

Utah FORGE– 2026 Annual R&D Workshop

Probabilistic Estimation of Seismic Response Using
Physics-Informed Recurrent Neural Networks/6-3712

GTC Analytics

Georgia Institute of Technology

Texas A&M University

Probabilistic Estimation of Seismic Response Using Physics-Informed Recurrent Neural Networks/6-3712

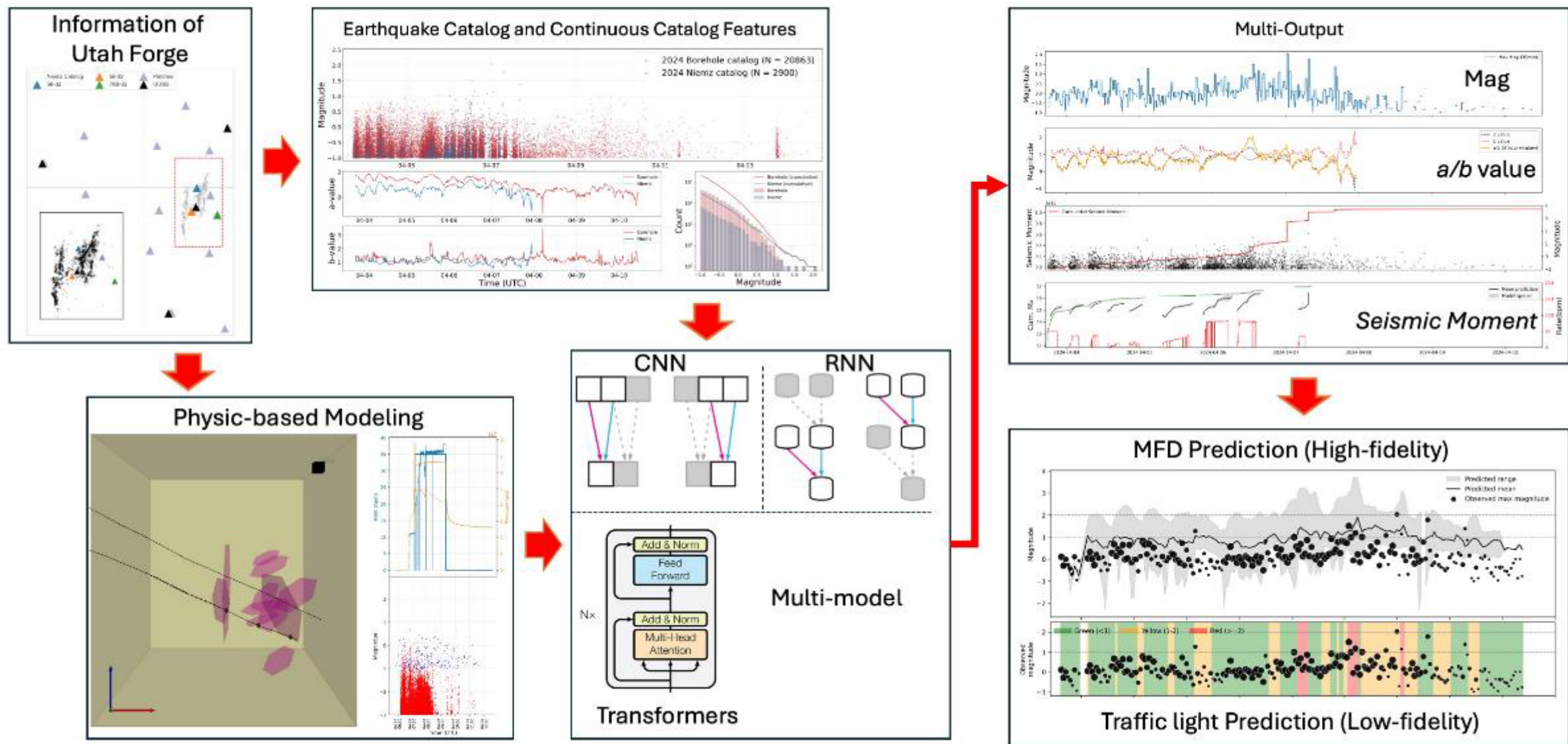
- PI and Presenter: Dr. Jesse Williams
- Organization: GTC Analytics
- Total Project Funding \$1,061,624.66
- Project Start and End Date: 04/01/2024 – 8/30/2026
- Date of Presentation: 10/01/2026

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

Objectives and Purpose

- Main Objective
 - Develop machine learning-based predictive tools to estimate the magnitude-frequency response of stimulation-induced seismicity at the Utah FORGE site
- Phase Objectives
 - Event identification through enhanced field data interpretation
 - Modeling framework to capture the fracture response during stimulation and validation by field data
 - Create deep learning (DL) architecture for metadata and time series data
 - Develop DL framework for low-fidelity, induced seismicity predictor
 - Estimate magnitude-frequency distribution (MFD) from time series data
 - Generate MFD and time series data from physics-based modeling
 - Develop DL framework for high-fidelity, induced seismicity predictor
- Impact of this research and development to geothermal development/deployment
 - Predictive system to aid in avoiding unwanted induced seismicity
 - Tool to assist operators define target stimulation parameters

