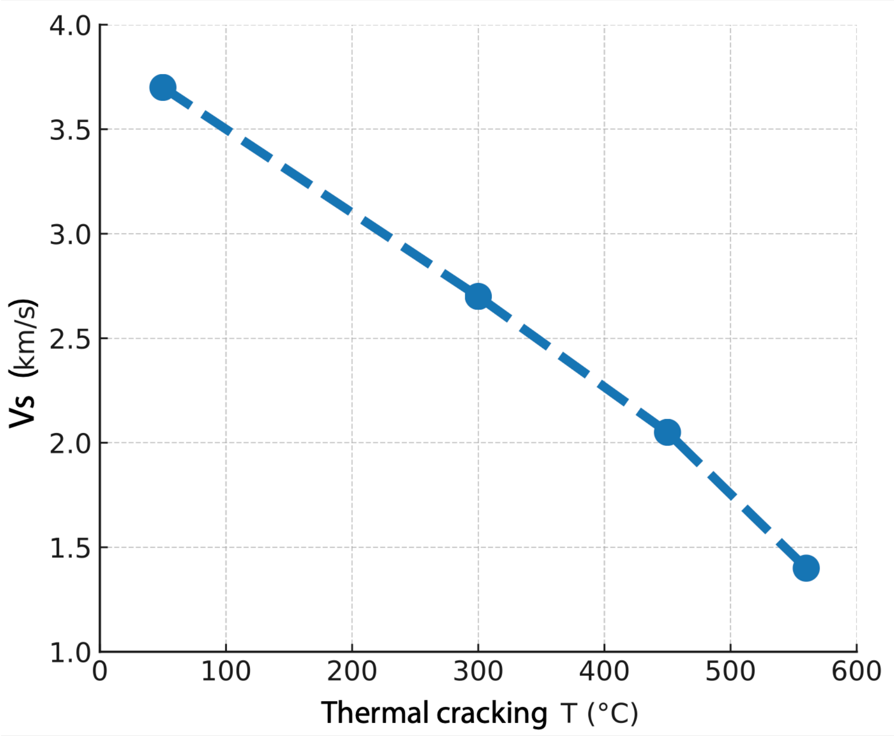
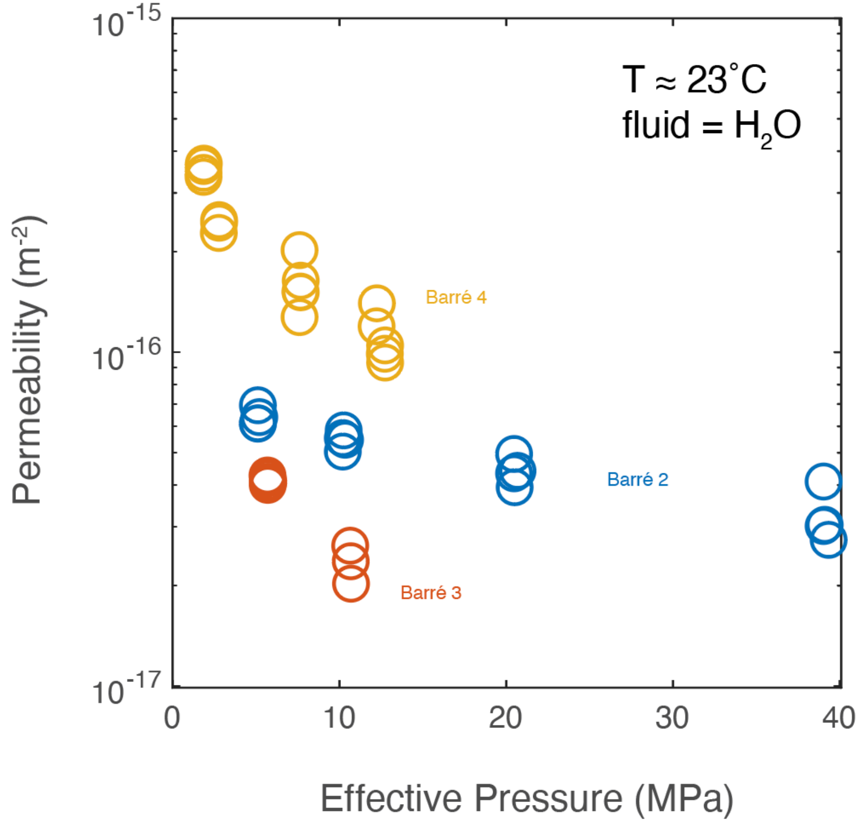
Technical Accomplishments and Progress

- Establishing testing protocol
  - Testing several thermal cracking paths (300,450,550˚C) to achieve optimal permeability for experiments.
  - Ultrasound sample characterization







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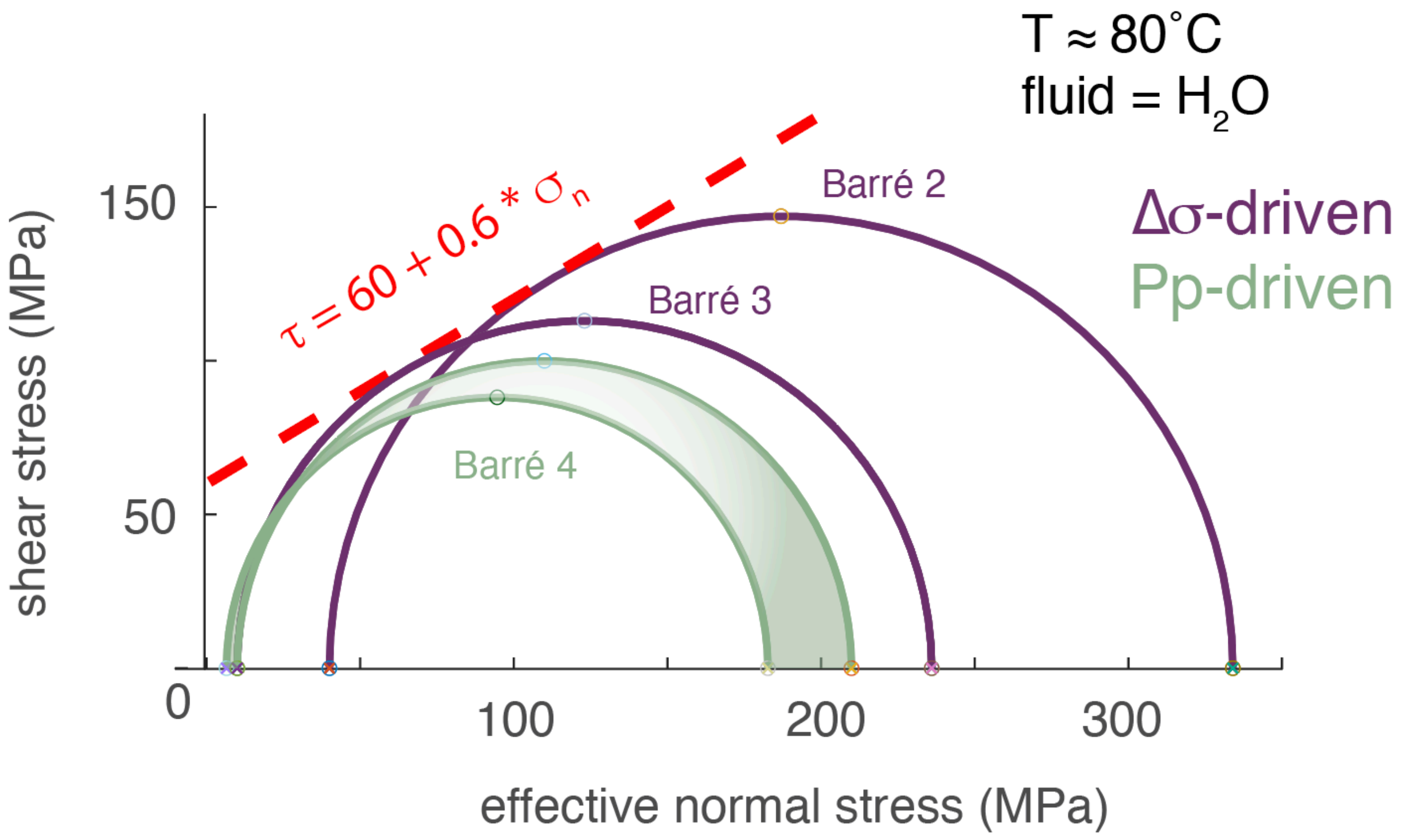
Technical Accomplishments and Progress

