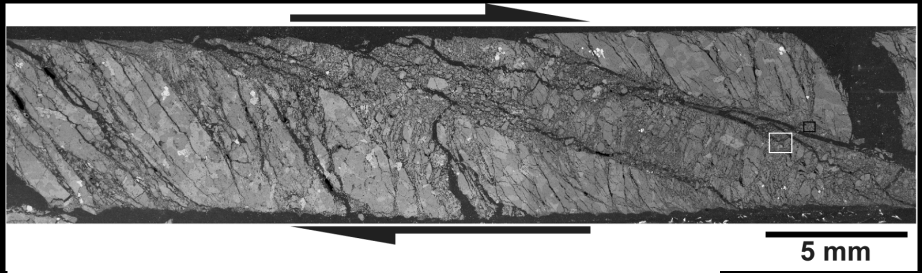
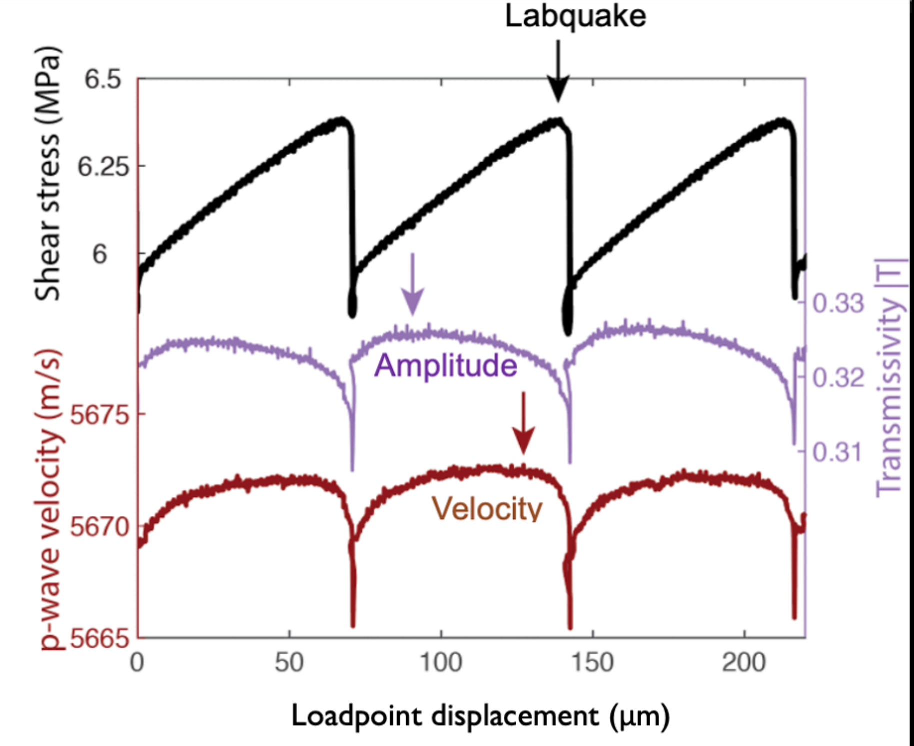
Learning Earthquake Physics from Labquakes, Data Science and Machine Learning

Chris Marone

La Sapienza, Università di Roma Italia e Penn State University USA



Lab earthquake fault zone



Shreedharan et al., JGR 2021

TECTONIC

European Research Council

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4TH INDUCED SEISMICITY WORKSHOP

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18-21 March 2025

Learning Earthquake Physics from Labquakes, Data Science and Machine Learning

nature communications

Article

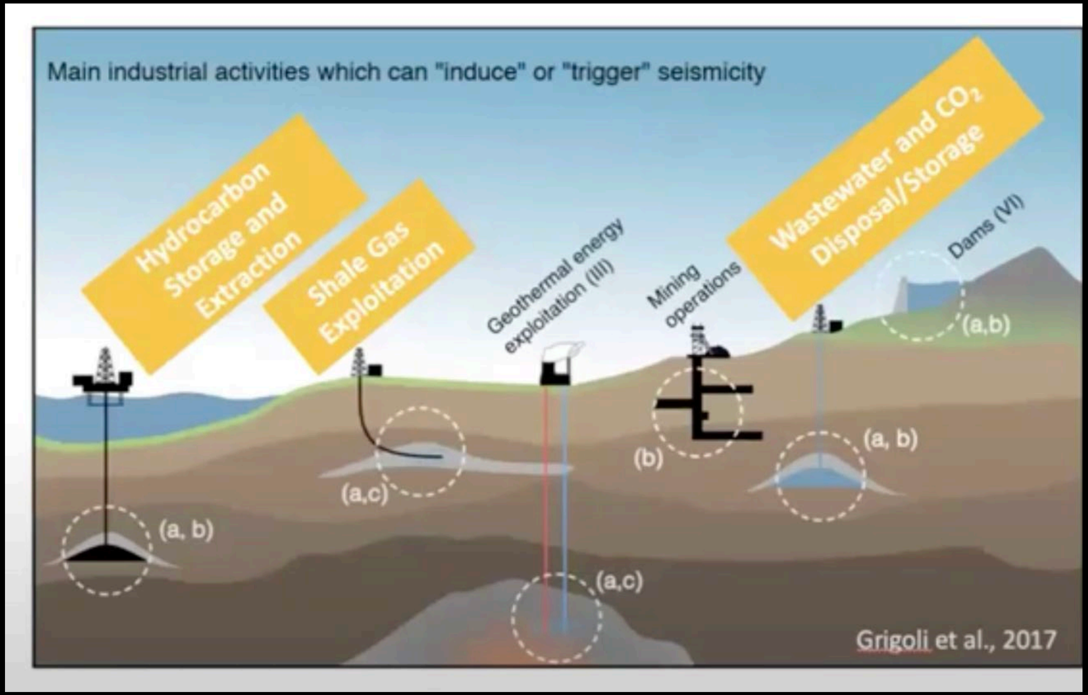
https://doi.org/10.1038/s41467-024-46238-3

Crustal permeability generated through microearthquakes is constrained by seismic moment

Received: 23 November 2023

Accepted: 20 February 2024

Pengliang Yu[1,2], Ankur Mali[3], Thejasvi Velaga[4], Alex Bi[5], Jiayi Yu[2], Chris Marone[1,6], Parisa Shokouhi[7] & Derek Elsworth[1,2]



Deep Learning Recovers Permeability Evolution from Fluid-Induced Microearthquakes for Hectometer-scale Stimulations

Pengliang Yu[1], Anne Obermann[2], Antonio Pio Rinaldi[2], Nima Gholizadeh Doonechaly[3], Chris Marone[1,4], Ankur Mali[5], Parisa Shokouhi[6], Derek Elsworth[1]

Submitted to GRL 2025

4TH INDUCED SEISMICITY WORKSHOP

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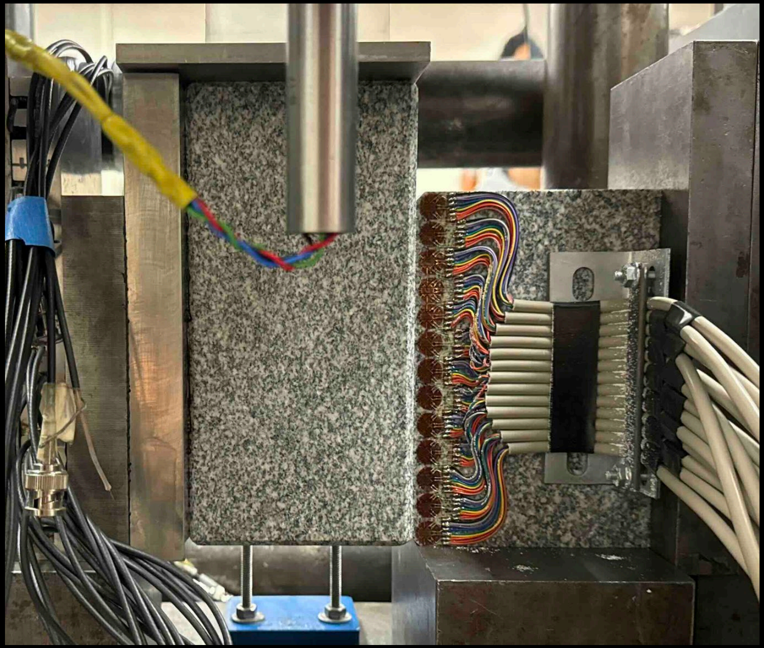
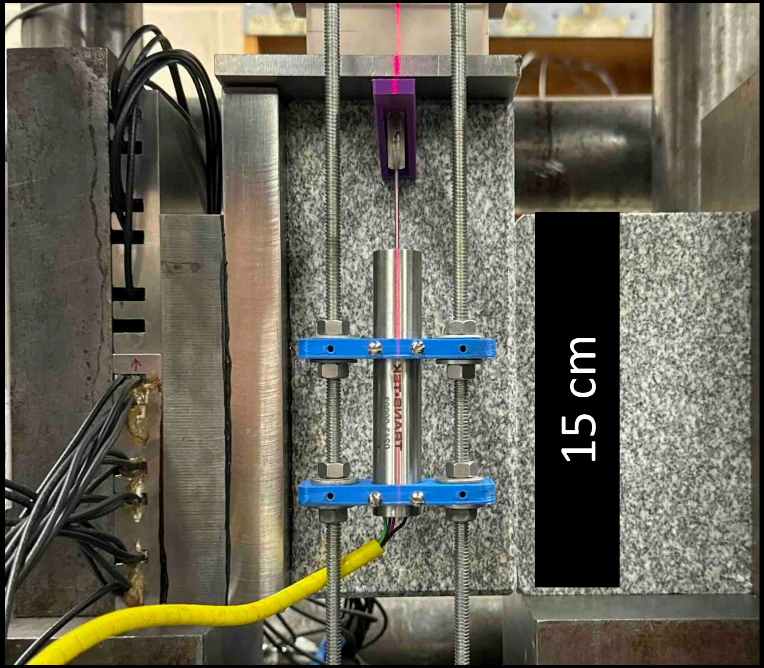
18-21 March 2025