Methods/Approach: Overall Strategy



Methods/Approach: Earthquake Monitoring



MFD Calculation (G-R relation)

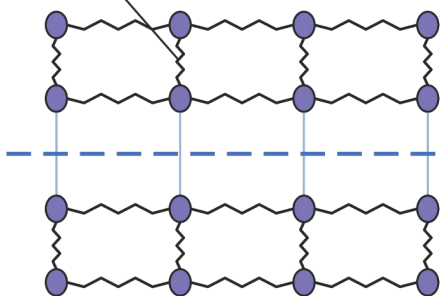
$$M_c = -1.0$$

$$N = 1, M = \frac{a}{b}$$

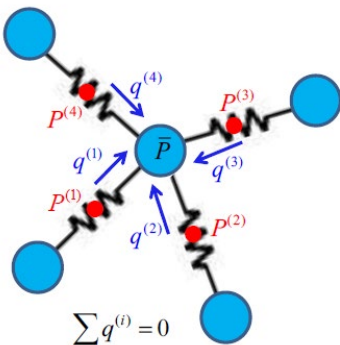
Methods/Approach: Physics-based numerical investigations

XSite coupling

Intact-rock spring pair
(normal + shear)



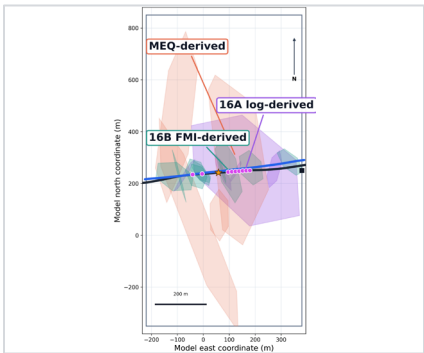
Pre-existing joint
(smooth-joint model,
frictional)



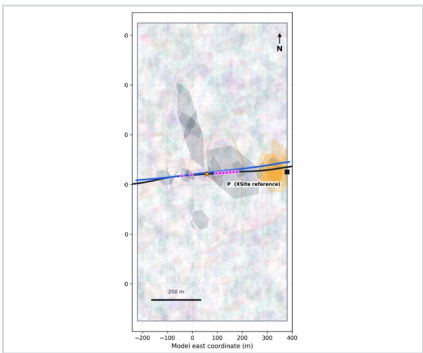
Representative model properties

Property	Value used
Young's modulus	55 GPa
Poisson's ratio	0.26
Fracture toughness	3 MPa·m ^{0.5}
Joint stiffness, $k_n = k_s$	0.5 GPa/m
Initial aperture	$5 \times 10^{-6} \sqrt{R}$ m
Stress gradients	0.0174 / 0.0199 / 0.0256 MPa/m $S_{hmin} / S_{hmax} / S_v$
Pore-pressure gradient	0.0098 MPa/m
Target-fault strength	$c = 0-3$ MPa; $\phi = 25-37^\circ$ varied by case

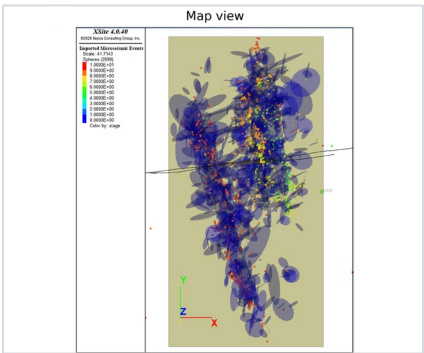
Fracture representations



18 deterministic planes



Stochastic DFN (3,423 Planes)