- Failure envelope consistent with Byerlee's rule for frictional sliding

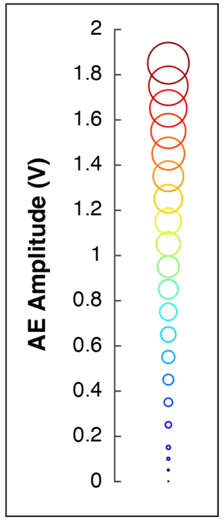


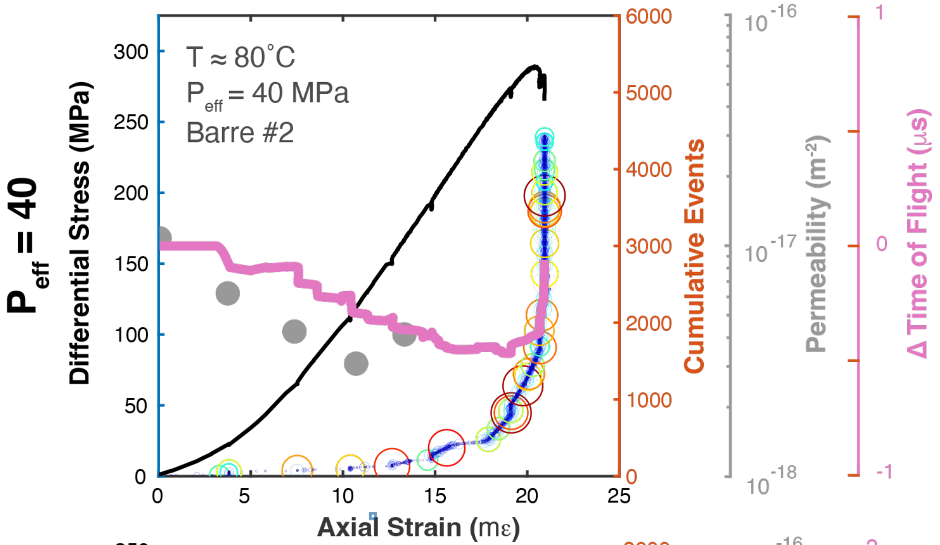
Technical Accomplishments and Progress

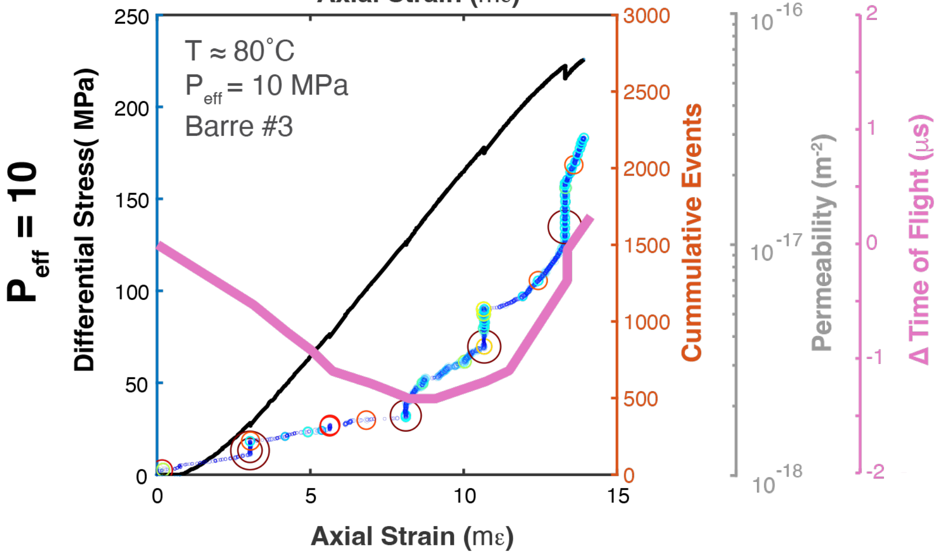
- First series of experiments
- **1000s of AEs** in **triggered** recording, **>10,000** in **continuous** recording
- Ultrasound, mechanical and permeability data