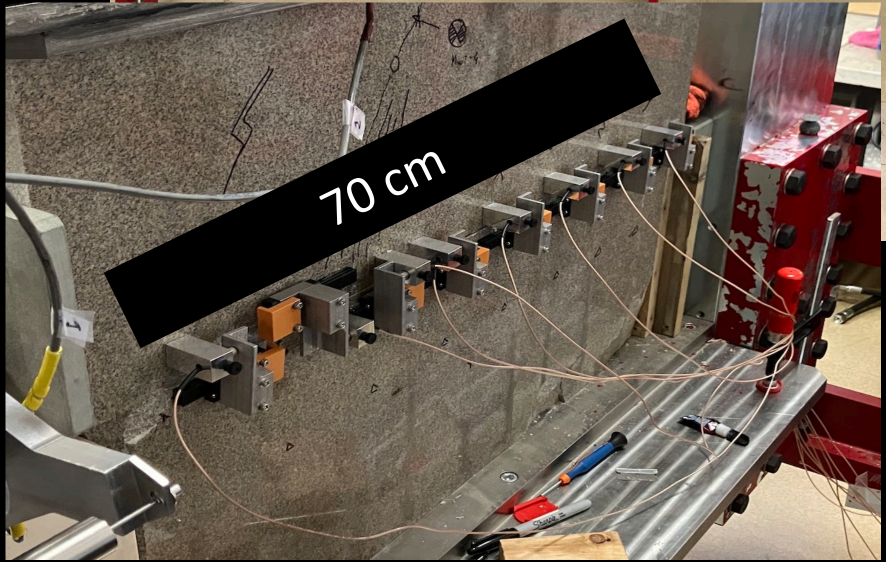
Learning from Labquakes



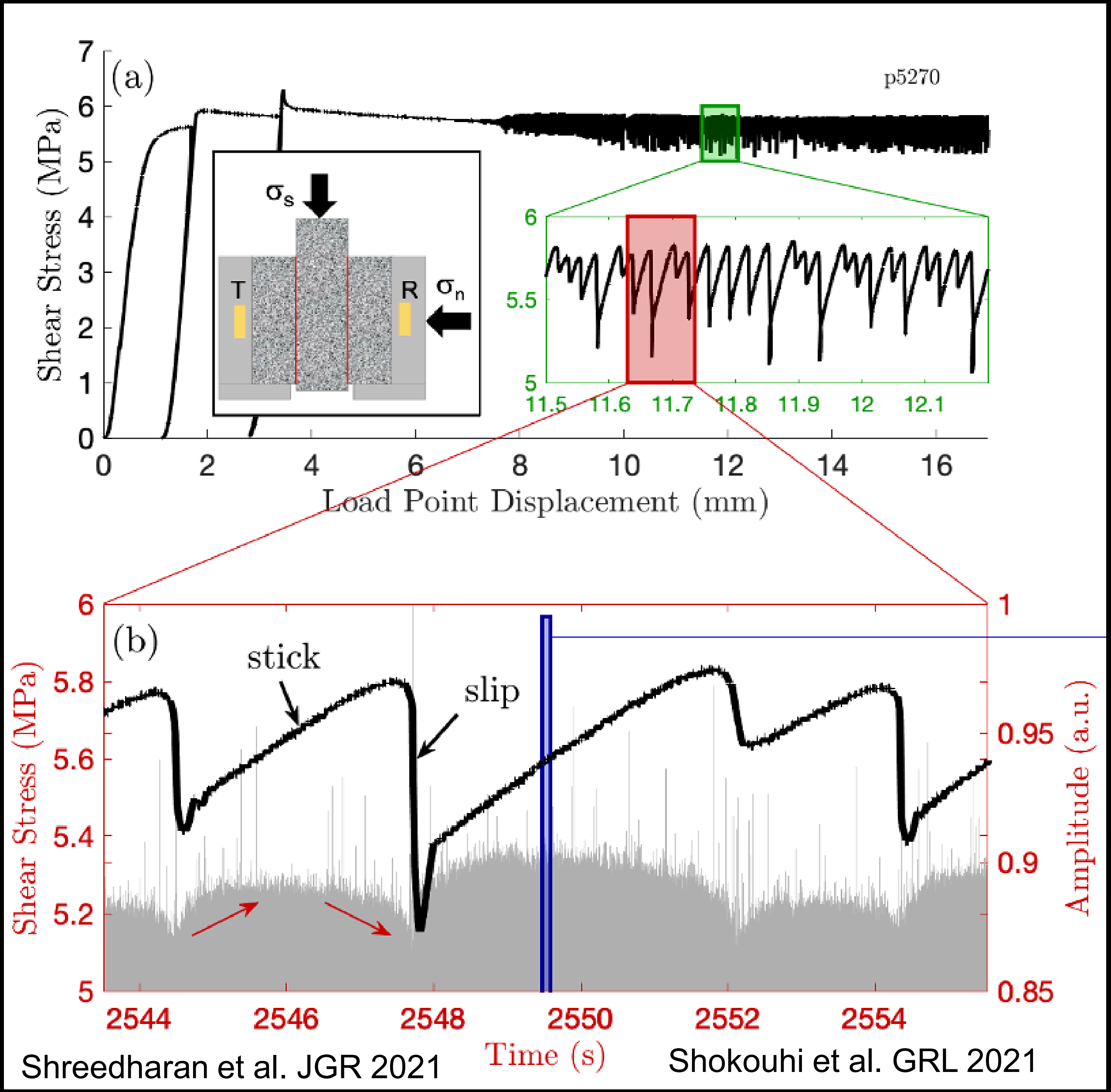


lab earthquakes

Fault normal stresses of 10’s of MPa



Repetitive stick-slip events: lab earthquakes as a tool for earthquake physics



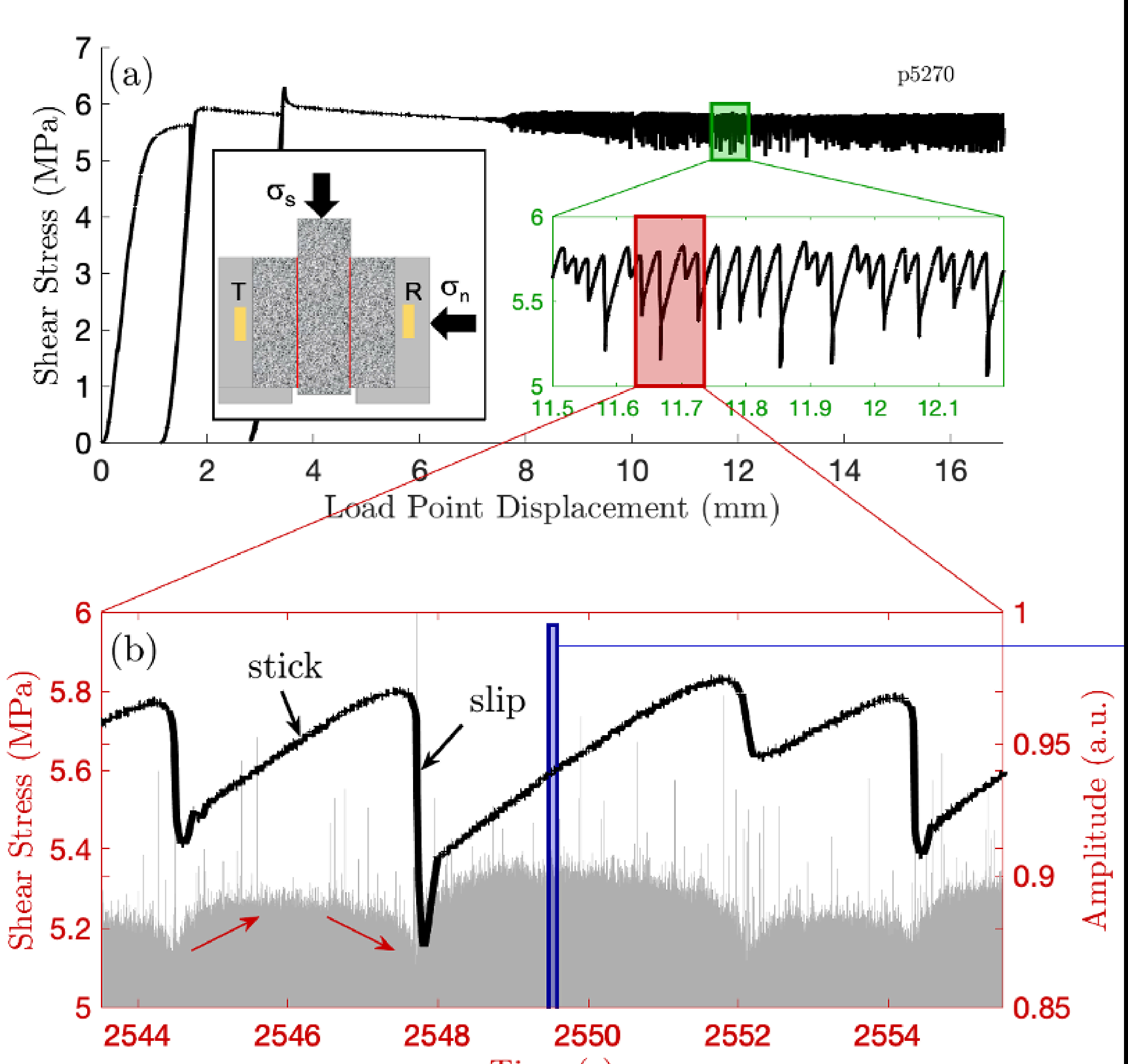
Explainable Machine Learning

100's of lab earthquakes in each experiment

- Carefully controlled conditions
- Systematic changes in behavior for small changes in control parameters

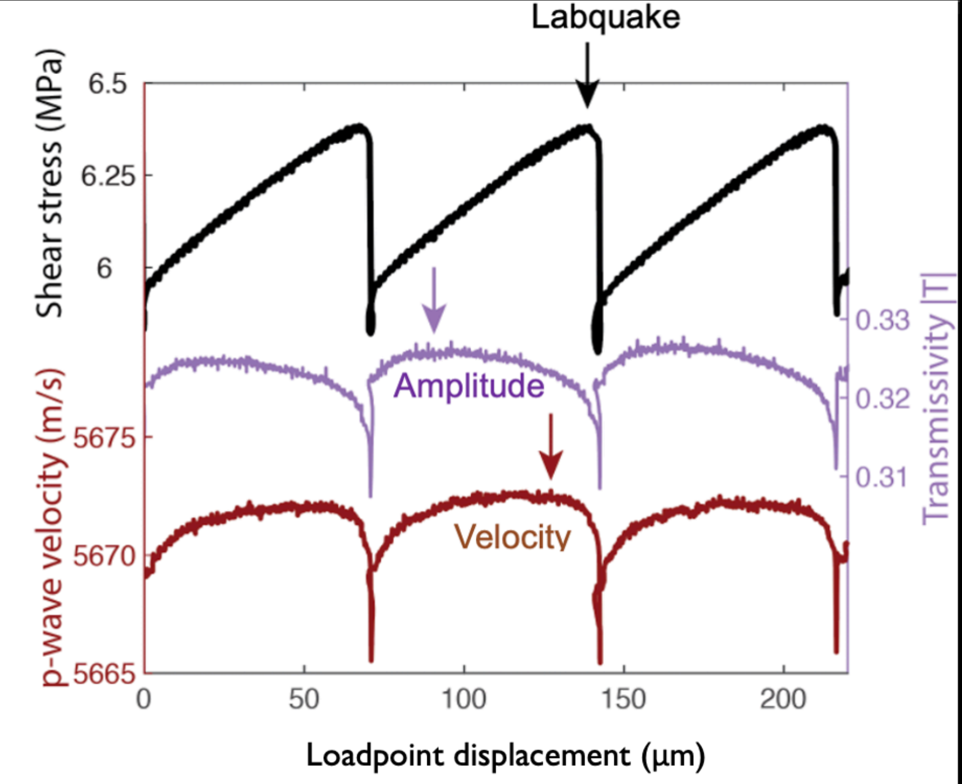
Lab seismometers close to the fault zone

Repetitive lab earthquakes, Physics of Earthquake Precursors



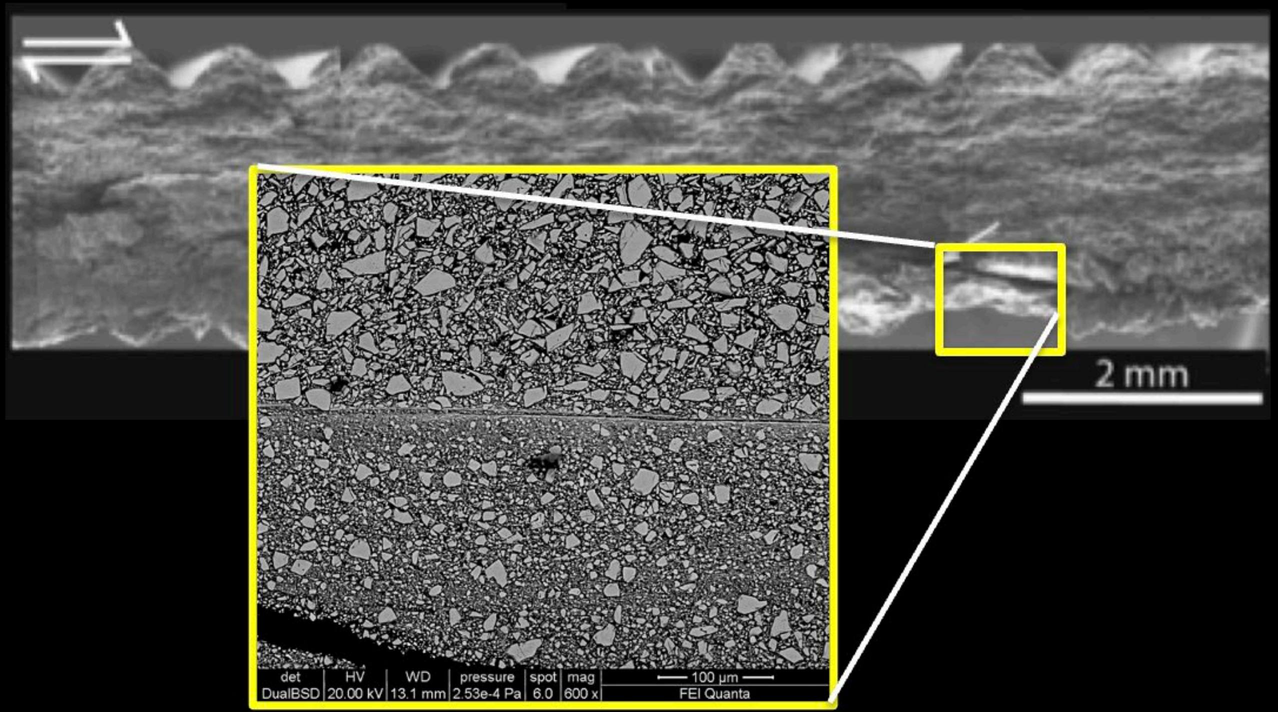
Shreedharan et al. JGR 2021

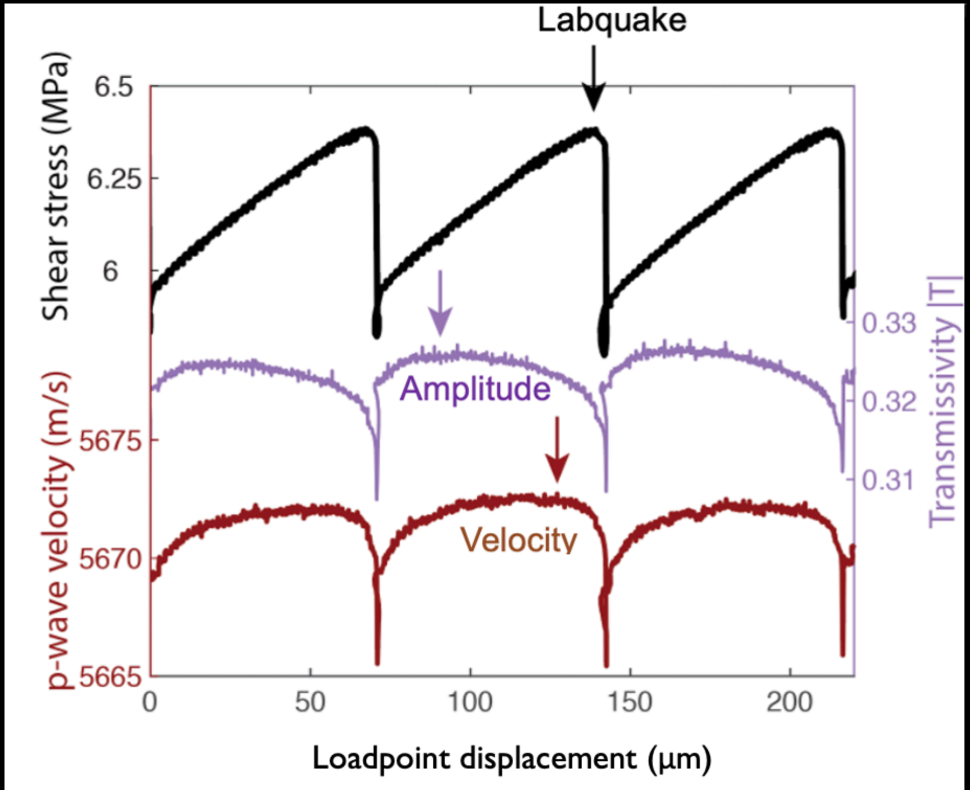
Shokouhi et al. GRL 2021



Shreedharan et al., JGR 2021

Repetitive lab earthquakes, Physics of Earthquake Precursors

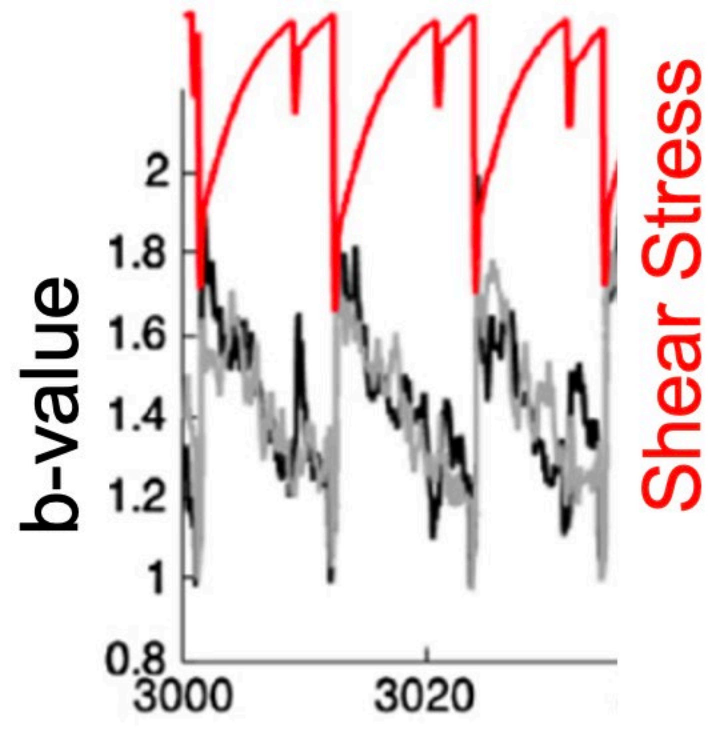




Shreedharan et al., JGR 2021

Evolution of *b*-value during the seismic cycle: Insights from laboratory experiments on simulated faults

J. Rivière [a,b,*], Z. Lv [c,b], P.A. Johnson [d], C. Marone [b]



31 August 1973, Volume 181, Number 4102 SCIENCE

Earthquake Prediction: A Physical Basis

Rock dilatancy and water diffusion may explain a large class of phenomena precursory to earthquakes.

Christopher H. Scholz, Lynn R. Sykes, Yash P. Aggarwal

The Dilatancy Model

Observations for a number of earthquakes made at Garm, U.S.S.R., and in the New York Adirondacks and observations of the San Fernando earthquake show that, prior to each of these earthquakes, the ratio of seismic velocities v_P/v_S decreased to anomalously low values. In each of these cases, earthquakes occurred shortly after the return of v_P/v_S to its normal value.

Nur (*4*) and Aggarwal *et al.* (*2*) independently put forward a model that would explain this phenomenon. The model is based on laboratory fracture studies which show that rock

AGU PUBLICATIONS

Geophysical Research Letters

RESEARCH LETTER

10.1002/2017GL074677

Machine Learning Predicts Laboratory Earthquakes

Bertrand Rouet-Leduc[1,2], Claudia Hulbert[1], Nicholas Lubbers[1,3], Kipton Barros[1], Colin J. Humphreys[2], and Paul A. Johnson[4]

[1]Theoretical Division and CNLS, Los Alamos National Laboratory, Los Alamos, NM, USA, [2]Department of Materials Science and Metallurgy, University of Cambridge, Cambridge, UK, [3]Department of Physics, Boston University, Boston, MA, USA, [4]Geophysics Group, Los Alamos National Laboratory, Los Alamos, NM, USA

Key Points:

- Machine learning appears to discern the frictional state when applied to laboratory seismic data recorded during a shear experiment
- Machine learning uses statistical characteristics of the recorded seismic signal to accurately predict slip failure time
- We posit that similar machine learning approaches applied to geophysical data in Earth will provide insight in fault frictional processes

Supporting Information:

- Supporting Information S1

Correspondence to:
B. Rouet-Leduc,
bertrandrl@lanl.gov

Abstract We apply machine learning to data sets from shear laboratory experiments, with the goal of identifying hidden signals that precede earthquakes. Here we show that by listening to the acoustic signal emitted by a laboratory fault, machine learning can predict the time remaining before it fails with great accuracy. These predictions are based solely on the instantaneous physical characteristics of the acoustical signal and do not make use of its history. Surprisingly, machine learning identifies a signal emitted from the fault zone previously thought to be low-amplitude noise that enables failure forecasting throughout the laboratory quake cycle. We infer that this signal originates from continuous grain motions of the fault gouge as the fault blocks displace. We posit that applying this approach to continuous seismic data may lead to significant advances in identifying currently unknown signals, in providing new insights into fault physics, and in placing bounds on fault failure times.