742-fracture reduced model

Controlled comparisons

Injection rate

50 / 100 / 150 bpm
Equal injected volume

Fracture network

Deterministic vs stochastic
Same Stage 8 schedule

Fault reactivation

Stimulation memory
Homogeneous fault strength
Along-strike heterogeneity

Methods/Approach: Predictive Modeling

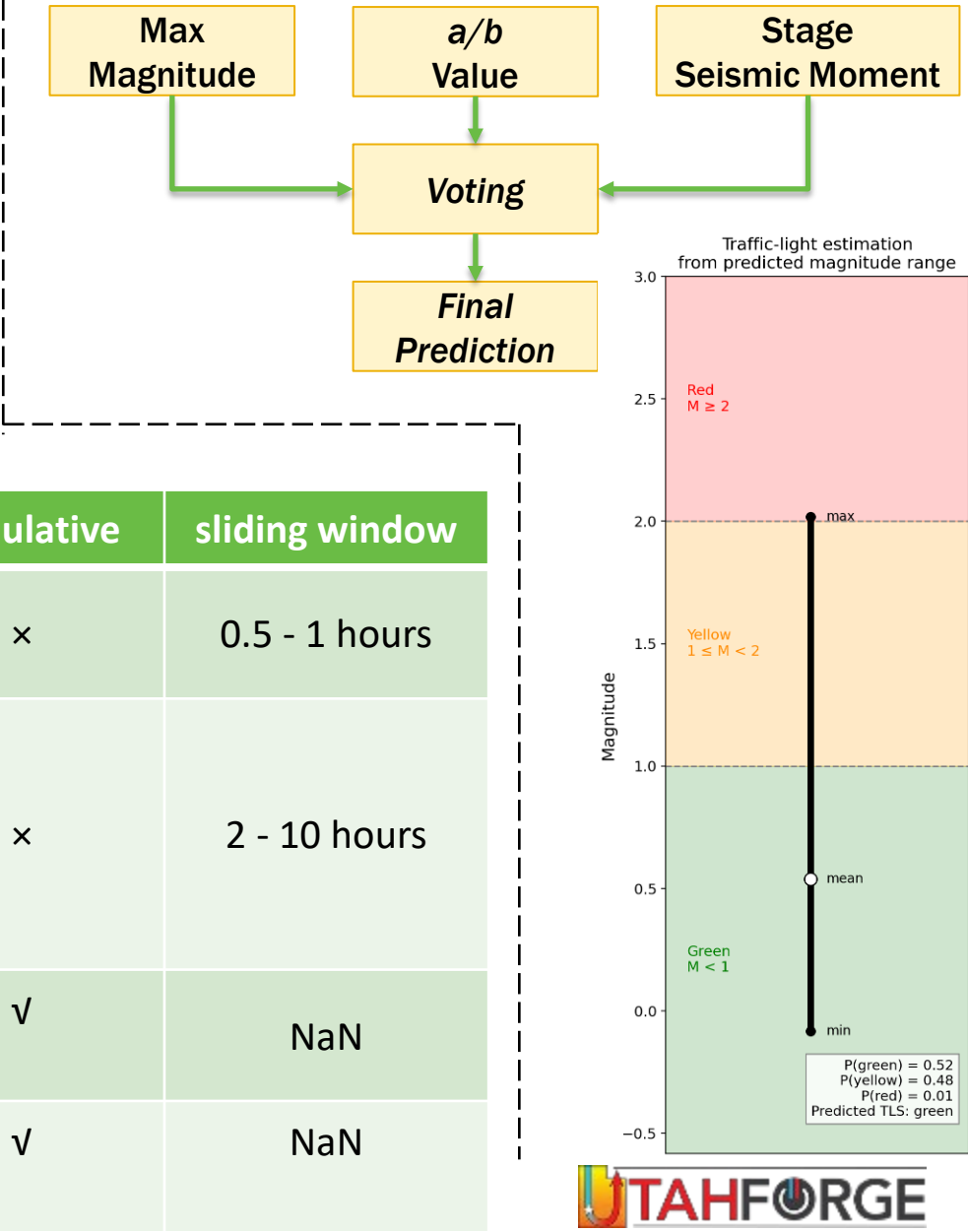
Input:
[a, b, seismicity rate, max magnitude, pressure, Injection rate]; in past 6hours
360*6

[Injection rate] in future 1 hour 60*1

Output:
[a, b] in future 1 hour 60 * 2

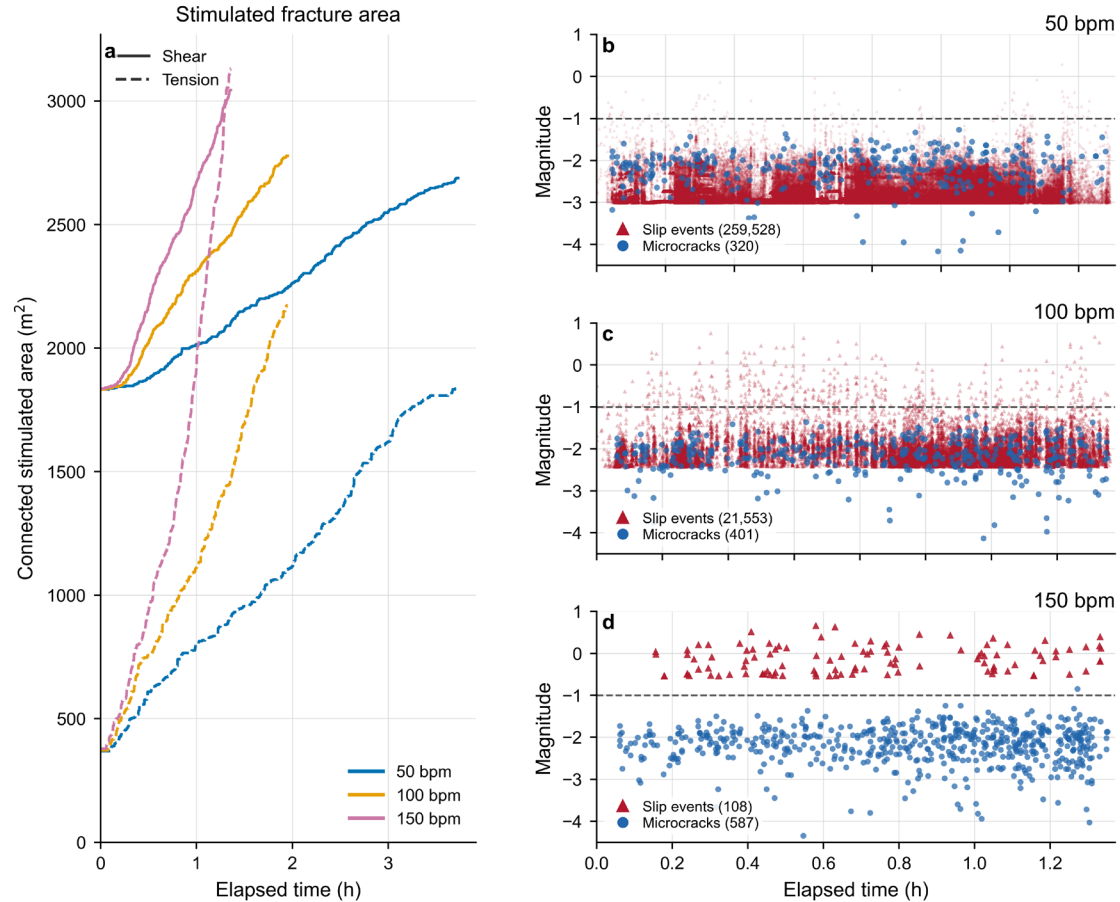
Method	Advantage	Disadvantage	Continuous	Cumulative	sliding window
Max Magnitude	Continuous results	Hard to select window	√	×	0.5 - 1 hours
a/b value	High interpretability	Hard to select window; Under fitting/over fitting	√	×	2 - 10 hours
Whole stage Seismic Moment	Easy to fit trends	Hard to split train/test data	√	√	NaN
Each stage Seismic Moment	Enough data	Not continuous	×	√	NaN