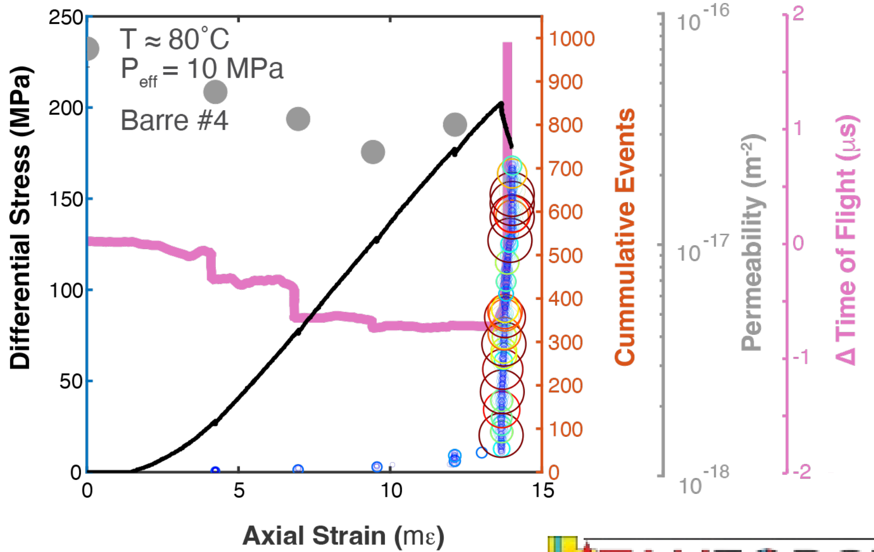
Stress-driven failure

Pore pressure-driven failure









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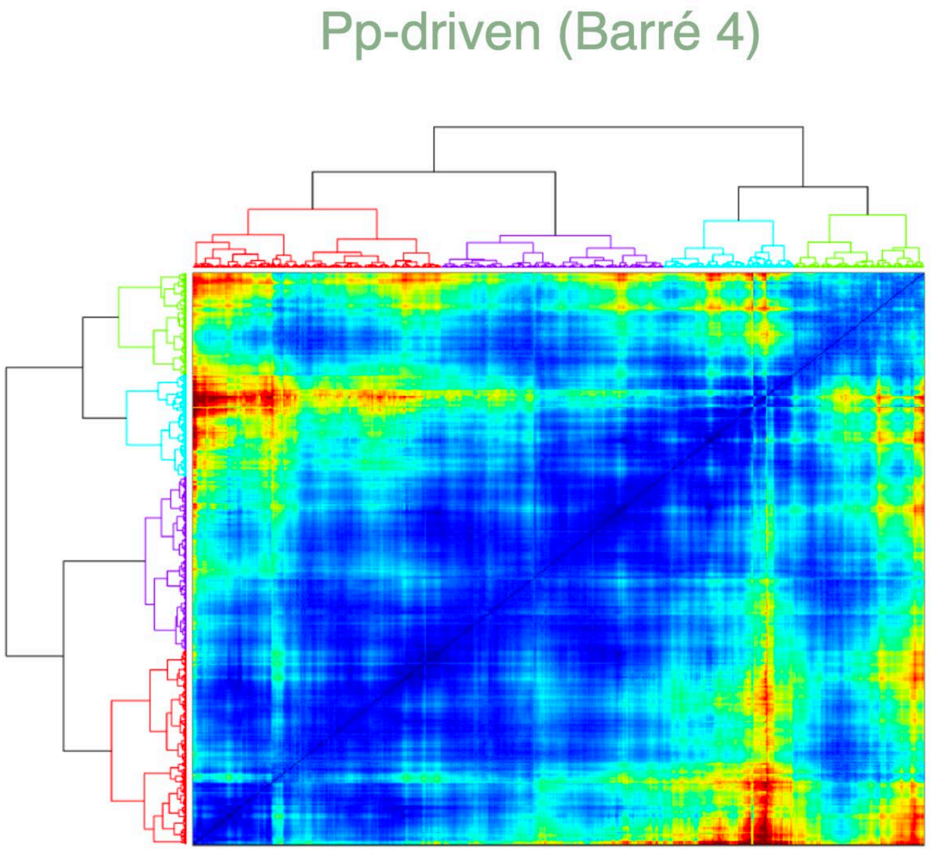
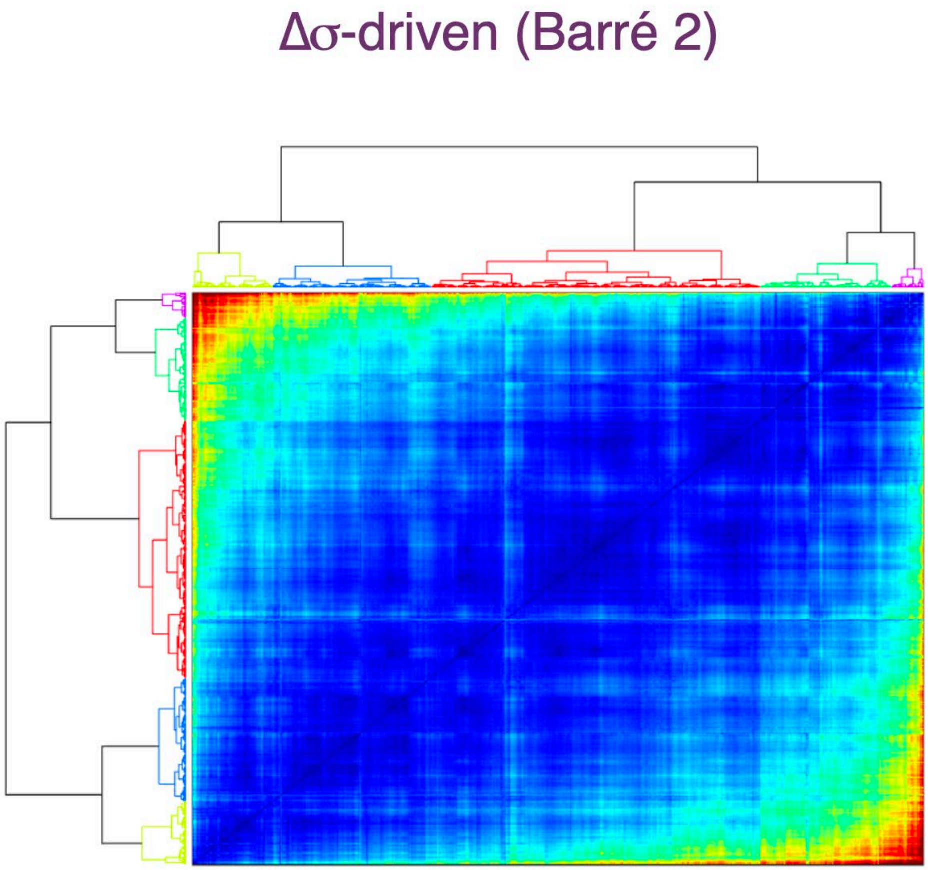
Technical Accomplishments and Progress

- Characterization of triggered AEs using unsupervised learning (DTW + Hierarchical Clustering)