Rouet-Leduc et al., 2017

Lab earthquakes are predictable

JGR Solid Earth

RESEARCH ARTICLE
10.1029/2021JB022195

Attention Network Forecasts Time-to-Failure in Laboratory Shear Experiments

2021

Hope Jasperson[1], David C. Bolton[2], Paul Johnson[3], Robert Guyer[3,4], Chris Marone[5,6], and Maarten V. de Hoop[7]

[1]Rice University, EEPS, Houston, TX, USA, [2]University of Texas Institute for Geophysics, Austin, TX, USA, [3]Los Alamos National Laboratory, Geophysics Group, Los Alamos, NM, USA, [4]Department of Physics, University of Nevada, Reno, NV, USA, [5]Department of Geosciences, Pennsylvania State University, State College, PA, USA, [6]Dipartimento Scienze della Terra, Sapienza Universitá di Roma, Rome, Italy, [7]Rice University, CAAM, Houston, TX, USA

Special Section:
Machine learning for Solid Earth observation, modeling and understanding

Key Points:
- We use an attention network to forecast the time-to-failure and shear stress of lab earthquakes

Deep Learning Can Predict Laboratory Quakes From Active Source Seismic Data

Parisa Shokouhi[1], Vrushali Girkar[2], Jacques Rivière[1], Srisharan Shreedharan[3], Chris Marone[3], C. Lee Giles[2,4], and Daniel Kifer[2]

GRL, 2021

Characterizing Acoustic Signals and Searching for Precursors during the Laboratory Seismic Cycle Using Unsupervised Machine Learning

by David C. Bolton, Parisa Shokouhi, Bertrand Rouet-Leduc, Claudia Hulbert, Jacques Rivière, Chris Marone, and Paul A. Johnson

SRL 2019

Prediction
- **Timing**
- **Size (stress drop, fault slip velocity)**
- **Fault Zone Stress**

Geophysical Research Letters

2018

RESEARCH LETTER
10.1029/2018GL079712

Earthquake Catalog-Based Machine Learning Identification of Laboratory Fault States and the Effects of Magnitude of Completeness

Nicholas Lubbers[1], David C. Bolton[2], Jamaludin Mohd-Yusof[3], Chris Marone[2], Kipton Barros[1], and Paul A. Johnson[4]

Key Points:
- Machine learning can model important characteristics of laboratory fault physics by training on finely resolved catalogs of slip events

Machine Learning Predicts the Timing and Shear Stress Evolution of Lab Earthquakes Using Active Seismic Monitoring of Fault Zone Processes

JGR, 2021

Srisharan Shreedharan[1,2], David Chas Bolton[1], Jacques Rivière[3], and Chris Marone[1,4]

Contents lists available at ScienceDirect

Earth and Planetary Science Letters

ELSEVIER

www.elsevier.com/locate/epsl

Deep learning for laboratory earthquake prediction and autoregressive forecasting of fault zone stress

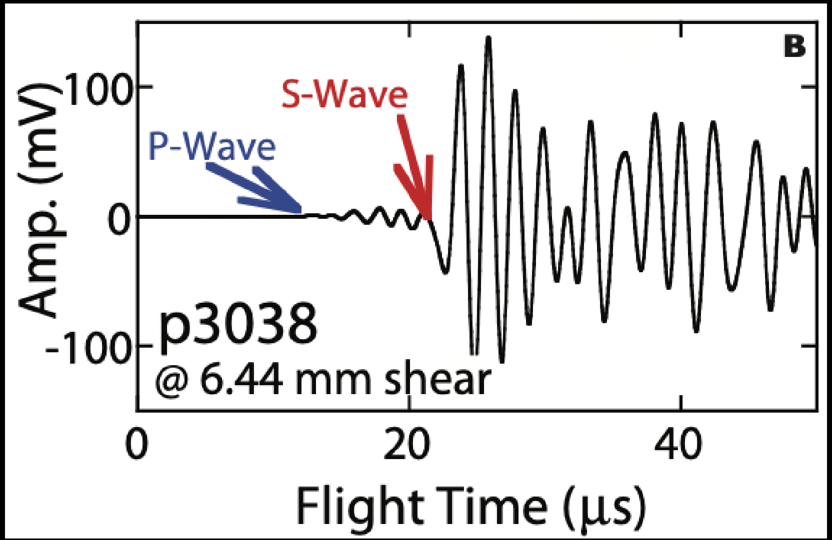
2022

Laura Laurenti[a,*], Elisa Tinti[a,b], Fabio Galasso[a], Luca Franco[a], Chris Marone[a,c]

Lab earthquake prediction

State Of The Art

Deep Learning Methods to measure the evolution of fault zone elastic properties during the lab seismic cycle



nature communications 2023

Article

https://doi.org/10.1038/s41467-023-39377-6

Using a physics-informed neural network and fault zone acoustic monitoring to predict lab earthquakes

Received: 8 December 2022

Accepted: 7 June 2023

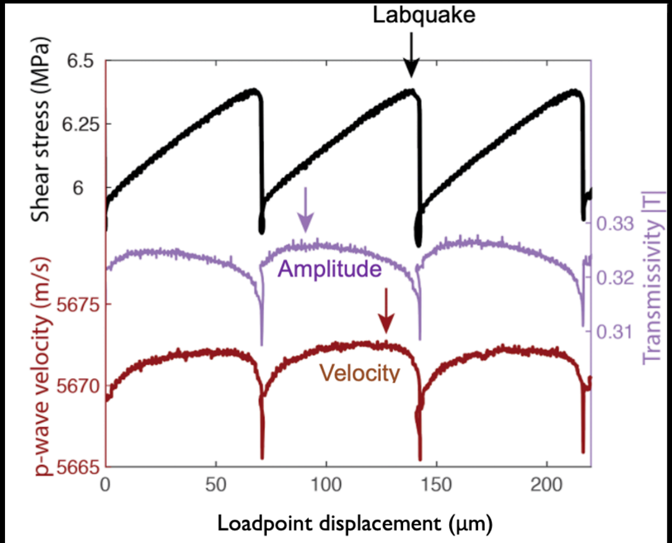
Prabhav Borate[1], Jacques Rivière[1], Chris Marone[2,3], Ankur Mali[4], Daniel Kifer[5] & Parisa Shokouhi[1]

Nature **scientific** reports *2024*

Physics informed neural network can retrieve rate and state friction parameters from acoustic monitoring of laboratory stick-slip experiments

Prabhav Borate[1], Jacques Rivière[1], Samson Marty[2], Chris Marone[3,4], Daniel Kifer[5] & Parisa Shokouhi[1]

Explainable Machine Learning



Shreedharan et al., JGR 2021

Physics Constraints

$$\frac{d\left(\frac{\tau_i}{\sigma}\right)}{dt} = k(V_l - V_i) \quad (1)$$

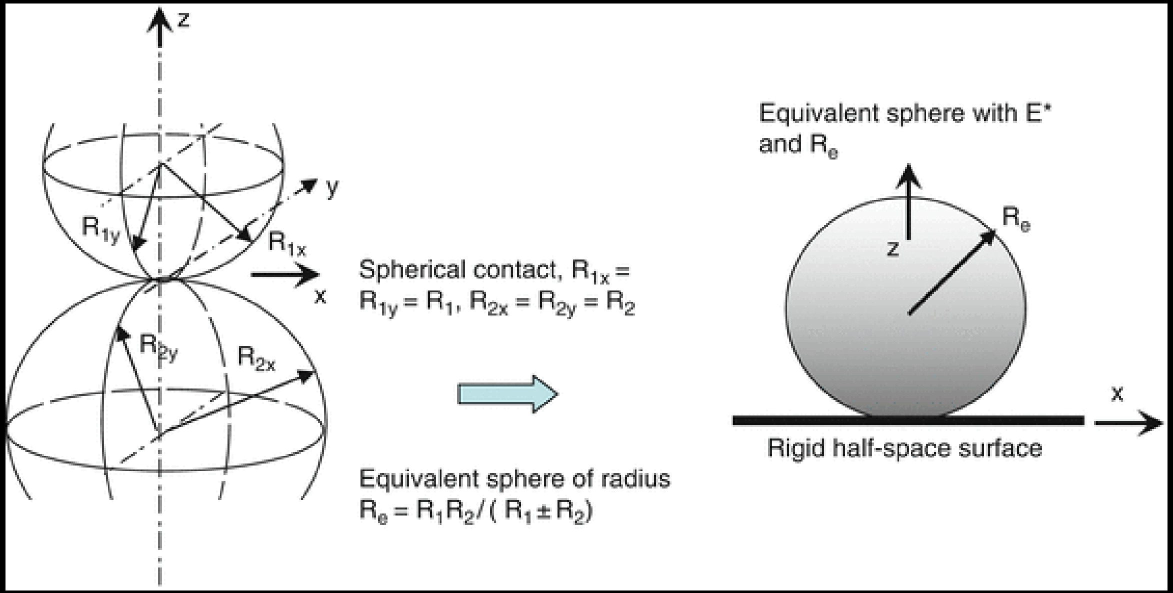
$$\frac{1}{k} = \frac{1}{K} + \frac{1}{k_f} \quad (2)$$

$$(T =)\ \frac{A_i}{A_{Intact}} = \frac{2k_f}{\sqrt{(2\pi f_0 \rho v_i)^2 + 4k_f^2}} \quad (3)$$

- Inputs
- Outputs
- Learned Parameters

- PINN #1 Model Constraint: Equation (1)
- PINN #2 Model Constraint: Equation (1) – (3)

Active acoustic studies of the lab seismic cycle



JKR contact theory

$$|T| = \frac{A}{A_0} = \frac{2k_I}{\sqrt{((\omega\rho v)^2 + 4k_I^2))}} \qquad TOF = tan^{-1}\frac{(\omega\rho v / 2k_I)}{(\omega)}$$

Tattersall, 1973

Explainable Machine Learning

Rate/State Friction and Contact Aging

Contact Age = Frictional State

Physics Constraints

$$\frac{d\left(\frac{\tau_i}{\sigma}\right)}{dt} = k(V_l - V_i) \quad (1)$$

$$\frac{1}{k} = \frac{1}{K} + \frac{1}{k_f} \quad (2)$$

$$(T =)\ \frac{A_i}{A_{Intact}} = \frac{2k_f}{\sqrt{(2\pi f_0 \rho v_i)^2 + 4k_f^2}} \quad (3)$$

Inputs
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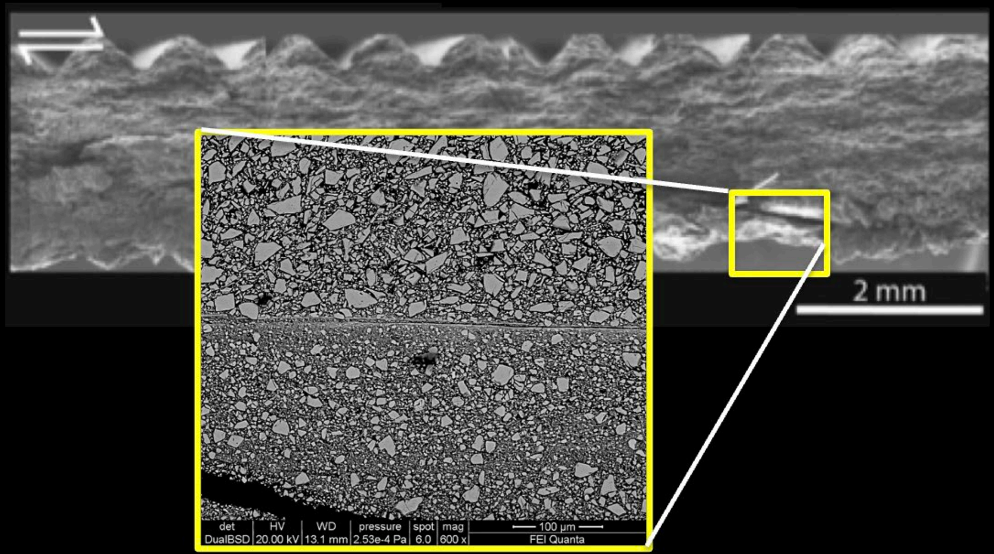
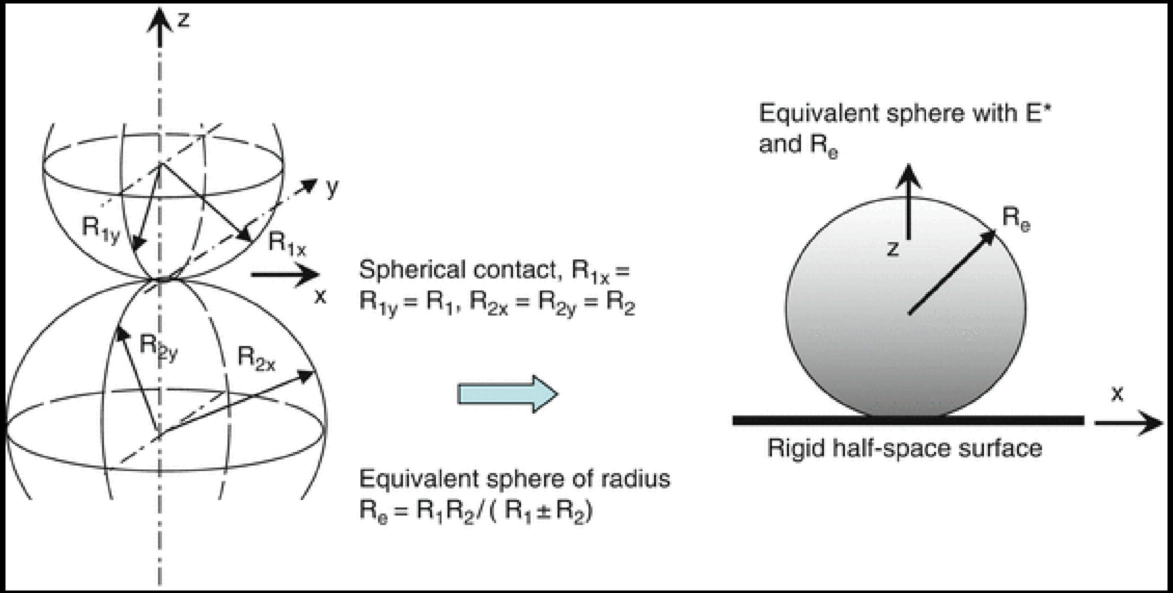


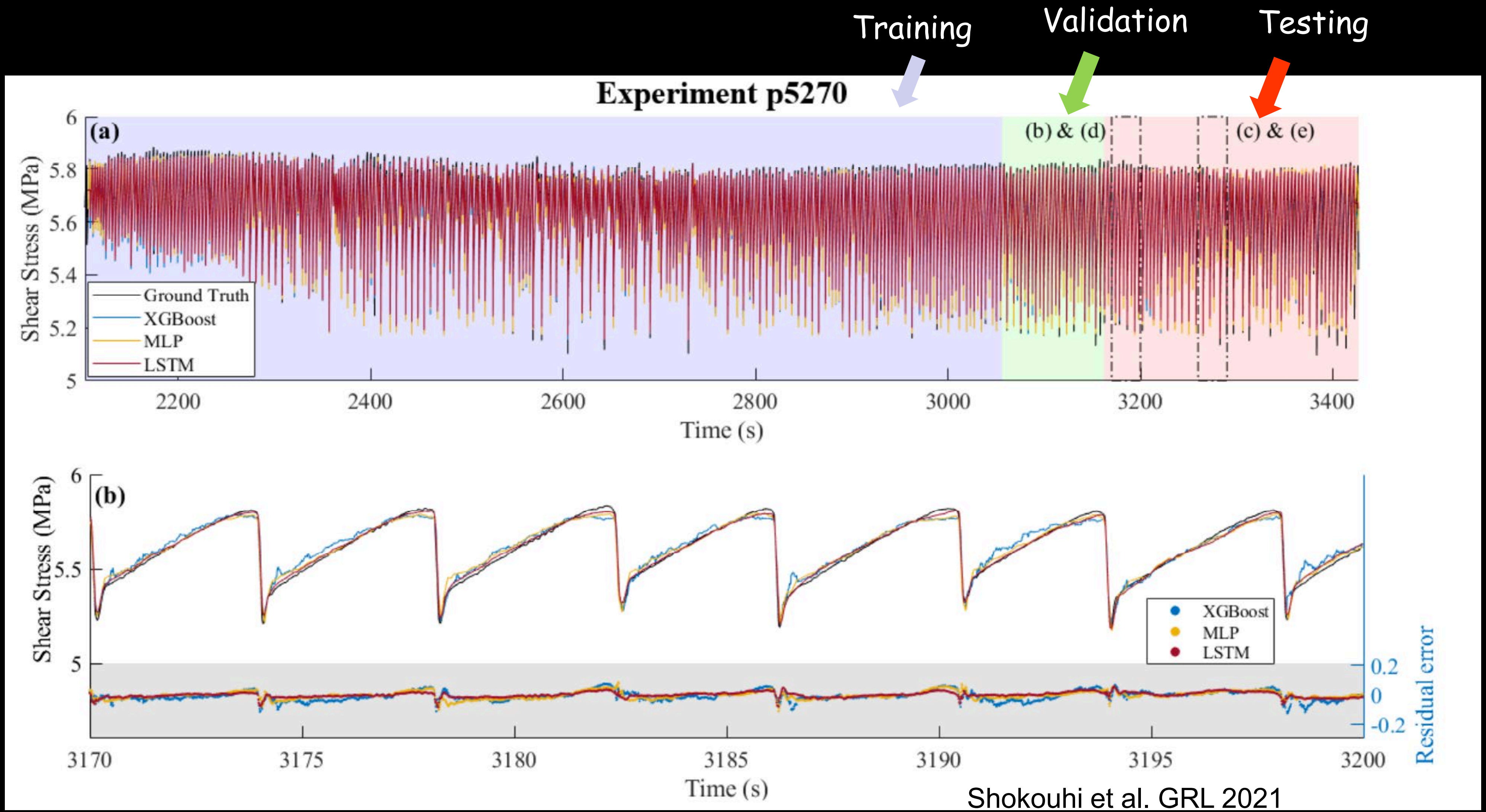


JKR contact theory

$$|T| = \frac{A}{A_0} = \frac{2k_I}{\sqrt{((\omega\rho v)^2 + 4k_I^2))}} \qquad TOF = tan^{-1}\frac{(\omega\rho v / 2k_I)}{(\omega)}$$