Several Models Assemble



Technical accomplishments: Rate and fracture-network effects

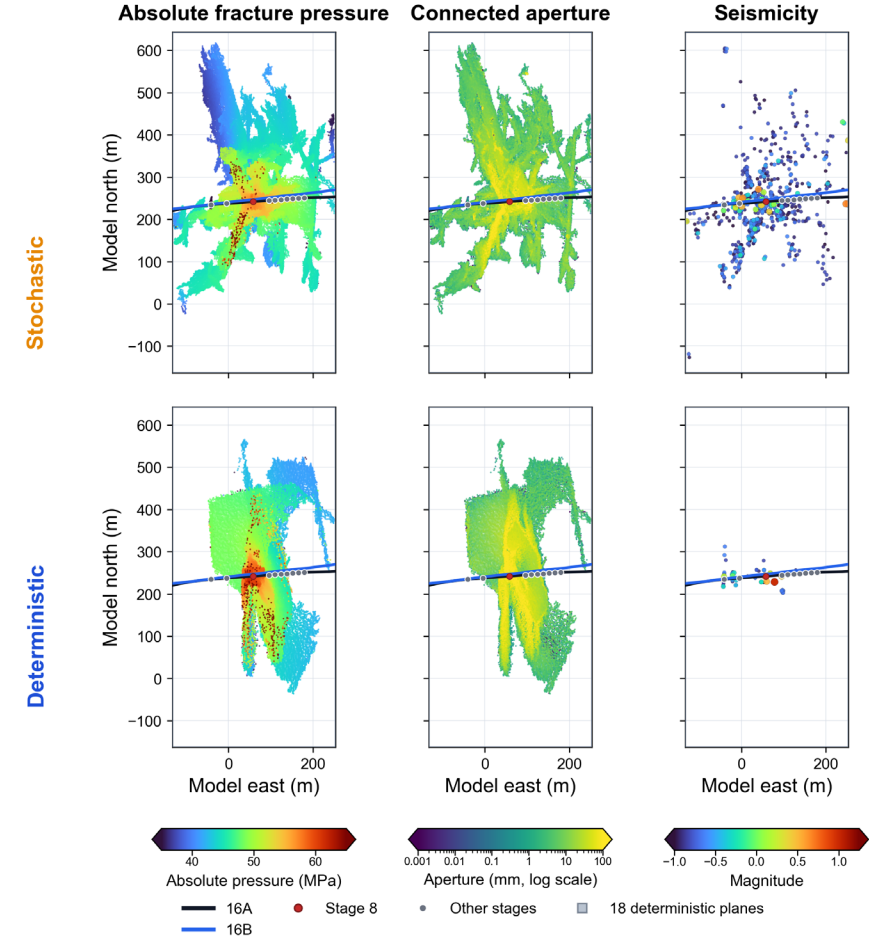
Injection-rate effects — Stage 3R



Rate shifts the failure mechanism

Shear-stimulated area changed modestly across cases, while faster injection accelerated tensile growth. Slip records decreased from 259,528 to 108 as rate rose from 50 to 150 bpm. Tensile microcracks increased from 320 to 587.