See O'Ghaffari et al. 2023

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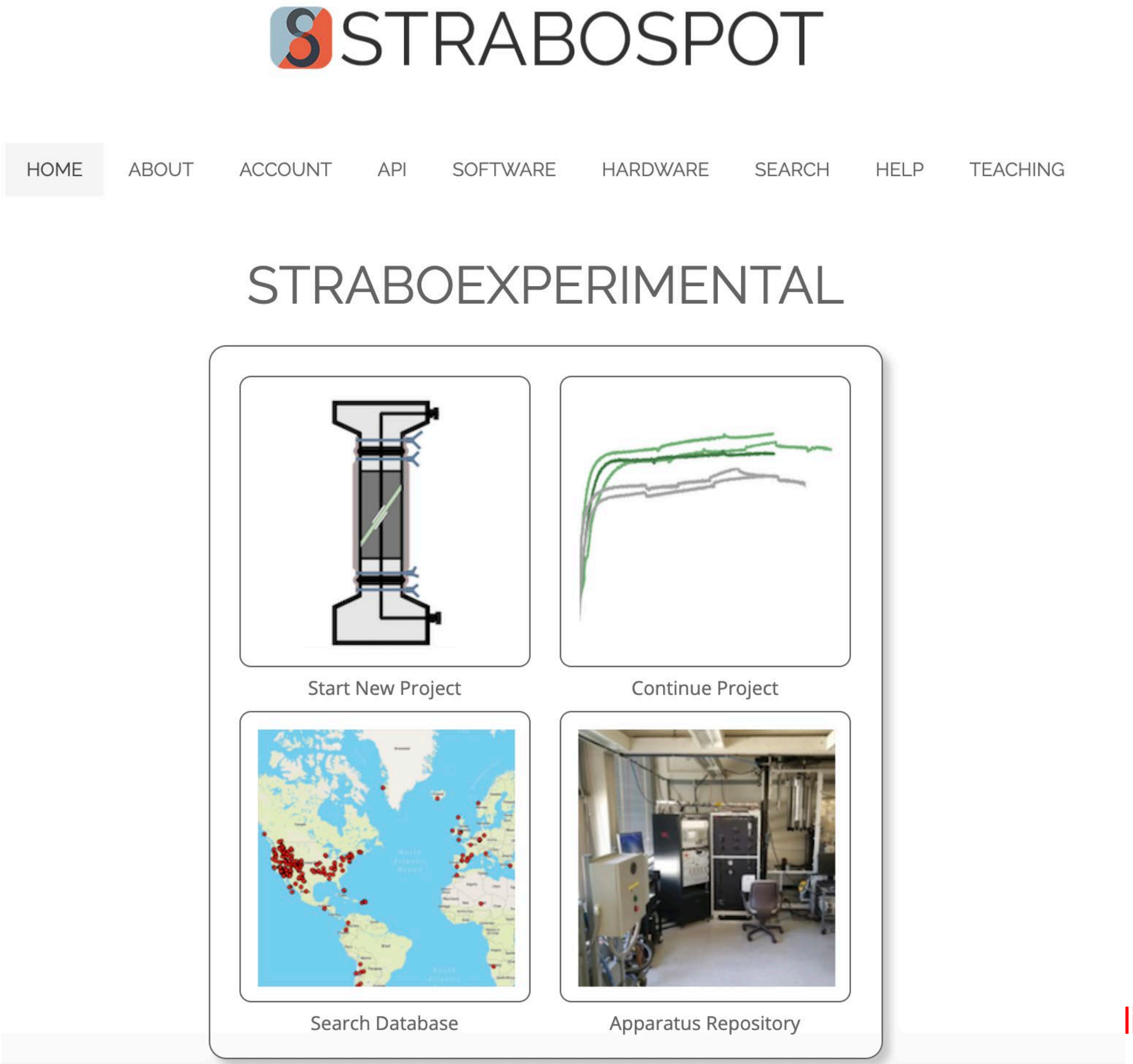
Technological Advancement and Data Dissemination



- Developing laboratory capabilities for testing hot rocks (higher T (>300˚C) under development)
- Submitted an AGU Fall meeting abstract and will present the first results there
- Experimental data is being input into ”StraboExperimental” community-driven database for open access upon project completion

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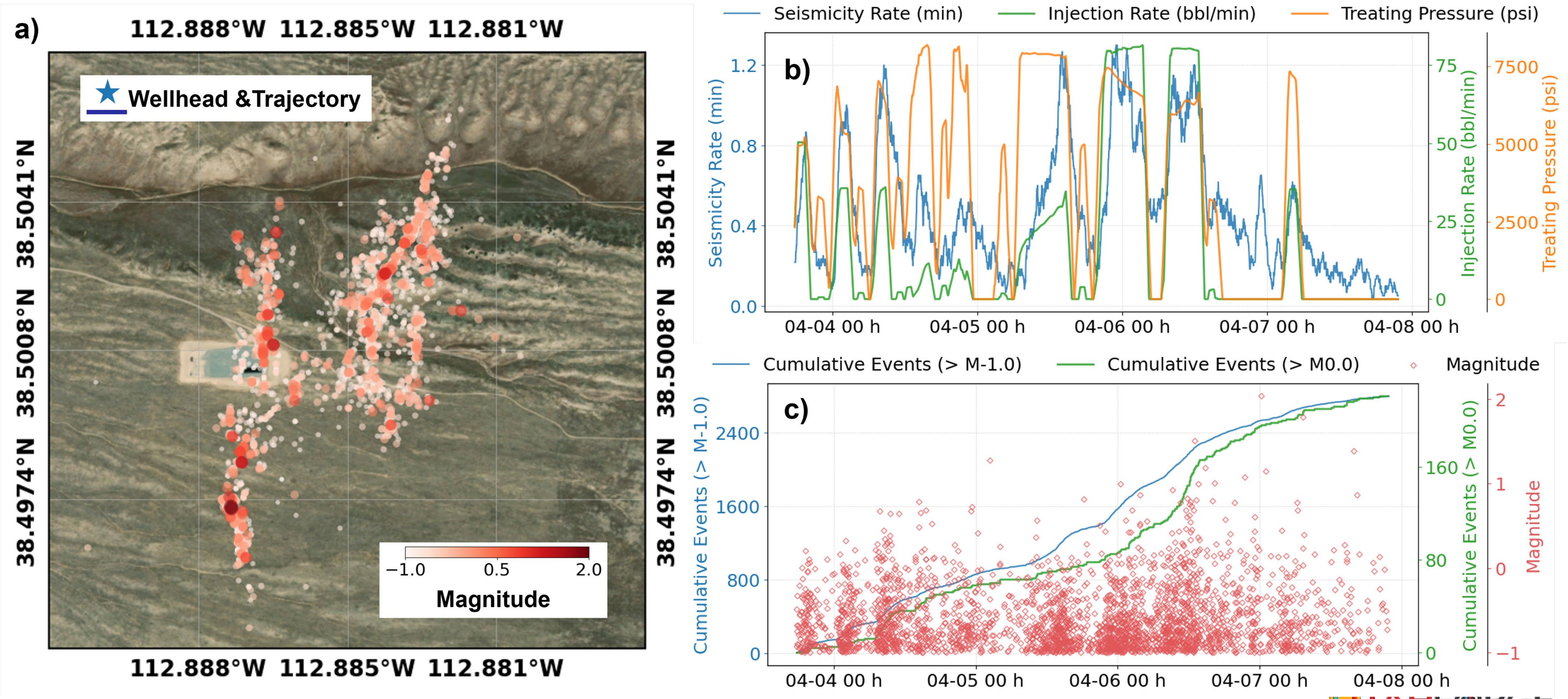
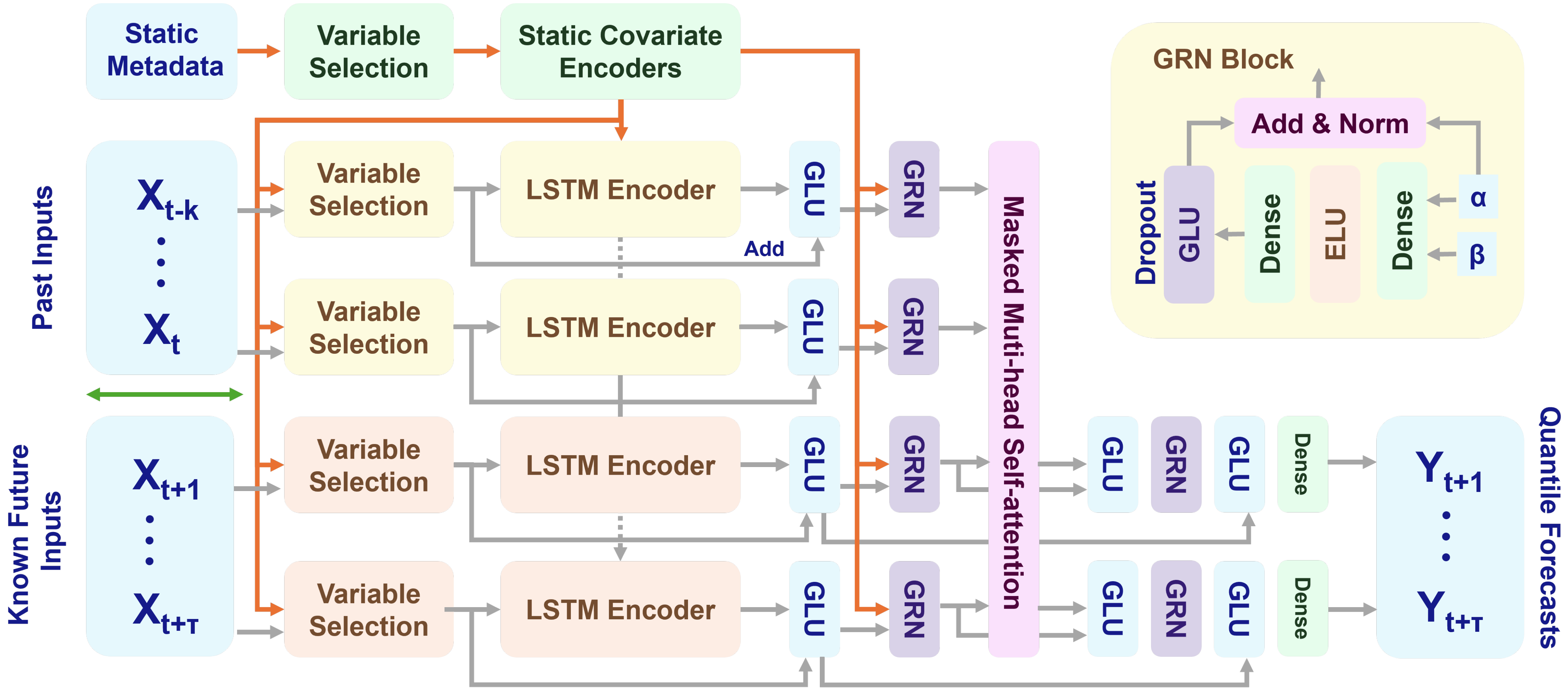
Technical Accomplishments and Progress