Tattersall, 1973

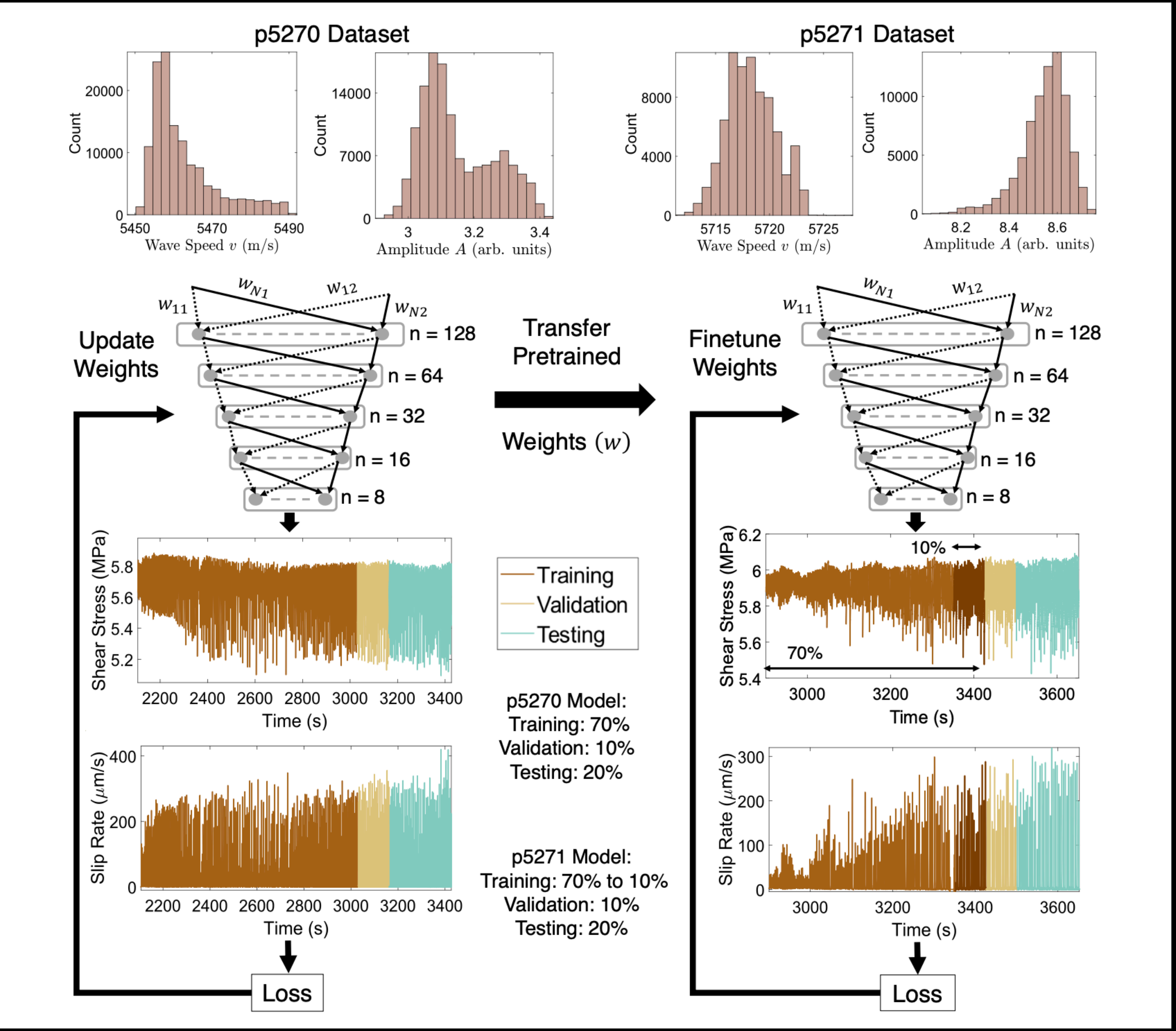
Machine learning:
Evolution of fault zone elastic properties to predict shear stress and time to failure

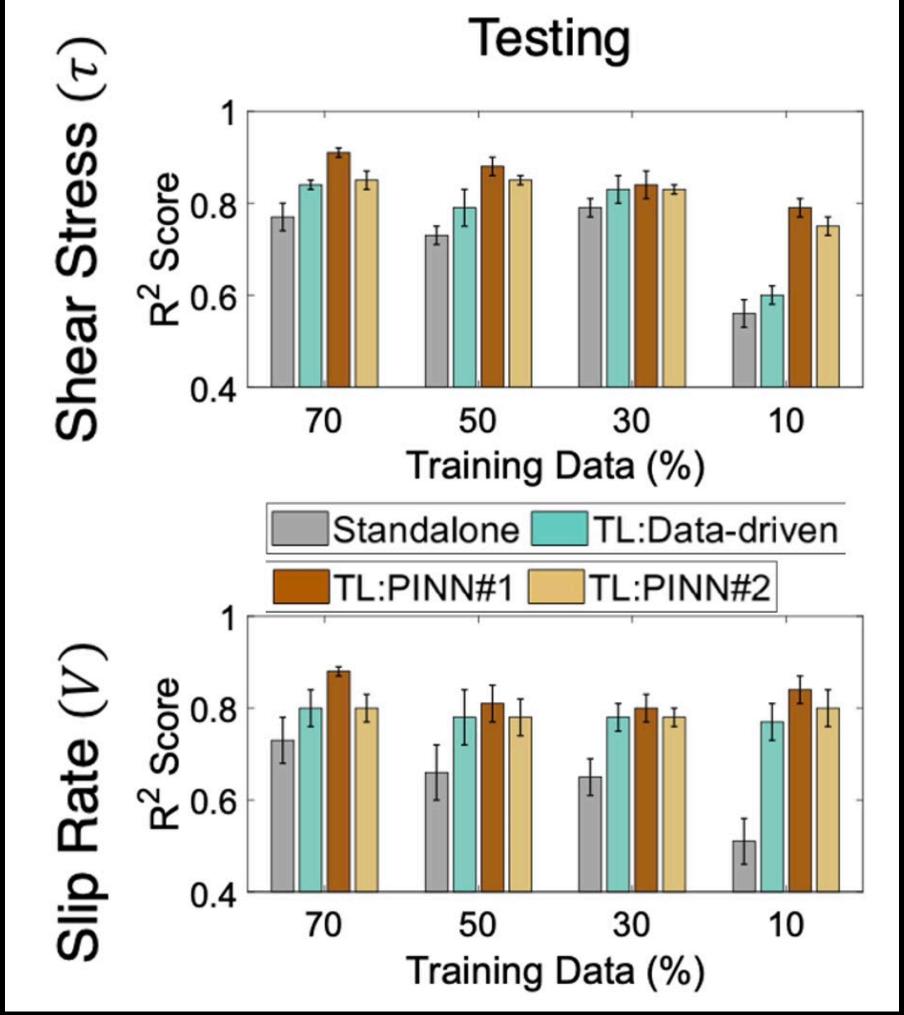


Shokouhi et al. GRL 2021

Lab seismometers

Explainable Machine Learning: Generalizable Models





Borate et al. Nat. Comm. 2023

nature communications

Article

https://doi.org/10.1038/s41467-024-54153-w

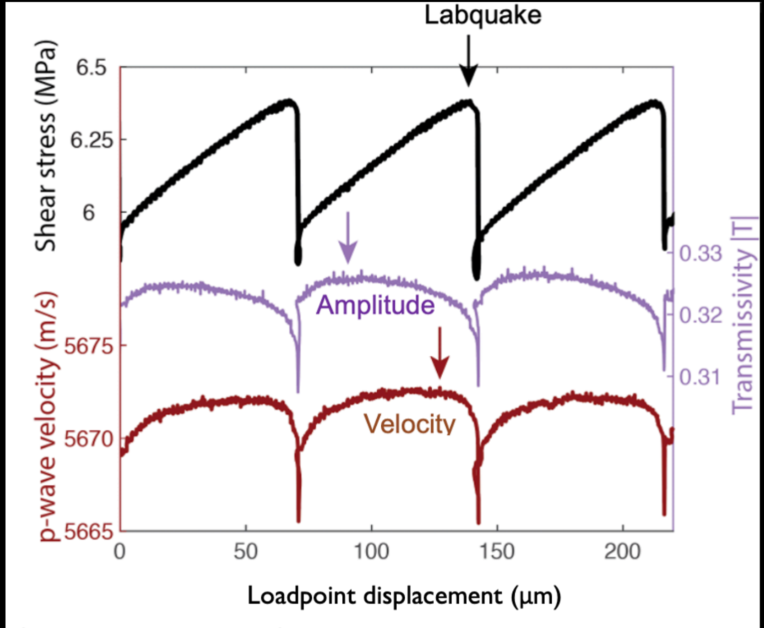
Probing the evolution of fault properties during the seismic cycle with deep learning

Received: 30 May 2024

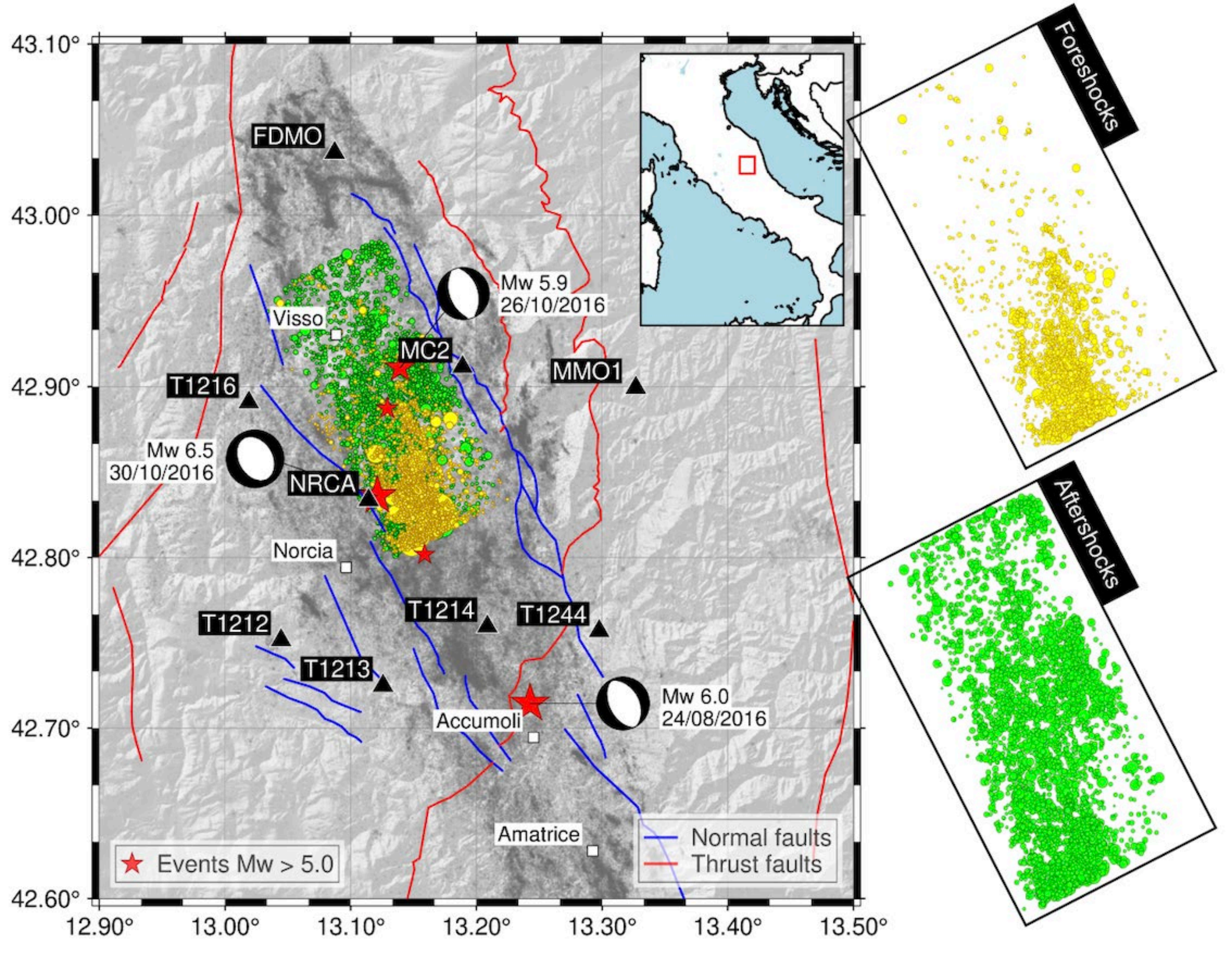
Accepted: 4 November 2024

Laura Laurenti[1], Gabriele Paoletti[2], Elisa Tinti[2], Fabio Galasso[3], Cristiano Collettini[2] & Chris Marone[2,4]