Fracture-network representation — Stage 8

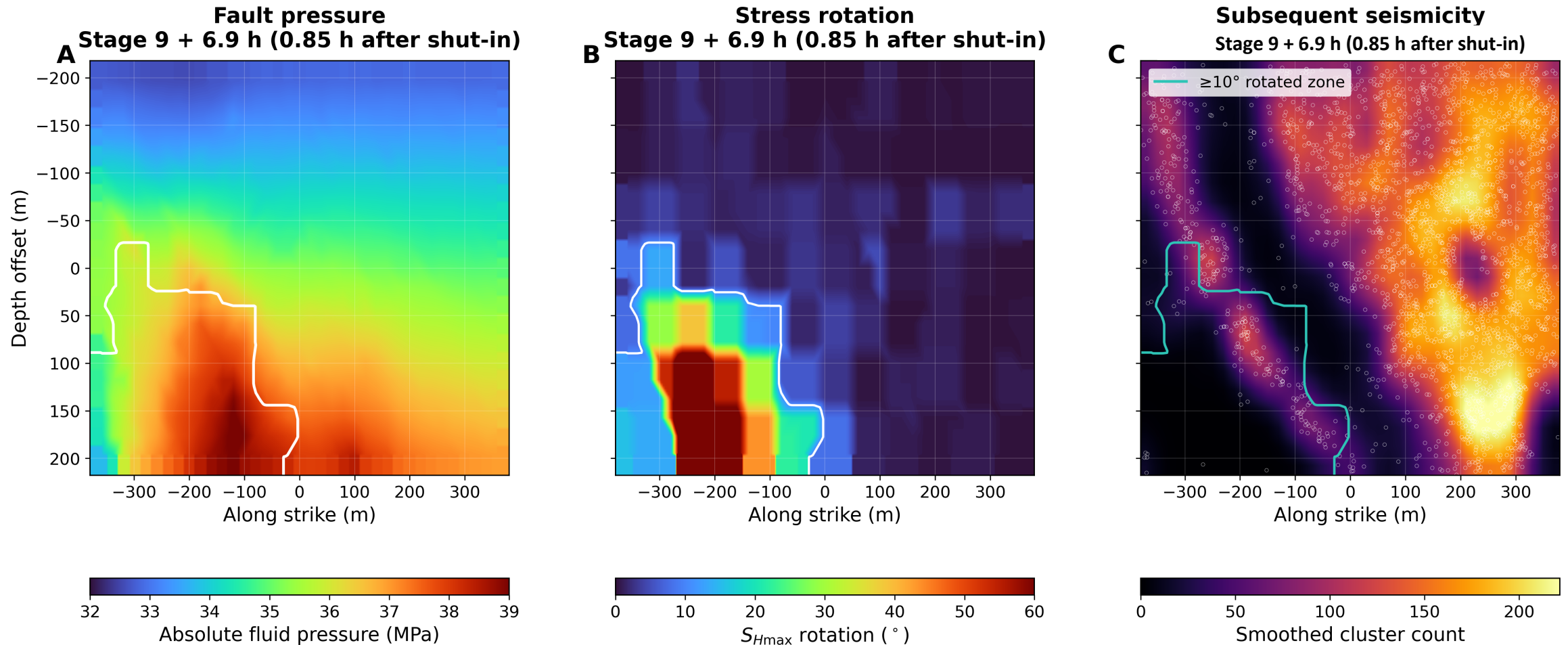


Network controls the internal response

The stochastic network produced 1,823 shear-dominated clusters across a broad footprint. The deterministic network produced 233 clusters localized near treatment and relied more on tensile growth. Similar well pressure did not imply the same connected network.

Technical accomplishments: Stress rotation and seismic suppression

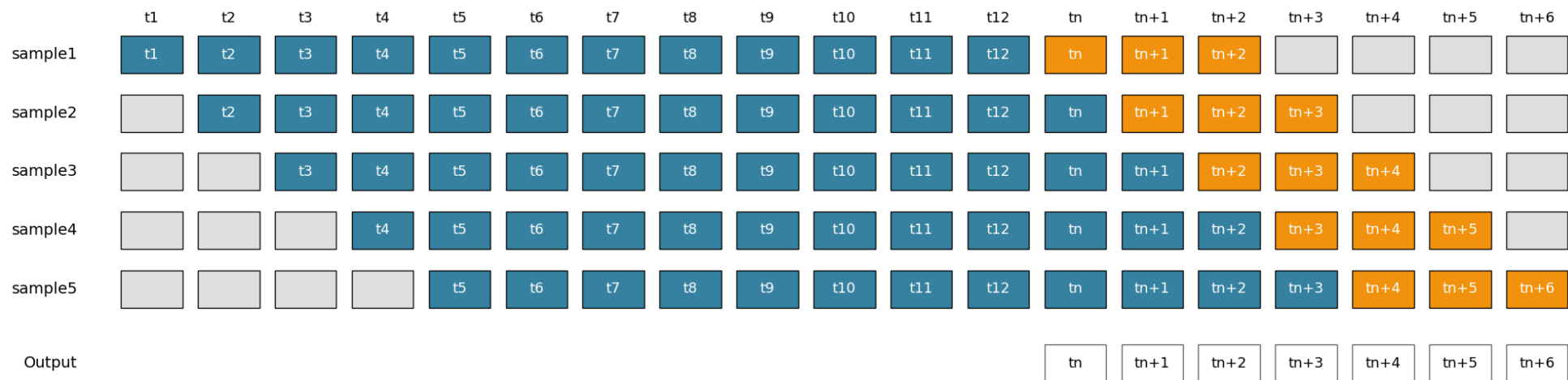
Target-fault stress rotation is referenced to the start of Stage 7.