Data (Utah FORGE 2024 simulation (10 stages, 5 days))



Methods/Approach

Temporal Fusion Transformer (TFT) Network Architecture for seismicity forecasting



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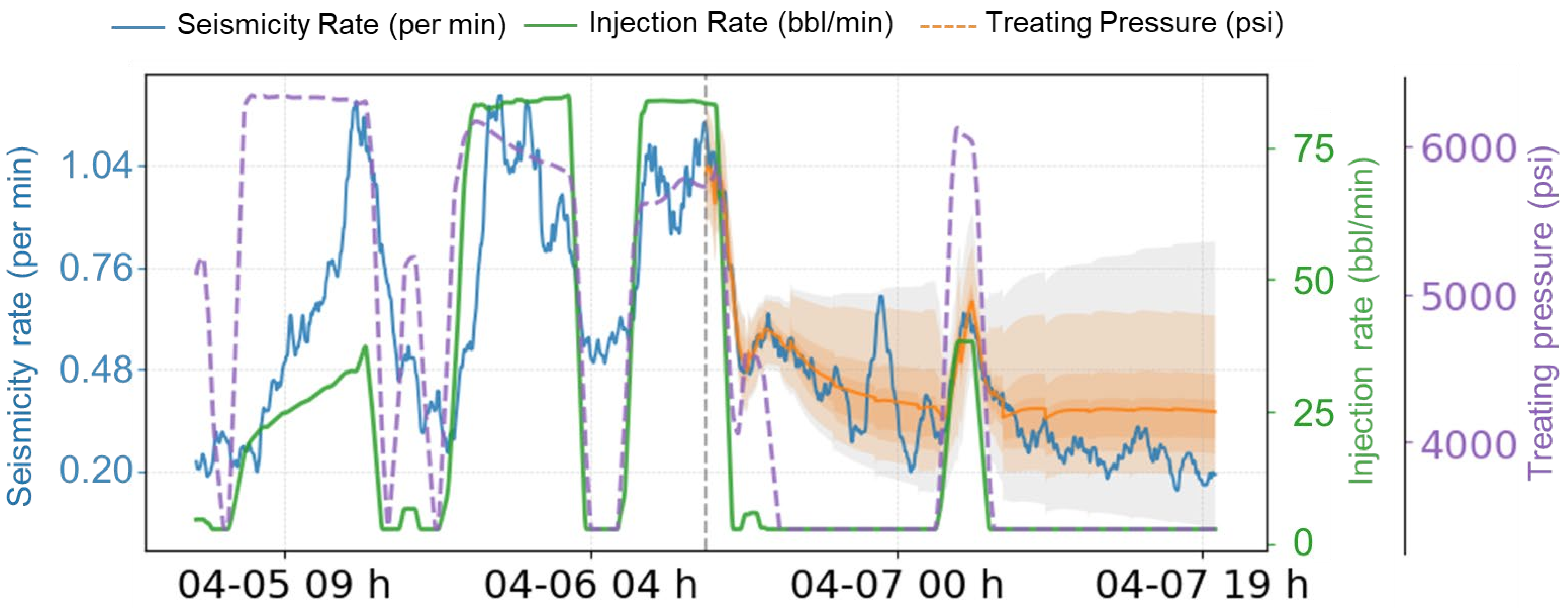
Technical Accomplishments and Progress

Seismicity forecasting (Utah FORGE 2024 simulation)



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Technical Accomplishments and Progress

Seismicity forecasting (Utah FORGE 2024 simulation)

Input data interpretability: e.g., feature importance

Category	Feature	Dataset	
		Geysers	FORGE
Past Inputs	Injection Rate	8.0	42.6
	Injection Gradient	45.5	11.9
	Treating Pressure	–	30.0
	Pressure Gradient	–	6.7
	Past Seismicity Rate	46.5	8.8
Future Inputs	Injection Rate	15.0	46.7
	Injection Gradient	85.0	13.0
	Treating Pressure	–	32.9
	Pressure Gradient	–	7.4