Application to TECTONIC faults

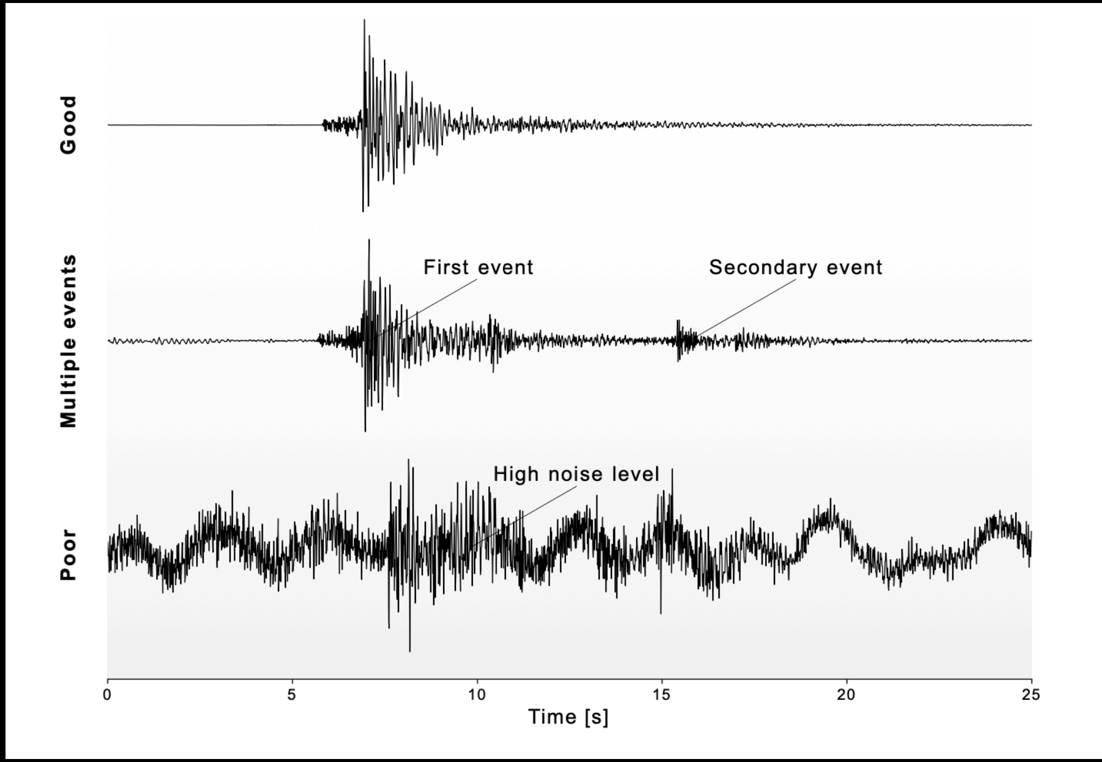


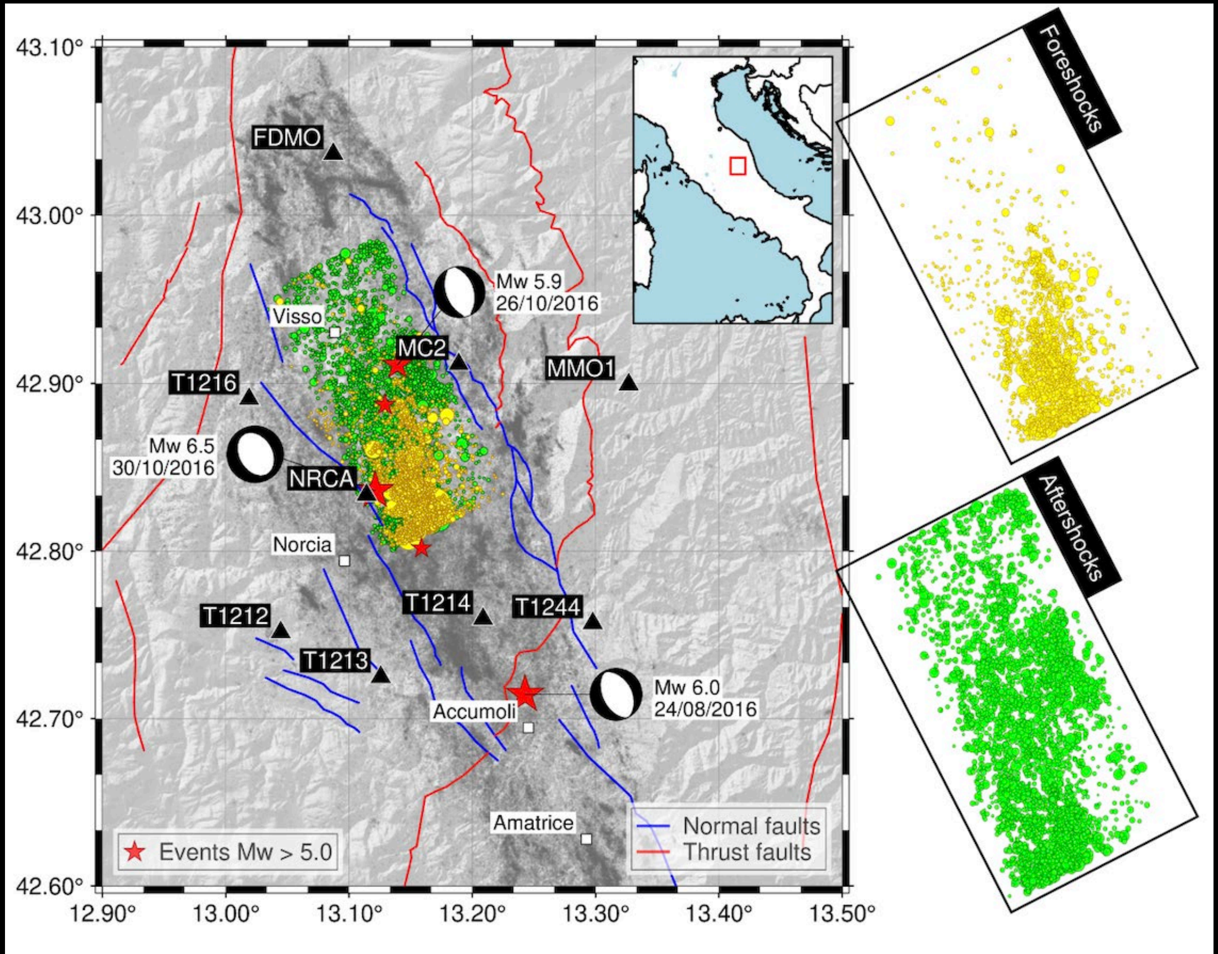
Shreedharan et al., JGR 2021



Laurenti et al., 2024

2016 Norcia Earthquake M6.5

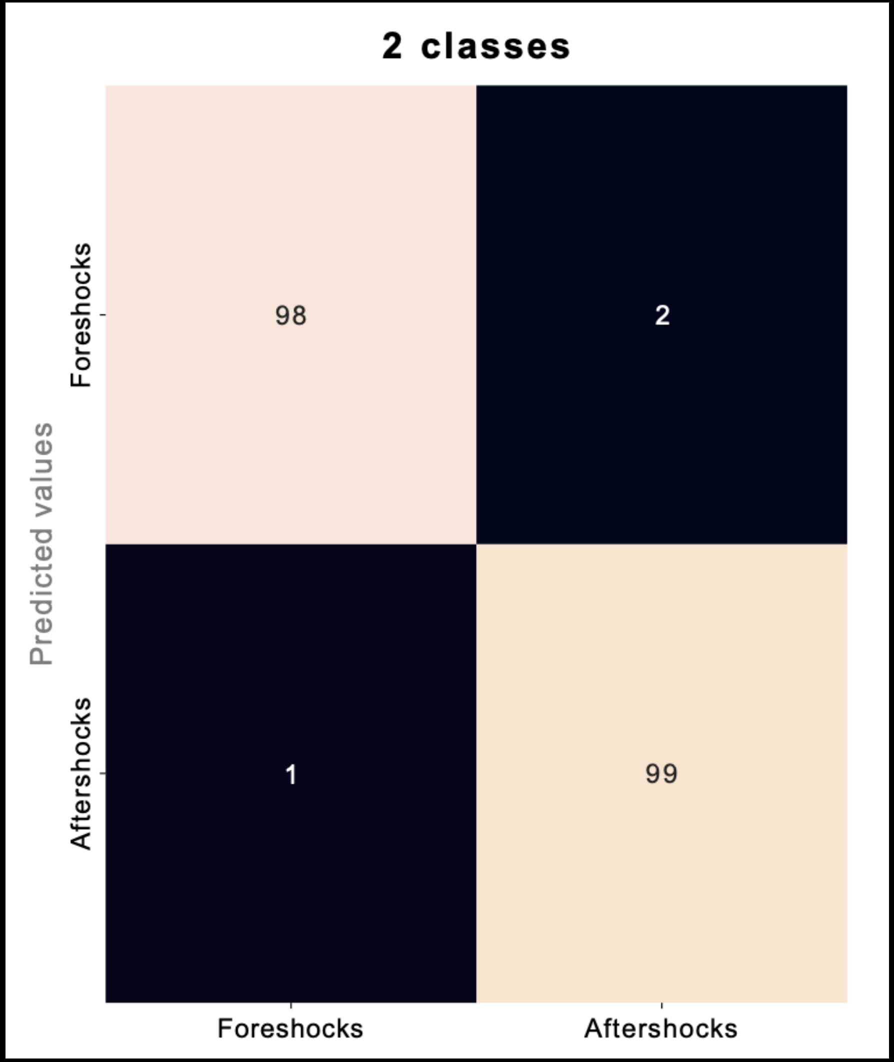


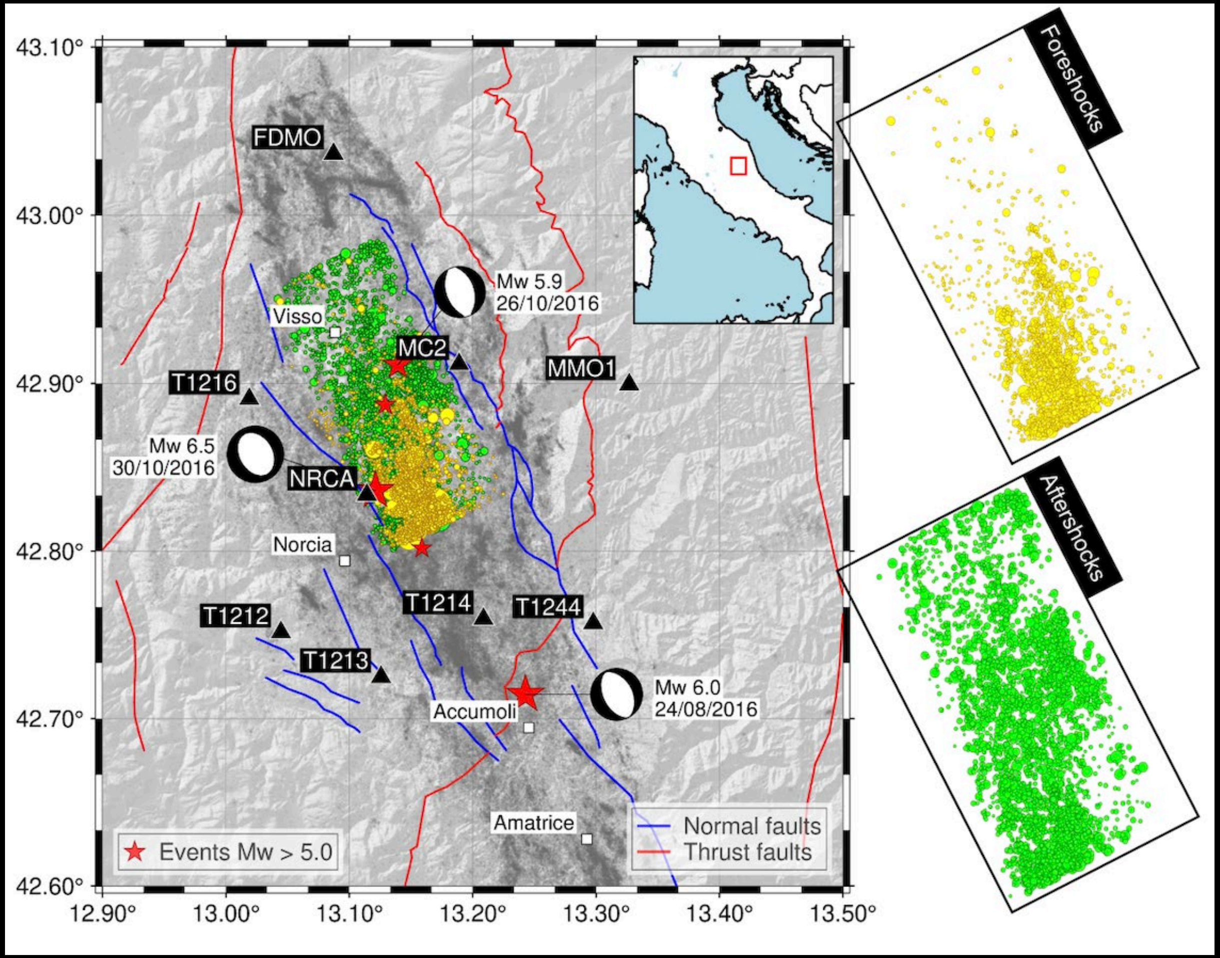


Laurenti et al., 2024

4,694 events pre mainshock
5,135 events post mainshock

Machine Learning Model
Binary Classification of Foreshocks and Aftershocks

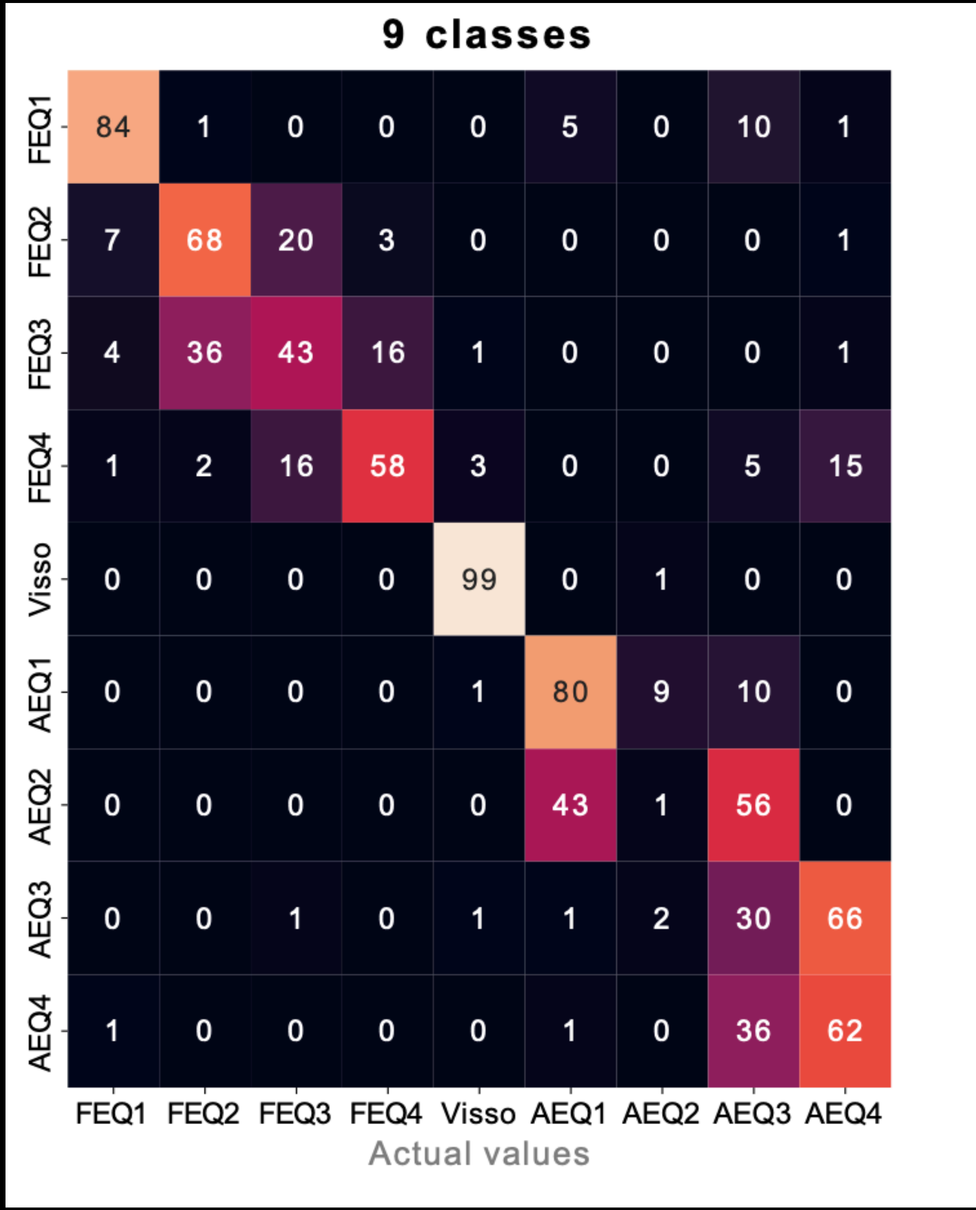


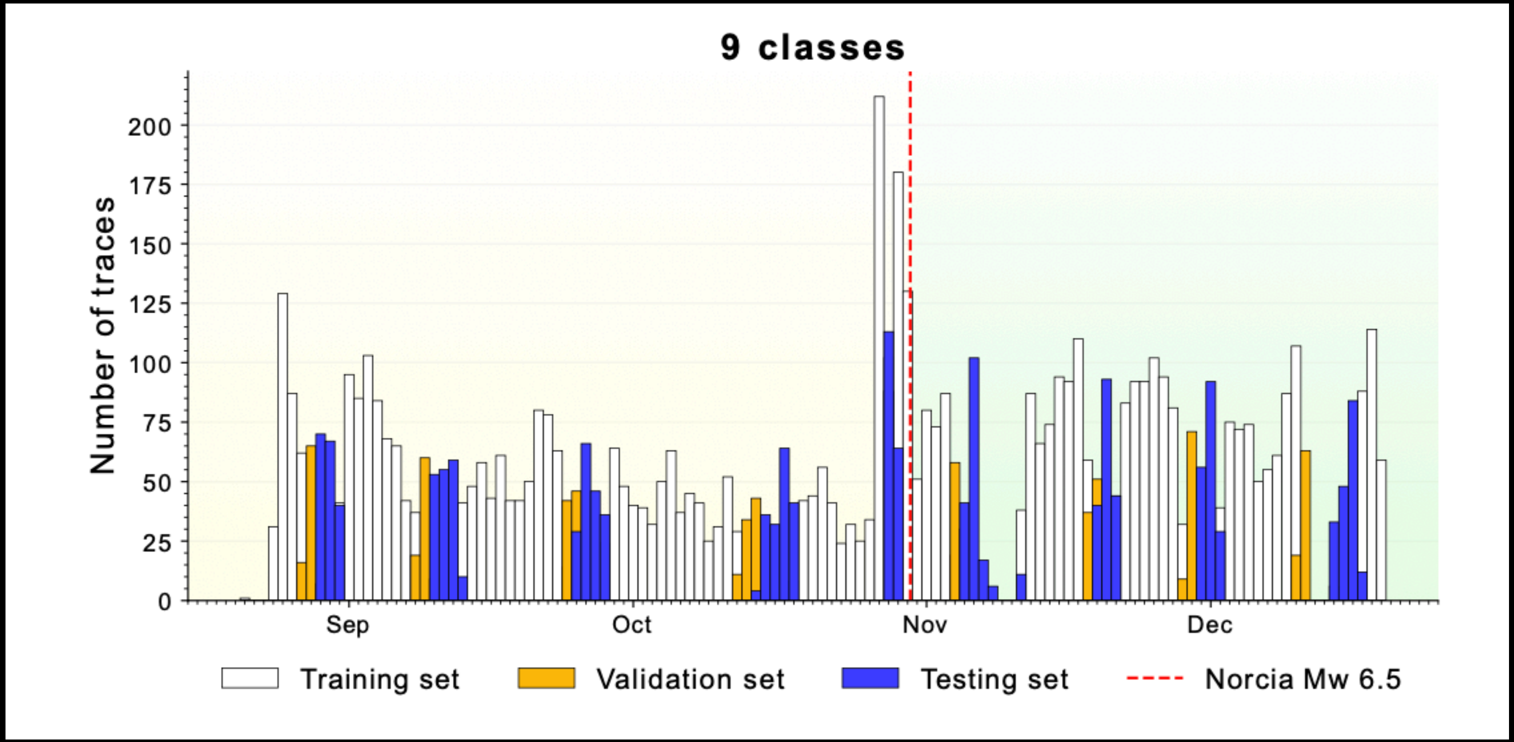