Pressure persists while seismicity is suppressed due to fracture propagation

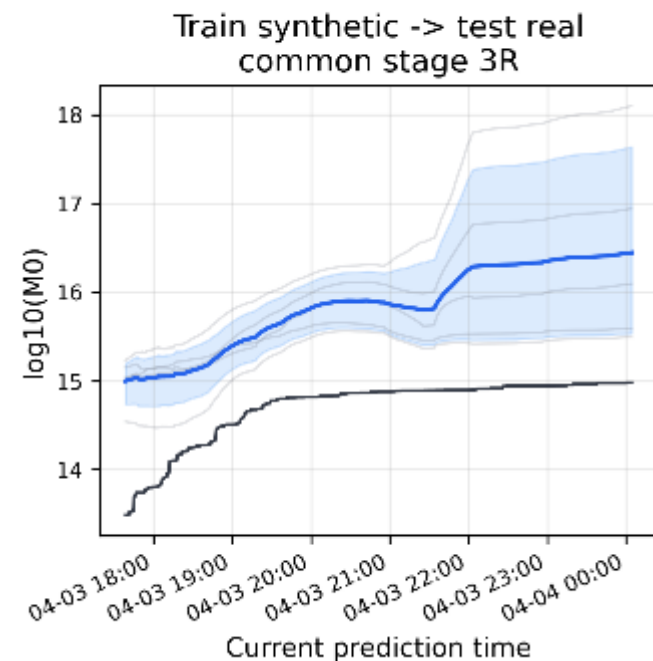
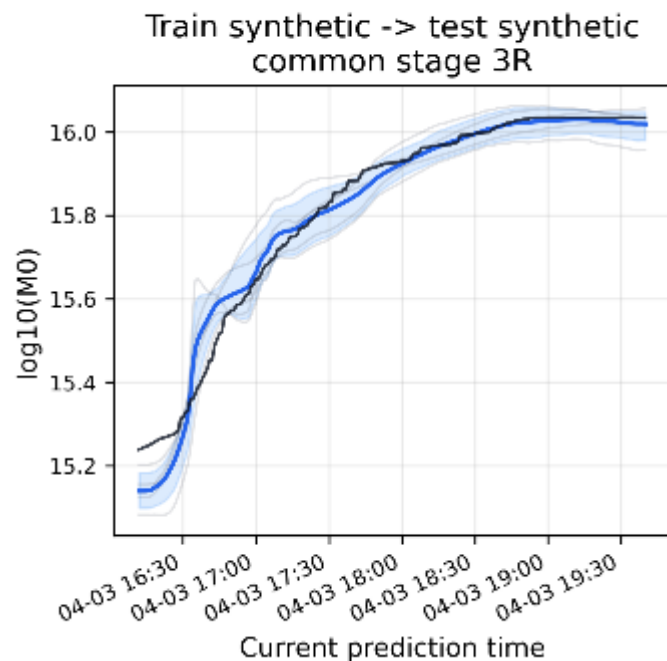
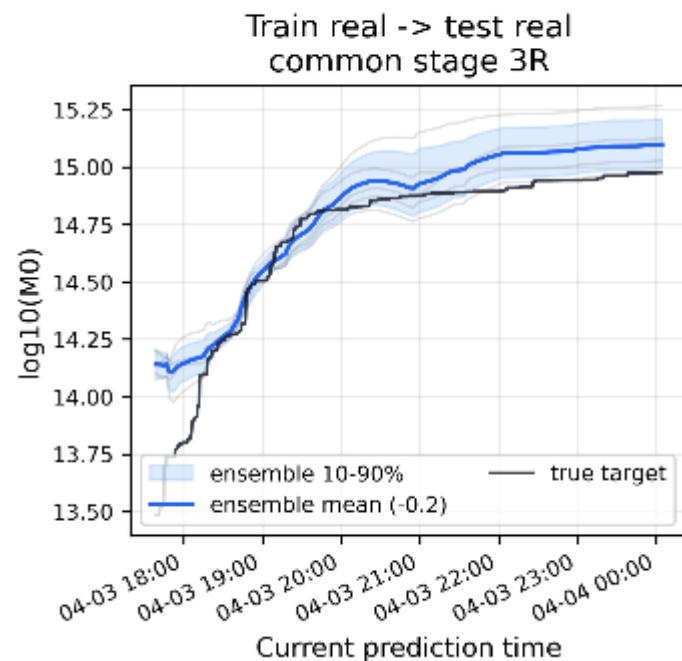
At 0.85 h after Stage 9 shut-in, the $\geq 10^\circ$ rotated zone remained more pressurized than the rest of the fault, yet it covered 18.9% of the mapped fault and contained only 5.5% of subsequent events. (Strong-fault case - Cohesion = 3 MPa; friction angle = 37°)