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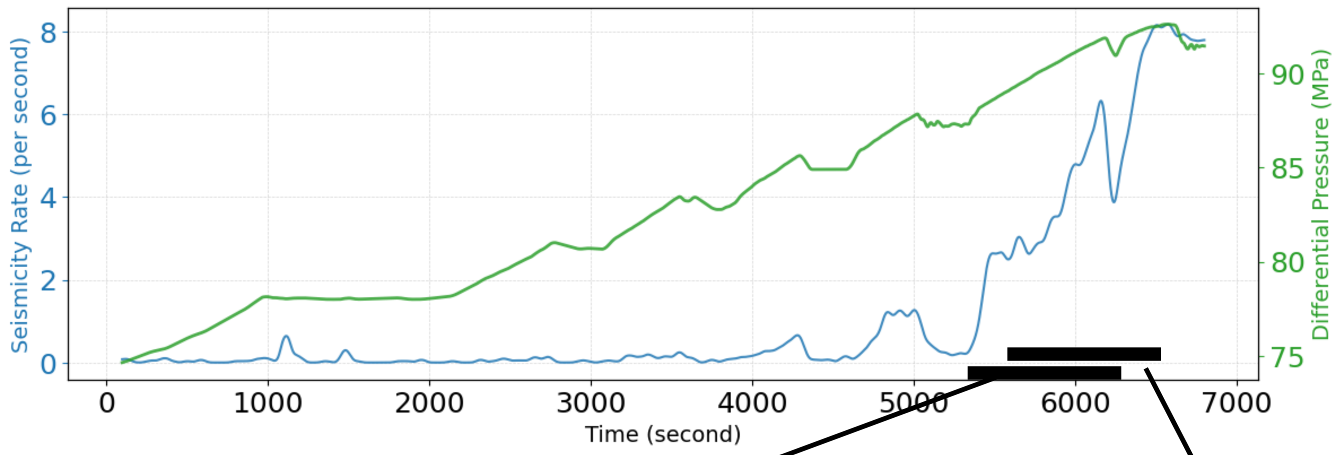
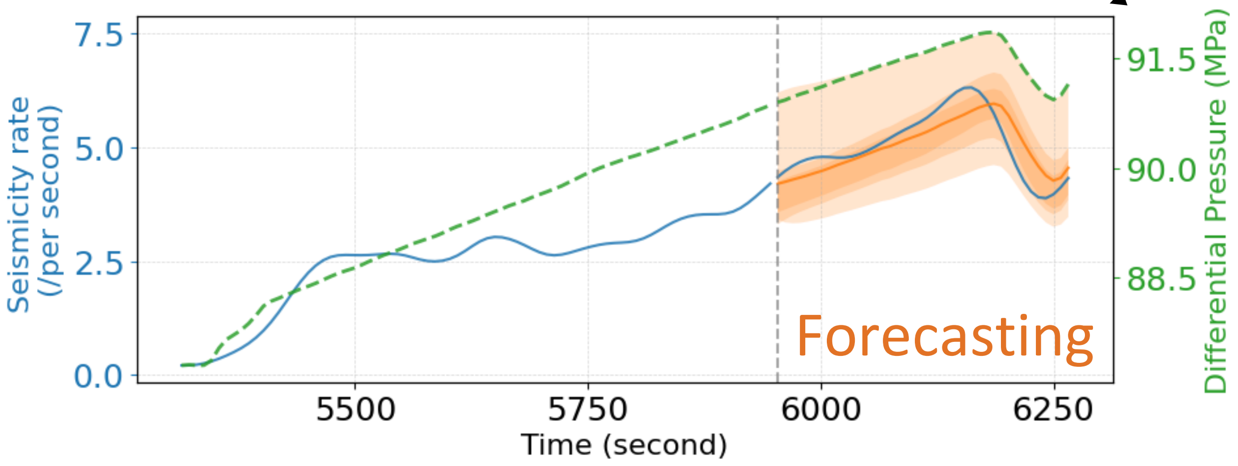
Technical Accomplishments and Progress

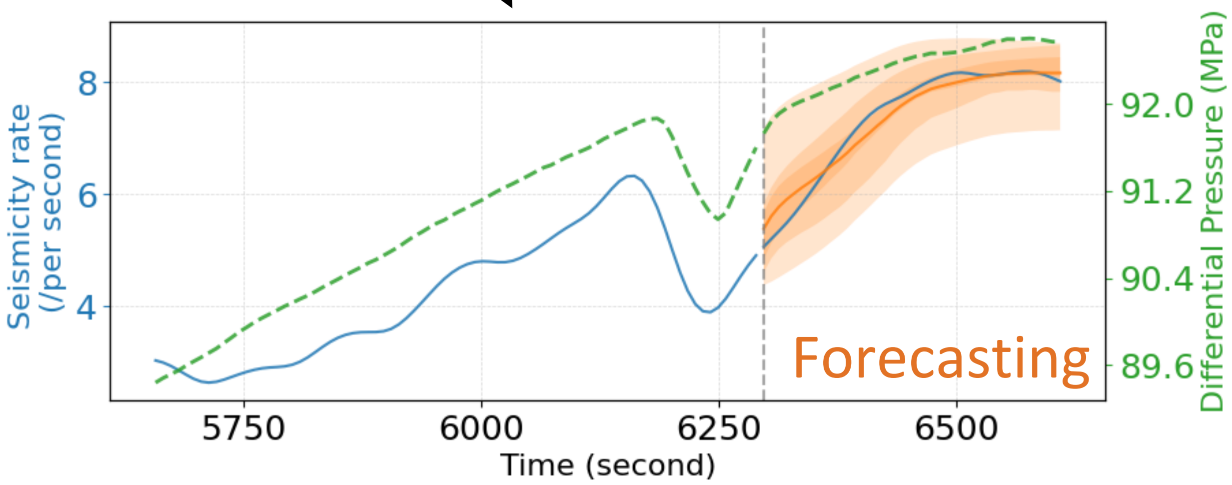
Seismicity forecasting (Laboratory experiment: Barre #2)

Experimental data



Forecasting results





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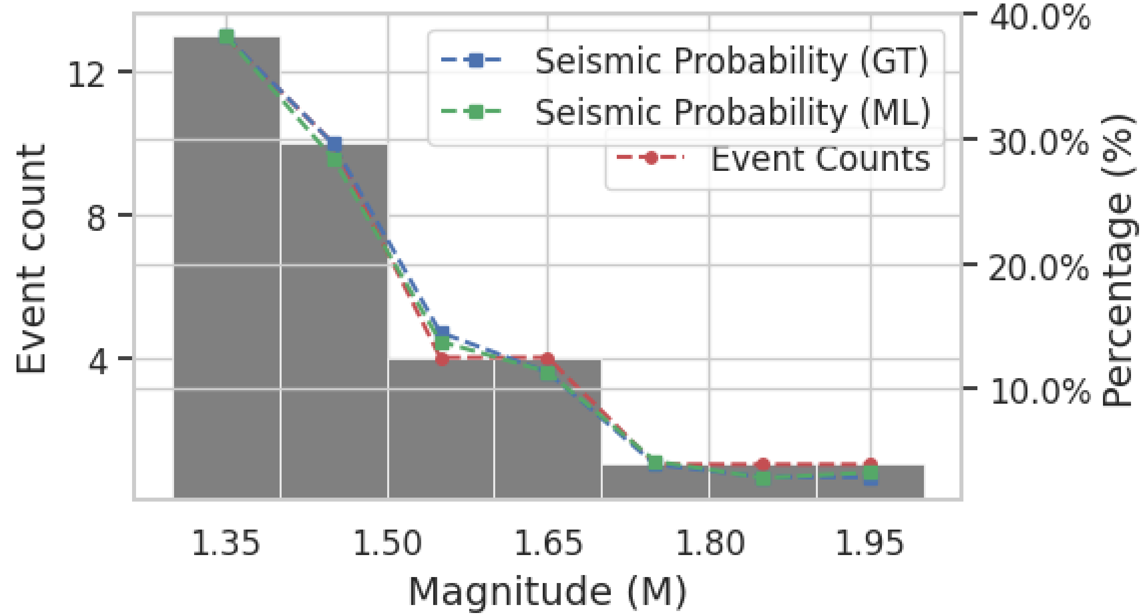
Technical Accomplishments and Progress