Laurenti et al., 2024

4,694 events pre mainshock
5,135 events post mainshock

Toward a prediction of time to failure

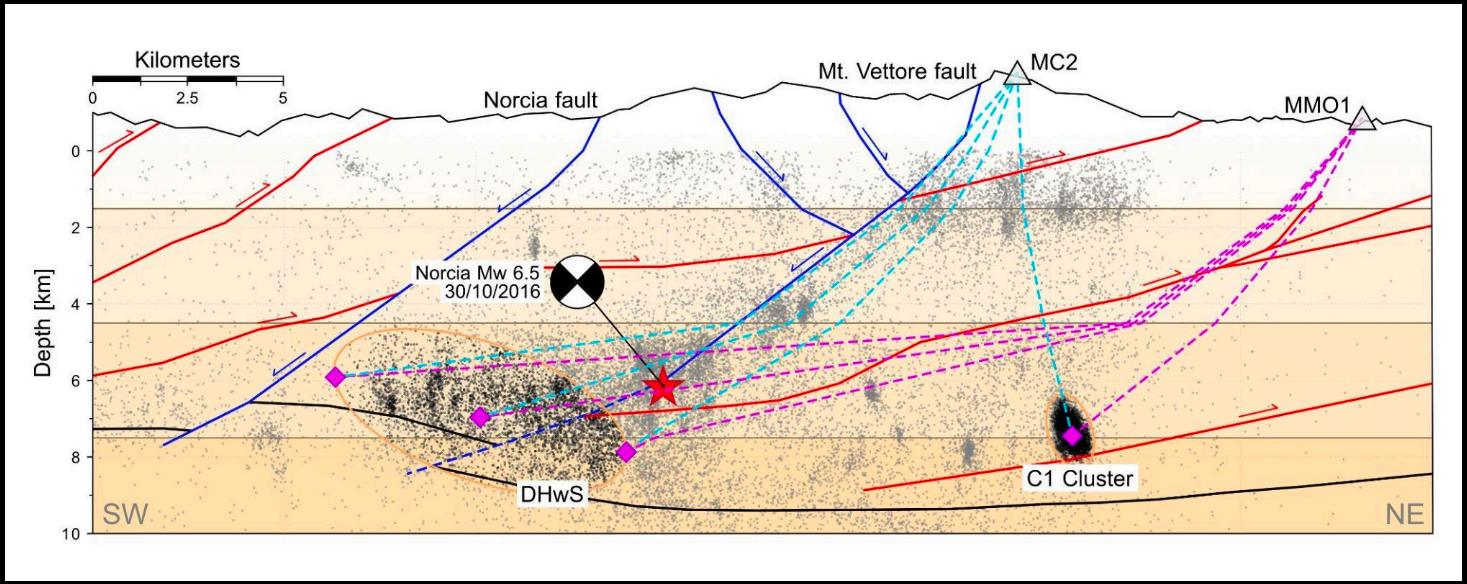


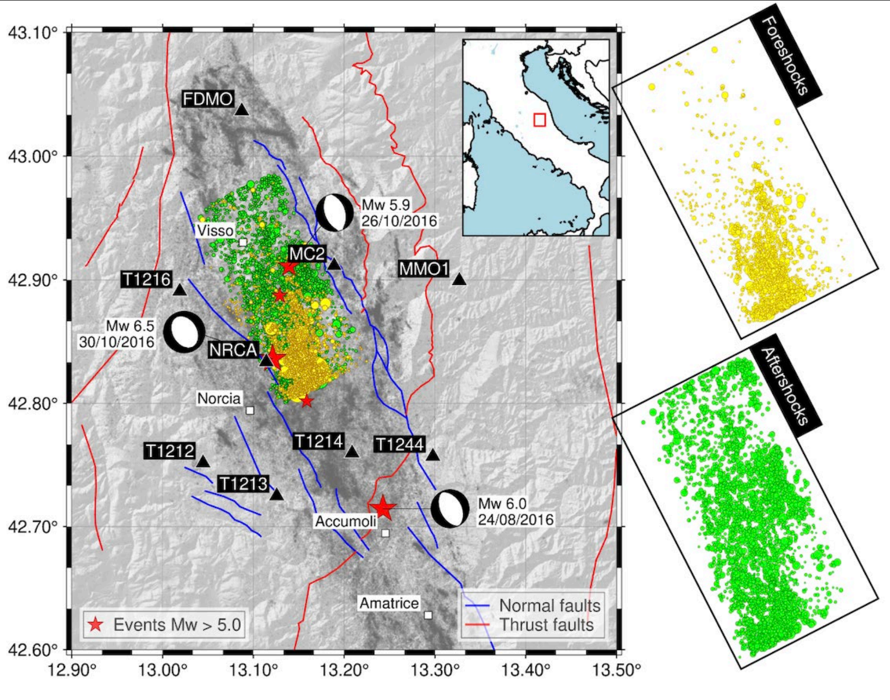


Laurenti et al., 2024

- CNN with batch normalization and ReLU activation layer.
- The network has 7 convolutional layers with an increasing number of filters up to a maximum of 256 in the last two convolutional blocks

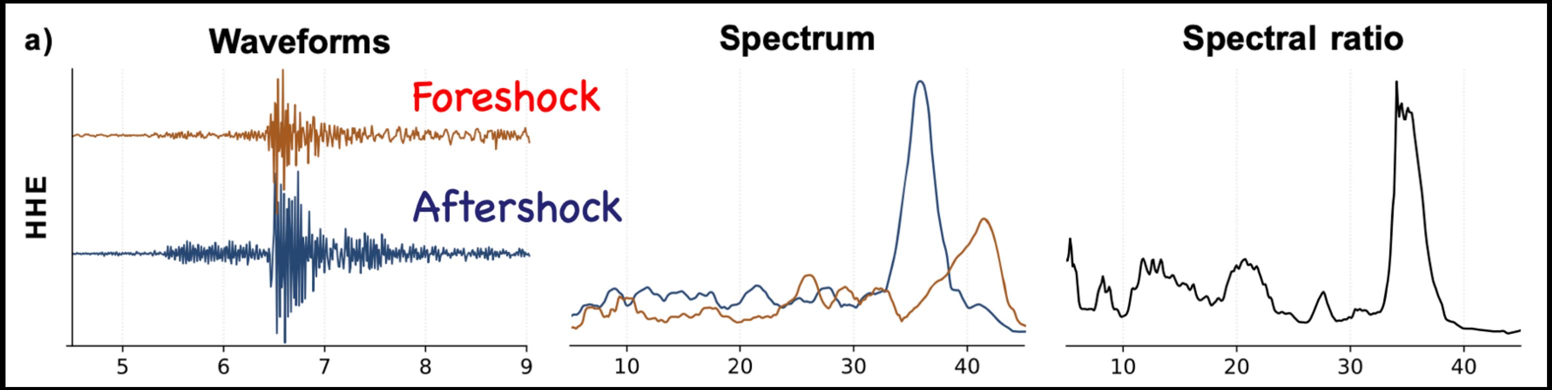
Explainable Machine Learning
How does it work?