Technical Accomplishments and Progress: Sequence Prediction



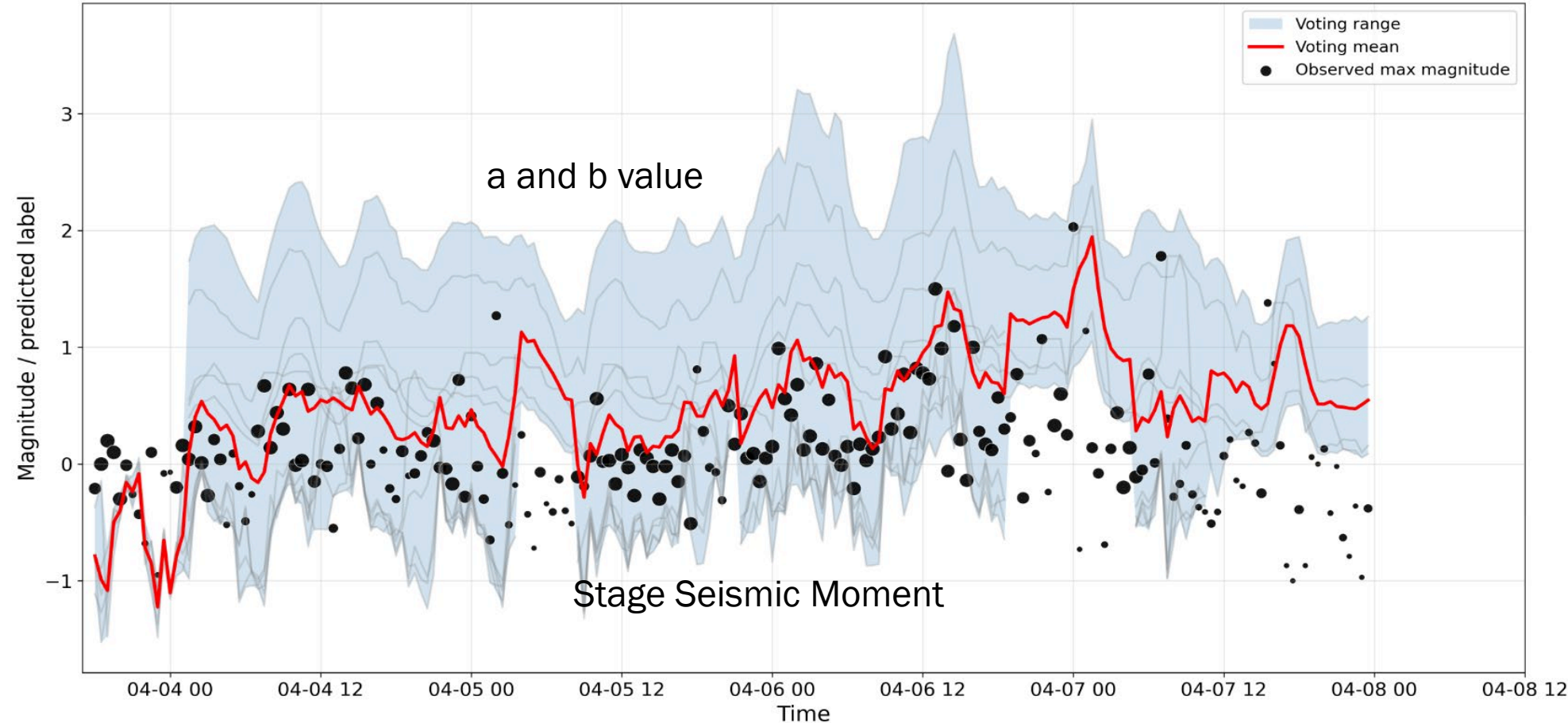
Stage-by-stage ensemble members, ensemble mean, and true target