Ongoing effort: Forecasting seismicity magnitude probability and spatiotemporal evolution

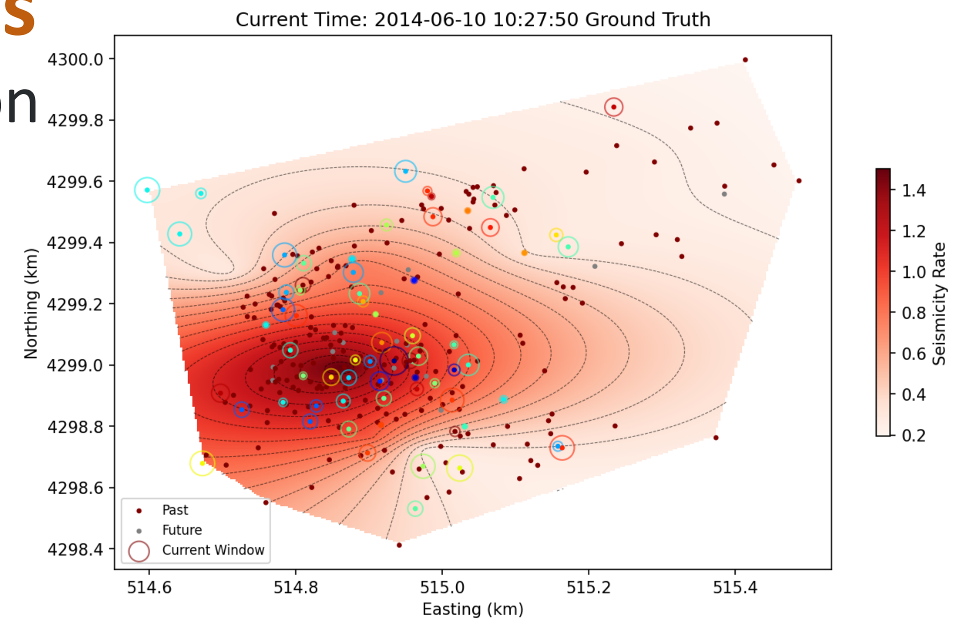
Magnitude probability

Start:2015-02-16 23:42:43.200001->
End:2015-04-17 23:42:43.200001

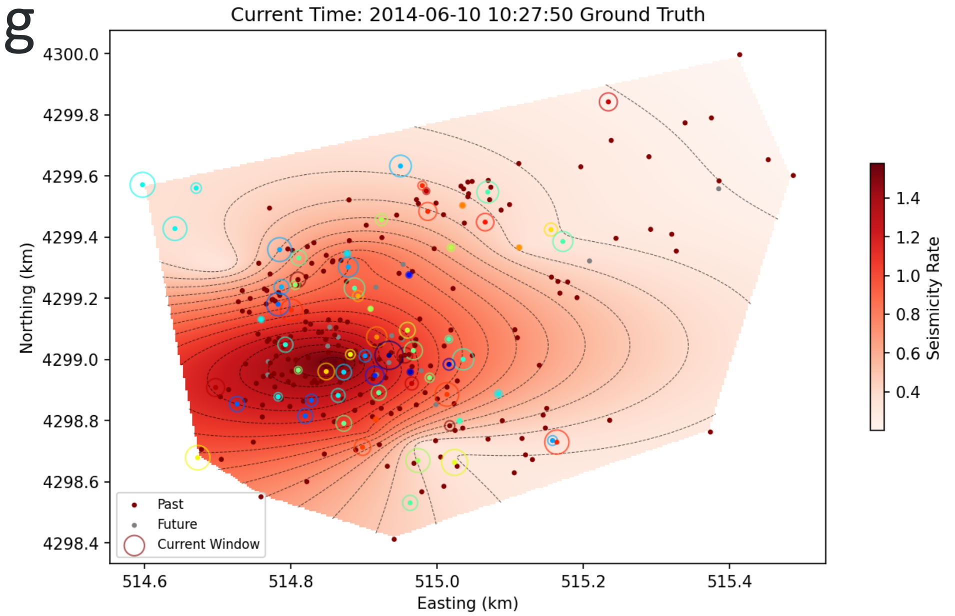


Spatiotemporal forecasting

Observation



Forecasting



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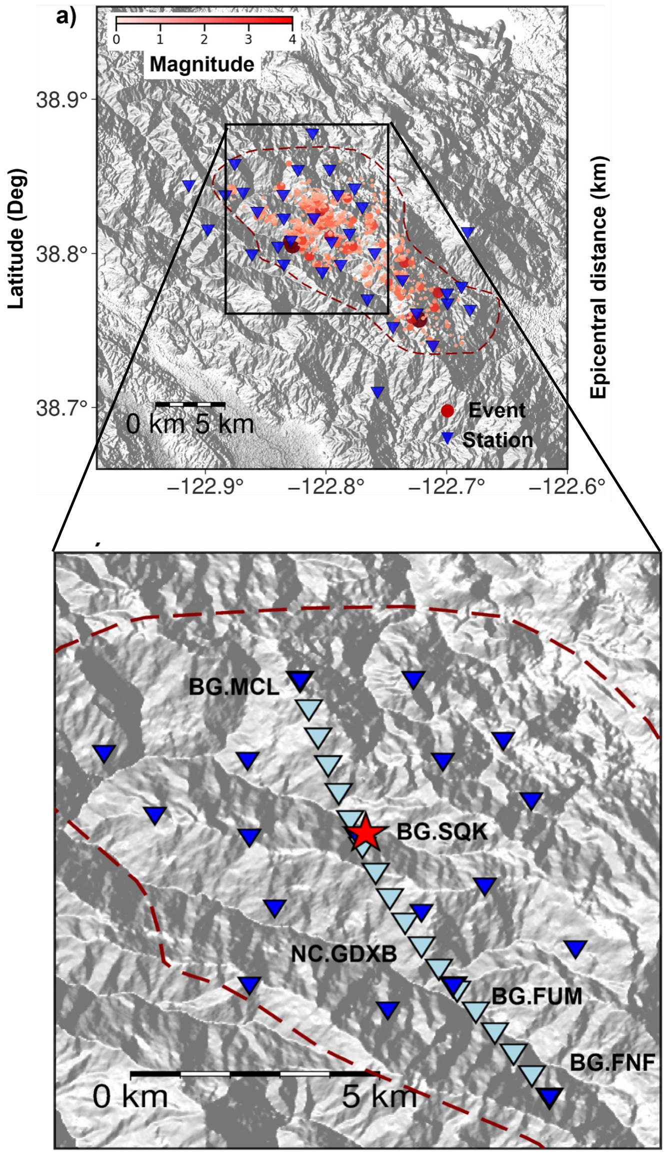
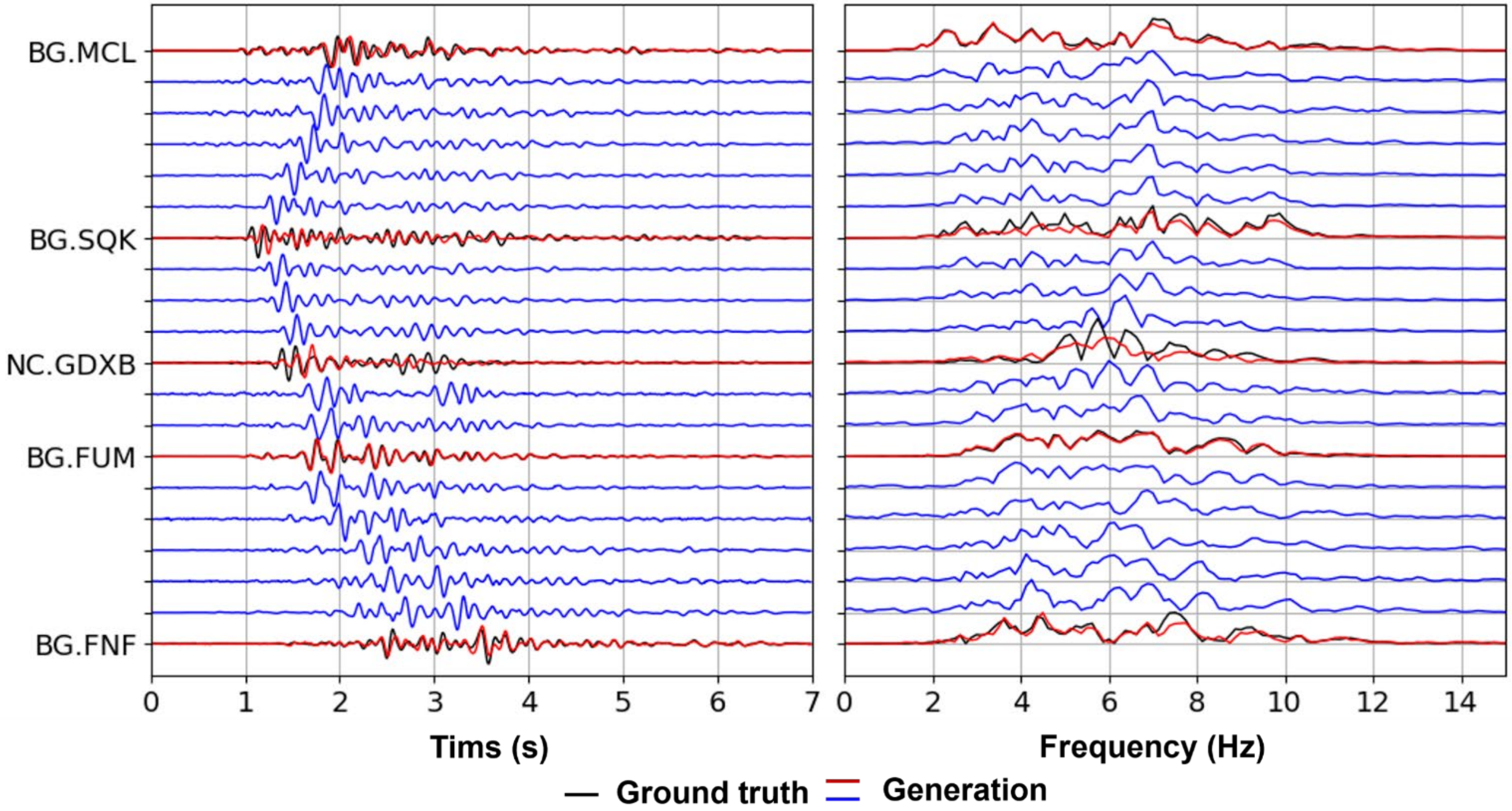
Technical Accomplishments and Progress

Ground motion modeling (Example at the Geysers Geothermal Field)





Blue: both sources and receivers are excluded from training
=> generating wavefields at arbitrary source and receiver locations

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Technological Advancement and Data Dissemination

- Prototype ML models for induced seismicity forecasting and ground motion
- AI-ready datasets compiled from geothermal & oil/gas fields
- Laboratory AE experiments start for generating labeled wet/dry datasets and for deeper mechanical understanding

- The laboratory data will be uploaded to GDR and ”StraboExperimental”.
- Publications
  - Bi, Z., N. Nakata, R. Nakata, P. Ren, X. Wu and M. W. Mahoney (2025) Advancing data-driven broadband seismic wavefield simulation with multi-conditional diffusion model, IEEE TGRS (in press)
  - Bi, Z. and N. Nakata, Forecasting induced seismicity rate in geothermal field with interpretable deep learning, (submitted).
  - Nori Nakata and Zhengfa Bi; 2025, Forecasting Induced Seismicity Using Temporal Fusion Transformer: A Case Study in the Geysers Geothermal Field, Proceedings of Geothermal Reservoir Engineering, SGP-TR-229
  - Nori Nakata and Zhengfa Bi; 2025, Interpretable Deep Learning Framework for Forecasting Induced Seismicity in Geothermal Fields, SSA annual meeting, April 14-18 (invited)