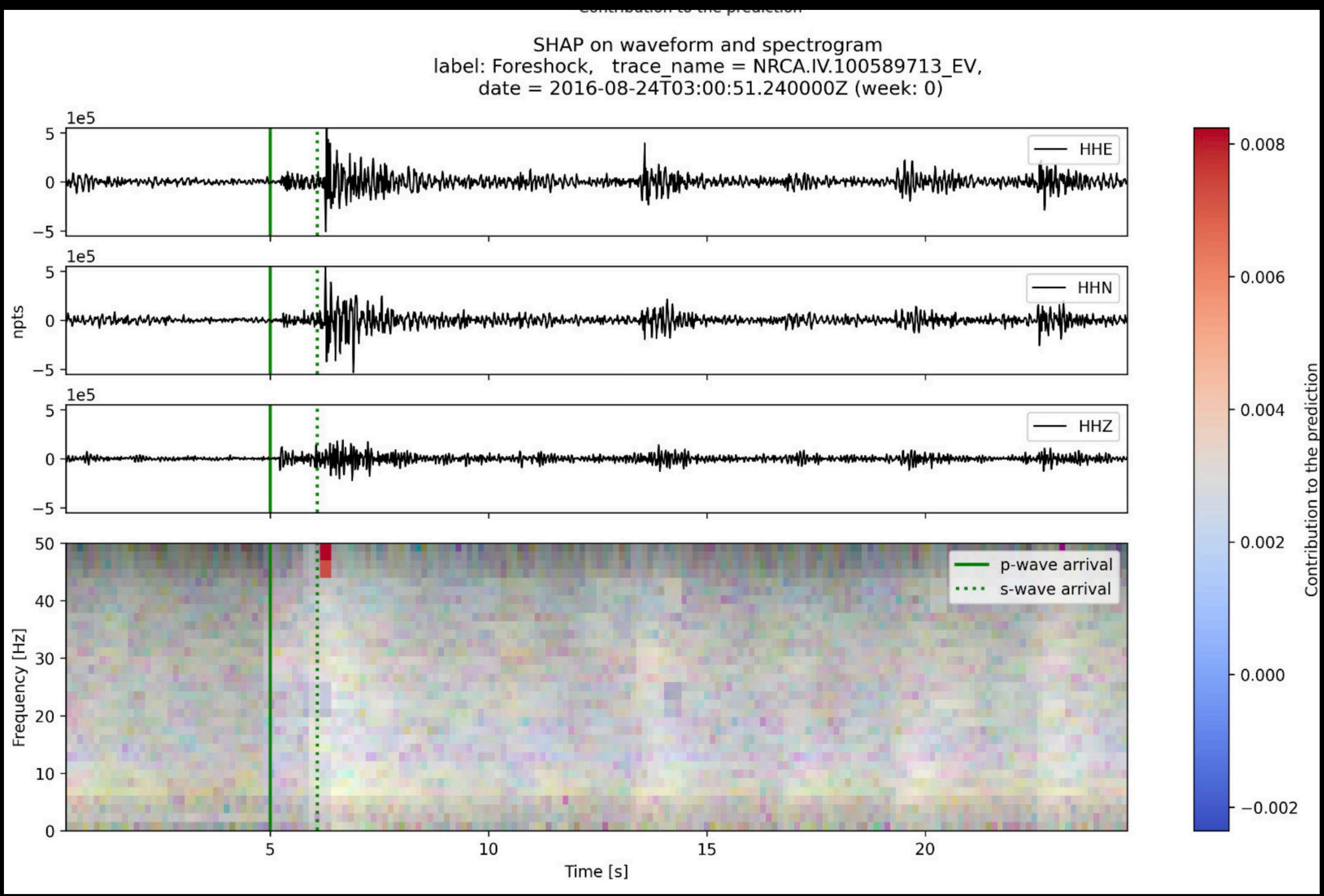


Laurenti et al., 2024

Compare waveforms of co-located events



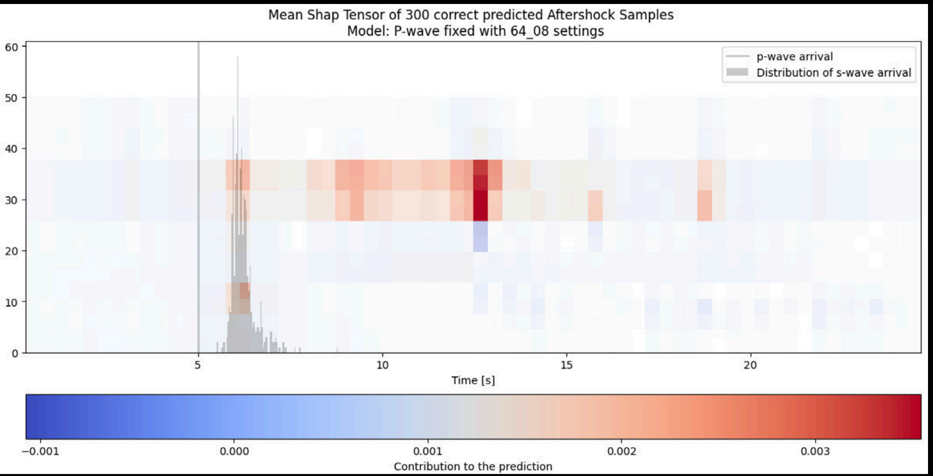
Spectrograms to create images for a CNN



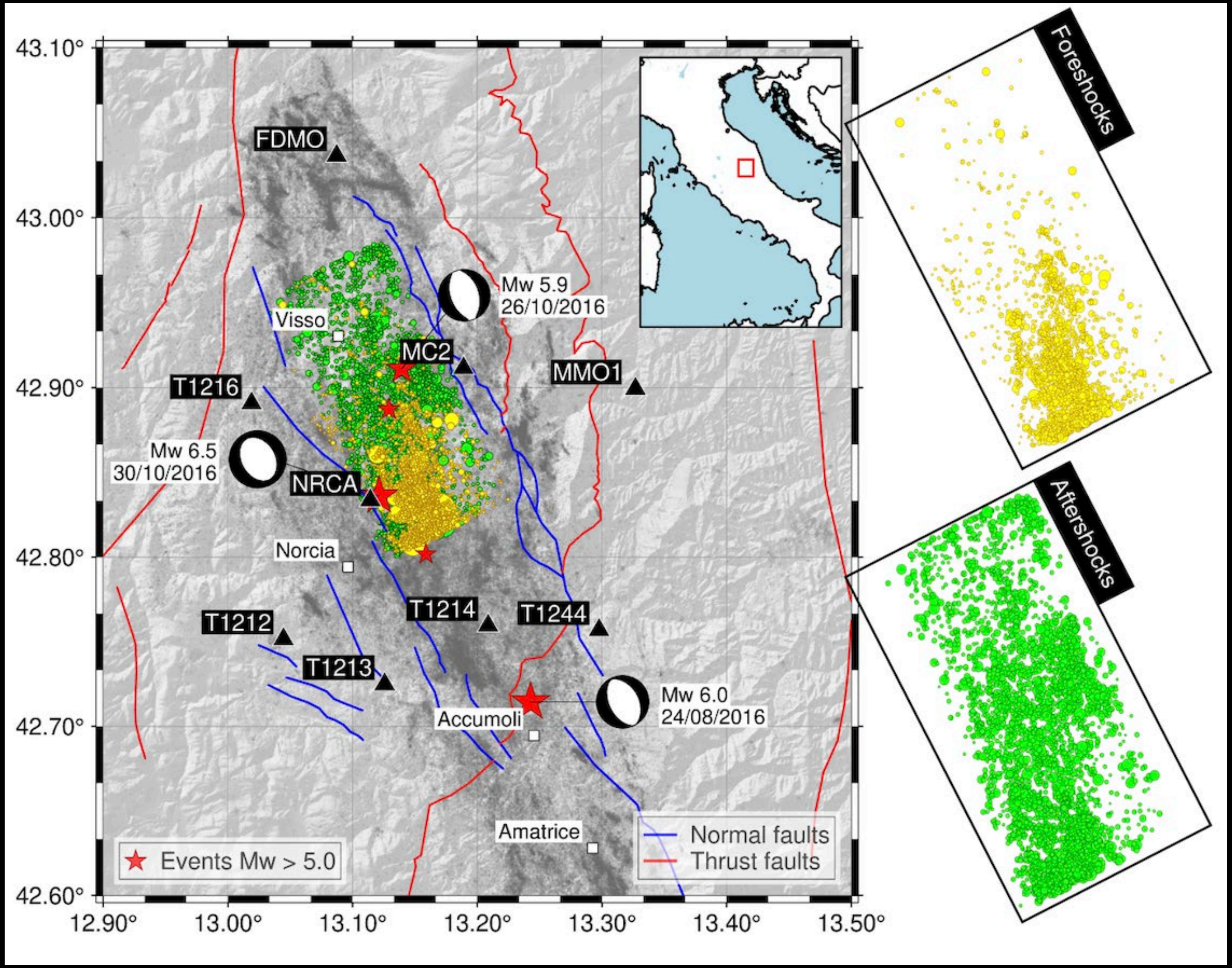
Magrini, Marrocco et al., in prep, 2025

Explainable Machine Learning

SHAP Shapley Additive Explanations

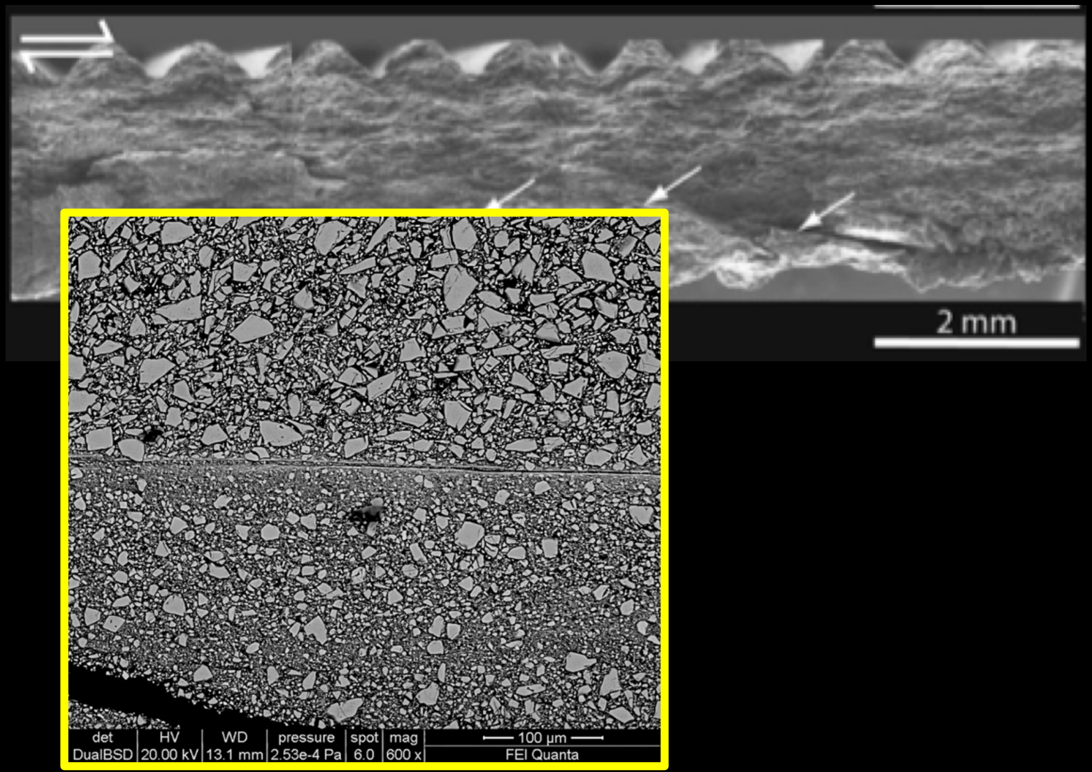


Proxy for fault zone stress state



Summary

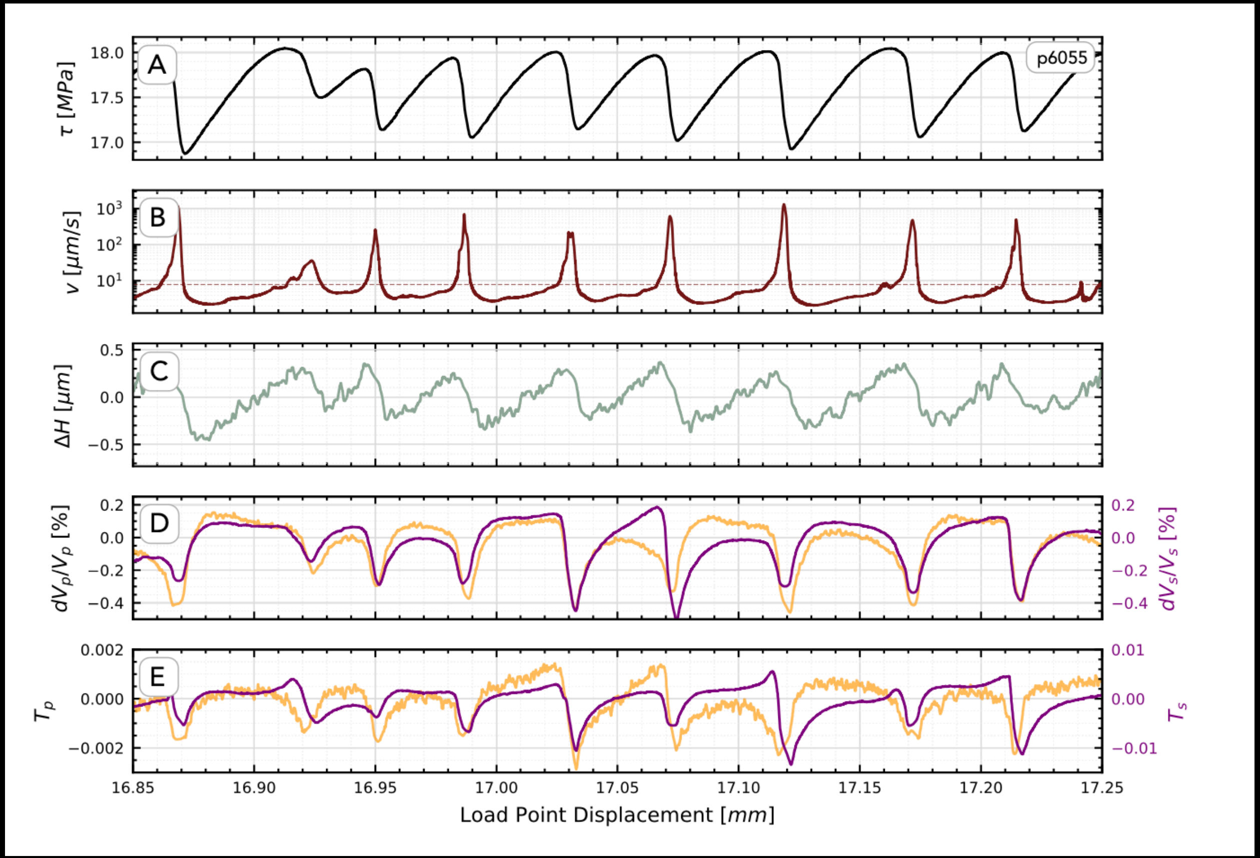
ML/DL models can predict lab earthquakes
Explainable ML can teach us earthquake physics



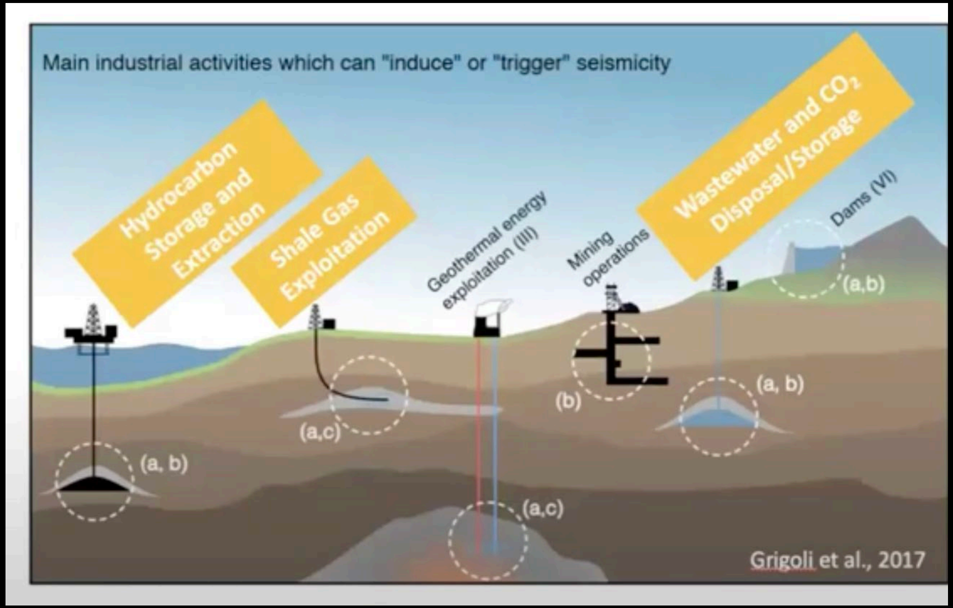
We have studied simple conditions
(room temp., limited set of fault rocks, etc.)

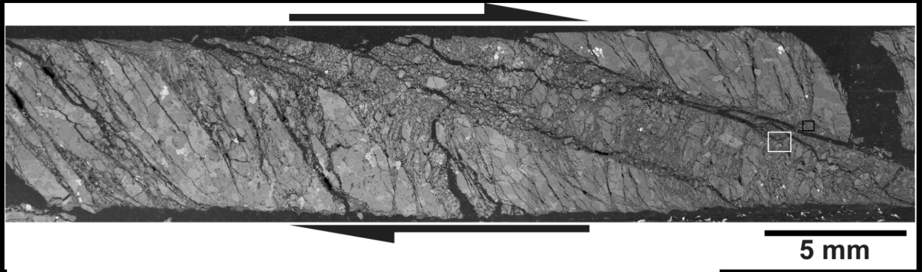
Precursors to Fluid Injection Induced Earthquakes?

Fluid injection during lab earthquakes



Affinito et al., in prep, 2025





Lab earthquake fault zone

Learning Earthquake Physics from Labquakes, Data Science and Machine Learning

1. Lab earthquakes can be predicted with machine learning
2. Predictions work for both passive and active seismic data
3. Explainable ML. The physics of lab earthquakes are consistent with rate and state friction constitutive laws
4. Applications of ML/DL models to seismic data

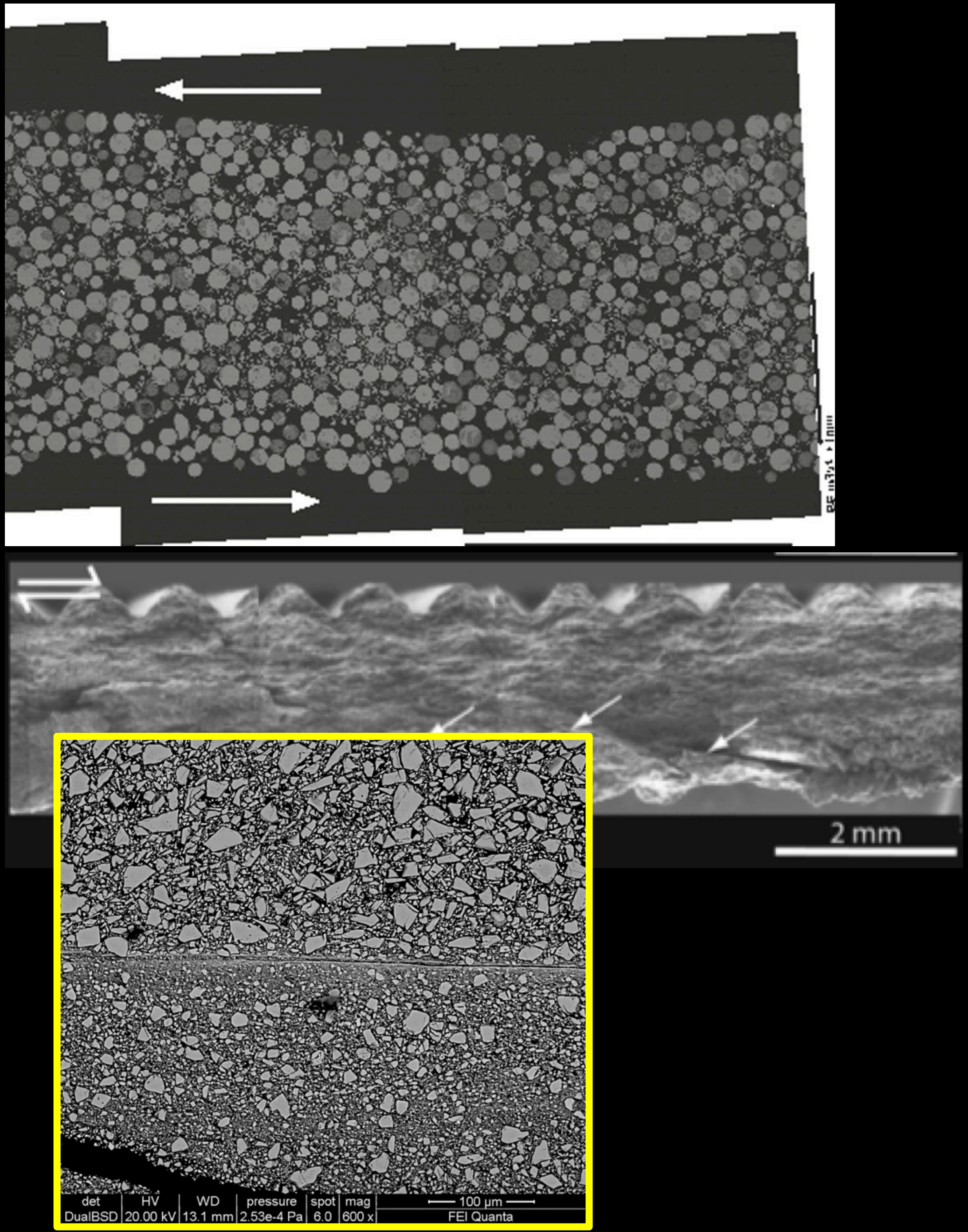
Grazie

Elisa Tinti, Cristiano Collettini, Fabio Galasso, Laura Laurenti, Gabriele Paoletti, Parisa Shokouhi, Michele Magrini, Francesco Marrocco, Paul Johnson, Bertrand Rouet-Leduc, Claudia Hulbert, Srisharan Shreedharan,

SCHATZALP

DAVOS

18-21 March 2025



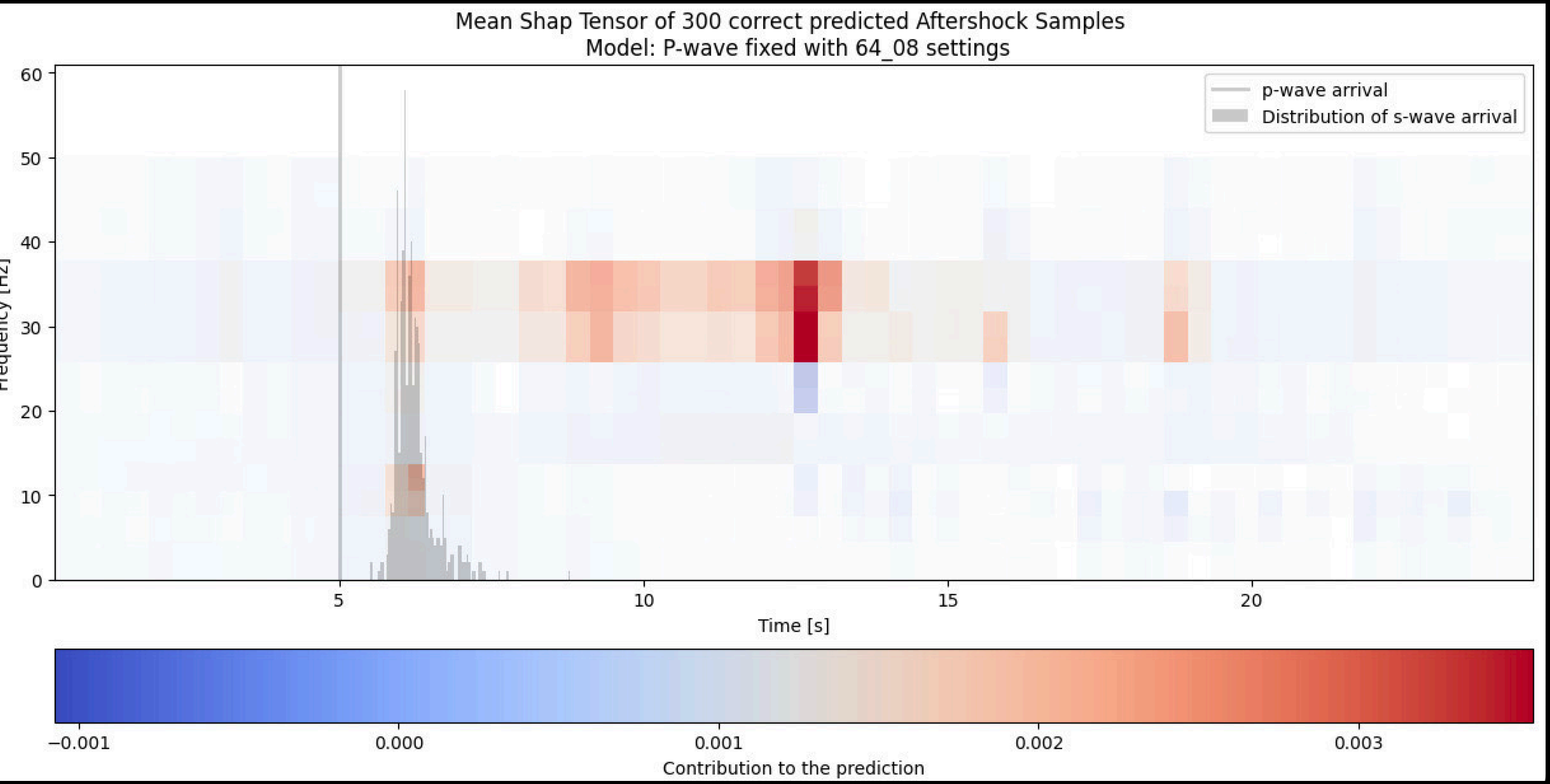
Summary

Machine learning works for the cases we have studied, but that's a small set.
There are many unanswered questions