Step = 1

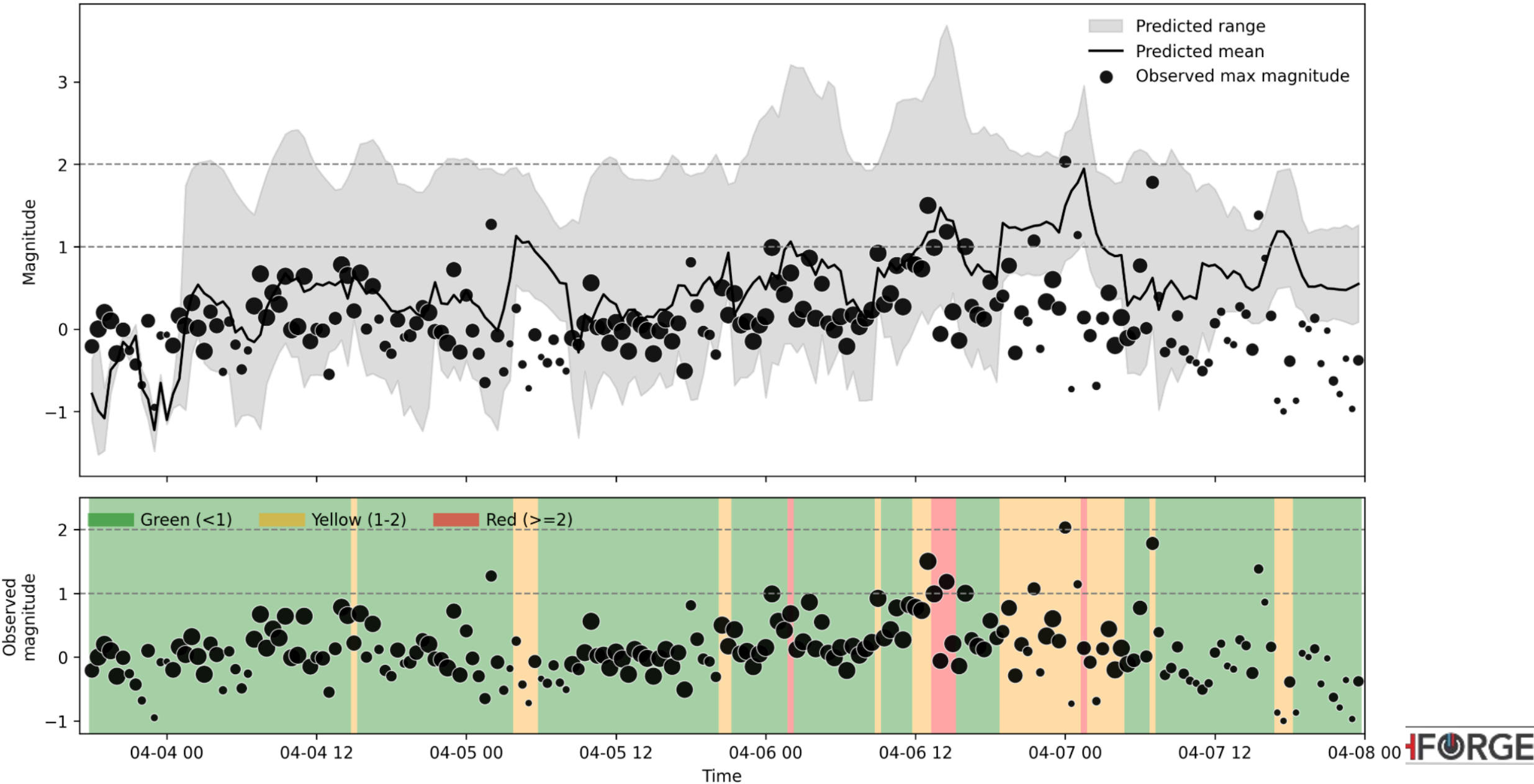


Technical Accomplishments and Progress: Different Models Comparison

	min_count	min_percent	max_count	max_percent
Max Magnitude	878.0	14.246309	417.0	6.766185
a/b_max	0.0	0.000000	5523.0	89.615447
a/b_min	2500.0	40.564660	0.0	0.000000
Stage_moment	2785.0	45.189031	223.0	3.618368



Technical Accomplishments and Progress: Voting Results



Technological Advancement and Data Dissemination

- Technical level of maturity
 - **End-to-end offline prototype demonstrated** using historical Utah FORGE stimulation and seismic data
 - **Core technical components have progressed beyond feasibility**, including seismic-data processing, calibrated physics-based simulation, and ensemble forecasting
 - **Forecasting has advanced from individual research models to an integrated decision-support workflow**, including uncertainty representation and traffic-light outputs
 - **Primary remaining maturity step is operational integration**, including automated live-data ingestion, continuous execution, and validation during real-time field operations
- Technology transition
 - We continue to mature the technology to build out a greater understanding of the subsurface state, including real-time event localization, stress state determination, and rock/media characterization
- Data dissemination
 - We have four submissions on the GDR
 - We have presented at the AGU-SEG Geothermal Workshop
 - We presented at the Stanford Geothermal Workshop and Geothermal Rising Conference
 - We are preparing work to be published in the peer-reviewed literature

Future Directions

Milestones	Status and Expected Completion Date
Curated and processed field-structured and metadata (2022 stimulation)	Done
Obtain field time series data with identified events (2022 stimulation)	Done
Physics based model validation via field MFD	Done
Build recurrent neural network framework	Done
Establish the metadata encoding architecture	Done
Go/No-Go	Passed
Obtain a time series of MMAX from different statistical methods	Done
Xsite modeling, link injection parameters and MFD response	Done
Establish the high-fidelity deep learning estimator	Done

The team is offering to connect the software to the live sensor feed for real-time use

Summary

- **Developed an integrated framework for forecasting stimulation-induced seismicity**, combining field seismic monitoring, physics-based reservoir modeling, and probabilistic machine learning.
- **Improved characterization of the seismic response at Utah FORGE** through enhanced event detection, catalog development, magnitude-frequency analysis, and interpretation of fracture behavior.
- **Physics-based modeling identified key controls on induced seismicity**, including injection rate, fracture-network connectivity, fault strength, stimulation history, and stress redistribution.
- **Demonstrated probabilistic forecasting of future seismic response**, integrating multiple predictive targets and model ensembles to retain uncertainty and support traffic-light-style decision outputs.
- **Identified key challenges in translating physics-based simulations into reliable real-world predictors**, including improved modeling of microseismic sequencing, post-injection response, and event clustering, which strongly influences predicted maximum magnitude.