  - Nori Nakata, Rie Nakata, Pu Ren, Zhengfa Bi, Maxime Lacour, Benjamin Erichson, Michael W. Mahoney; 2025, Simulating Seismic Wavefields using Generative Artificial Intelligence, SSA annual meeting, April 14-18

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Future Directions

- **Revise ML models**
  - improve performance, robustness, and generalization
  - spatiotemporal evolution with magnitudes
  - adapt for near-real-time use at Utah FORGE
- **Integrate lab AE data**
  - finish pore fluid pressure-driven failure experiments
  - train ML with wet/dry benchmarks
  - link AE features to stress & pore pressure with data analysis and microstructural sample characterization
  - explore new / more complex loading paths to better mimic natural operations
- **Advance ATLS & reservoir engineering**
  - build accurate, efficient, and physically interpretable ML frameworks
  - toward Best Practices

Milestones	Status and Expected Completion Date
Use various field datasets to develop the seismicity & ground-motion forecasting methods. Measure the accuracy of the models.	We have applied the current ML models to multiple datasets and will revise the models and understand the robustness vs accuracy. Year 2 Q2
Compile experimental datasets and report a method to classify and/or signal differences between wet and dry events in the laboratory setting	The first series of experiments was completed, and we will finish pore fluid pressure-driven failure experiments. Year 2 Q4

Summary

- **Built AI-ready datasets** from geothermal and oil/gas fields, plus ongoing effort for >10k AE lab experiments for wet/dry event calibration.
- **Developed experimental protocols** for testing pore-fluid pressure-driven and stress-driven failure
- **Developed prototype ML models** for induced seismicity forecasting and generative AI ground-motion prediction.
- **Laid foundation for near-real-time ATLS** and advanced reservoir engineering with interpretable, physics-linked ML frameworks.