Lab faults studied

- Glass beads
- Granular layers of angular quartz grains
- Granular layers of quartz powder
- Bare granite surfaces
- Granite surfaces dusted with powder
- Fracture of granite blocks
- Mixtures of clay and quartz
- Limited range of fluid pressures

SHAP   Shapley Additive Explanations

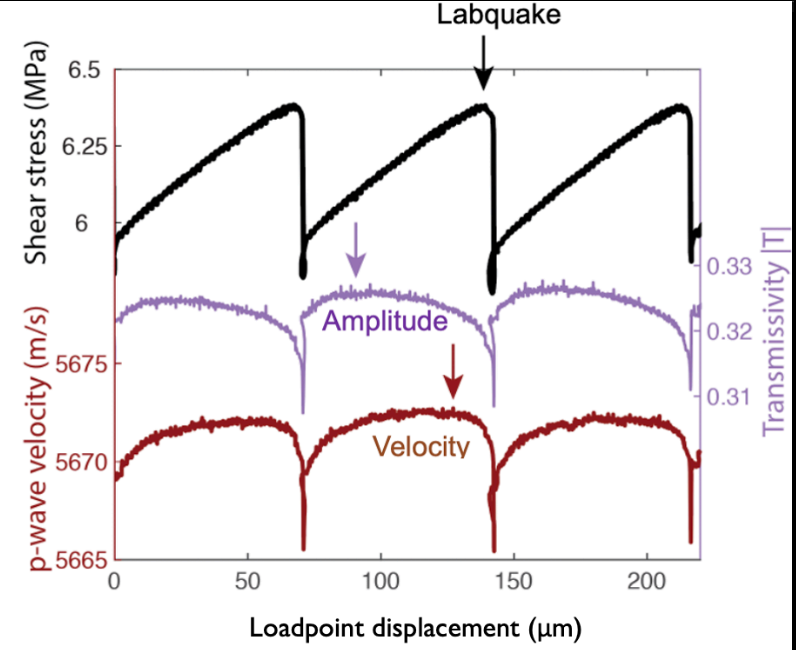


Magrini, Marrocco et al., in prep, 2025

Explainable Machine Learning

Proxy for fault zone stress state

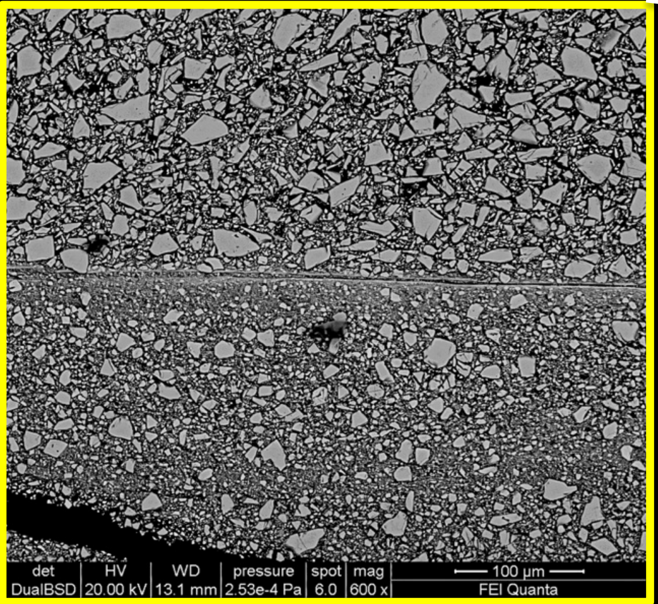
Labearthquake Precursors, Labquake Prediction and Machine Learning to Build Proxies for Fault Zone Stress State

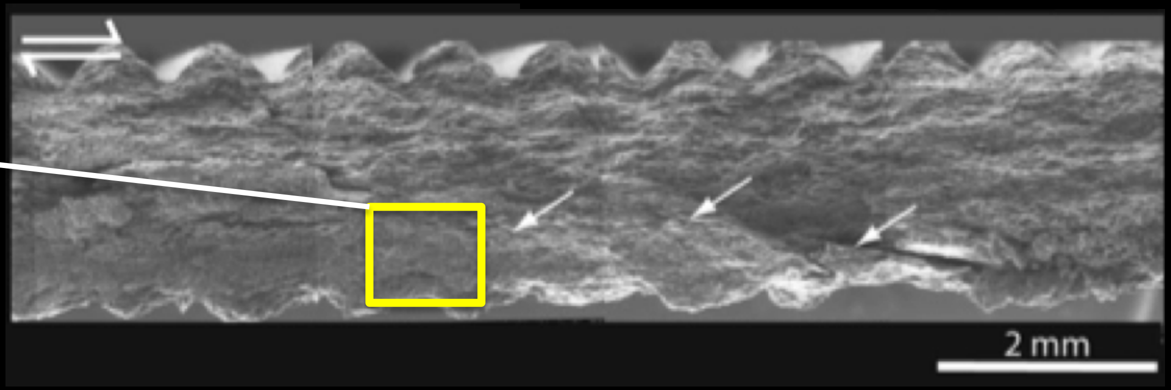


Shreedharan et al., JGR 2021

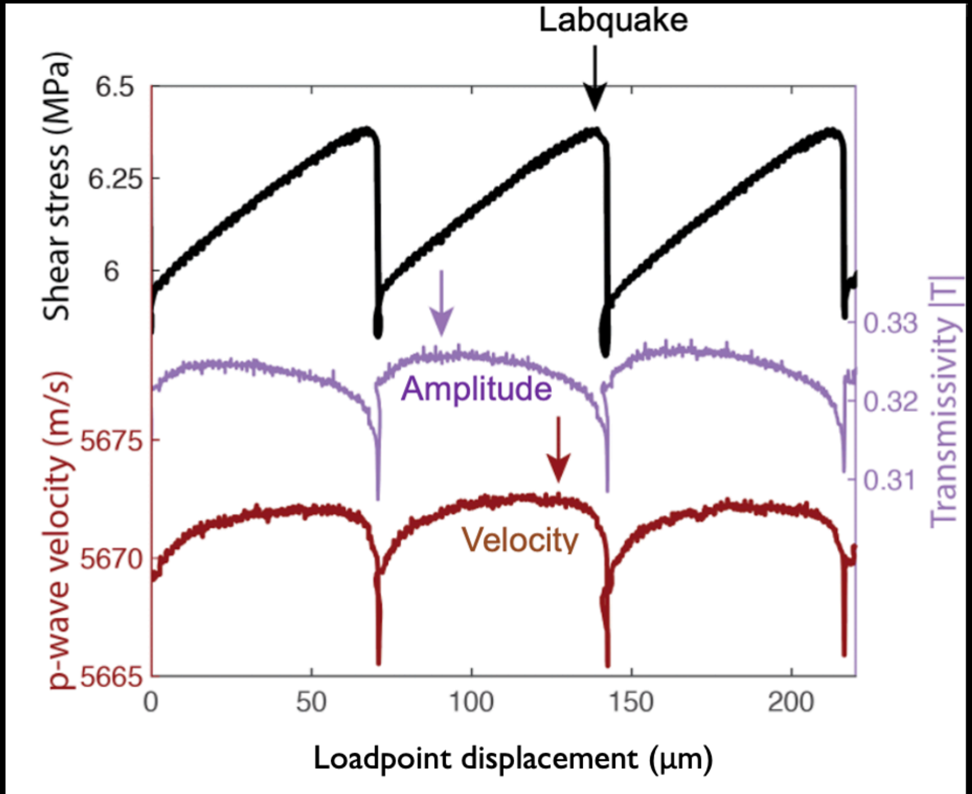
- Machine learning (ML) can predict lab earthquakes. Explainable ML.
- PINN for predicting the evolution of fault zone elastic properties during the lab seismic cycle.
- Applications of ML/DL to seismic data, distinguishing foreshocks from aftershocks
- Foundation models for seismic data processing

Explainable Machine Learning





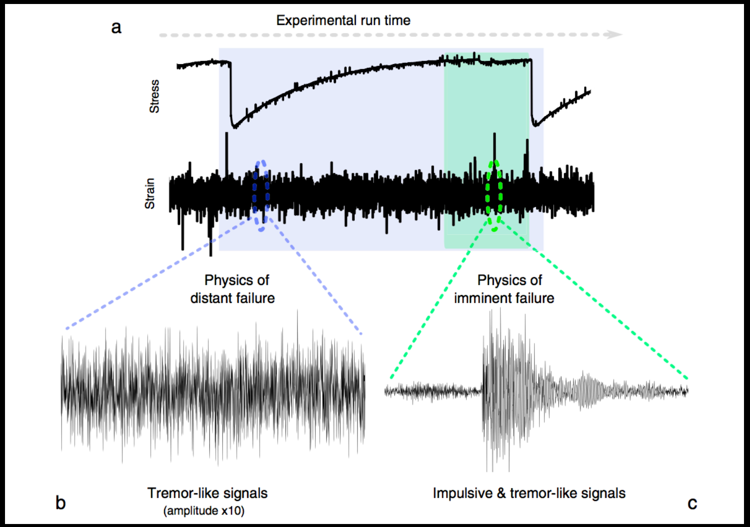
Contacts Age and Fractures Form During the lab Seismic Cycle

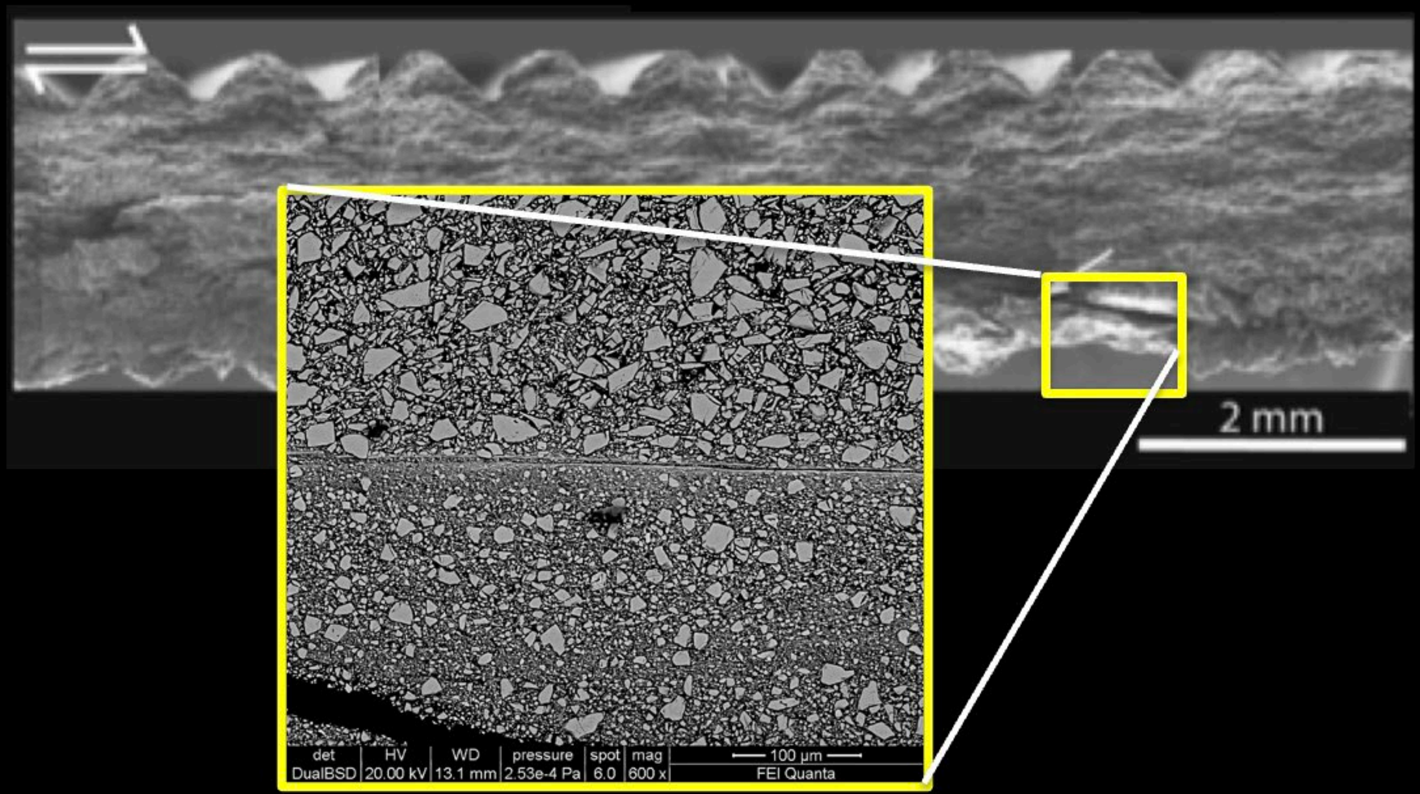


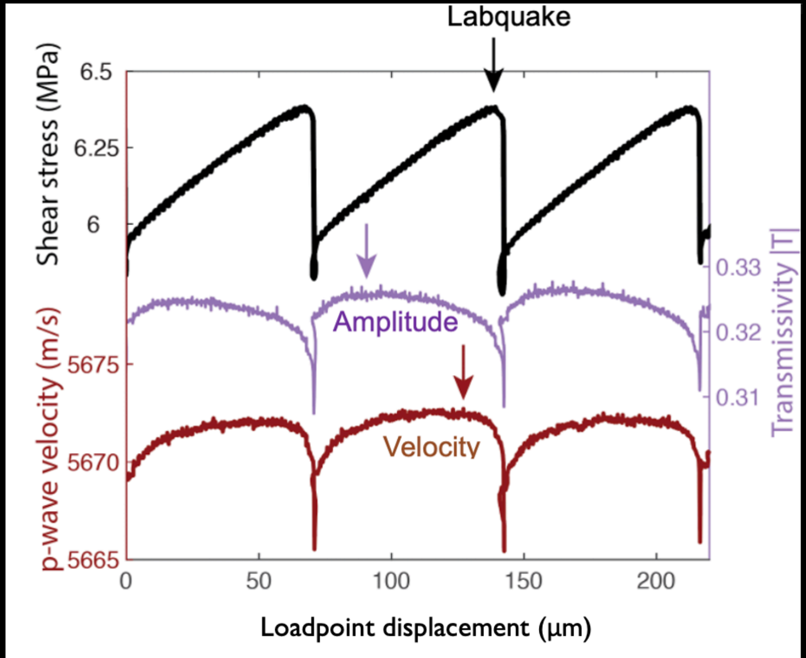
Shreedharan et al., JGR 2021

Labquake prediction

- Microearthquake Precursors in the Fault Zone
- Evolution of fault Zone Elastic Properties







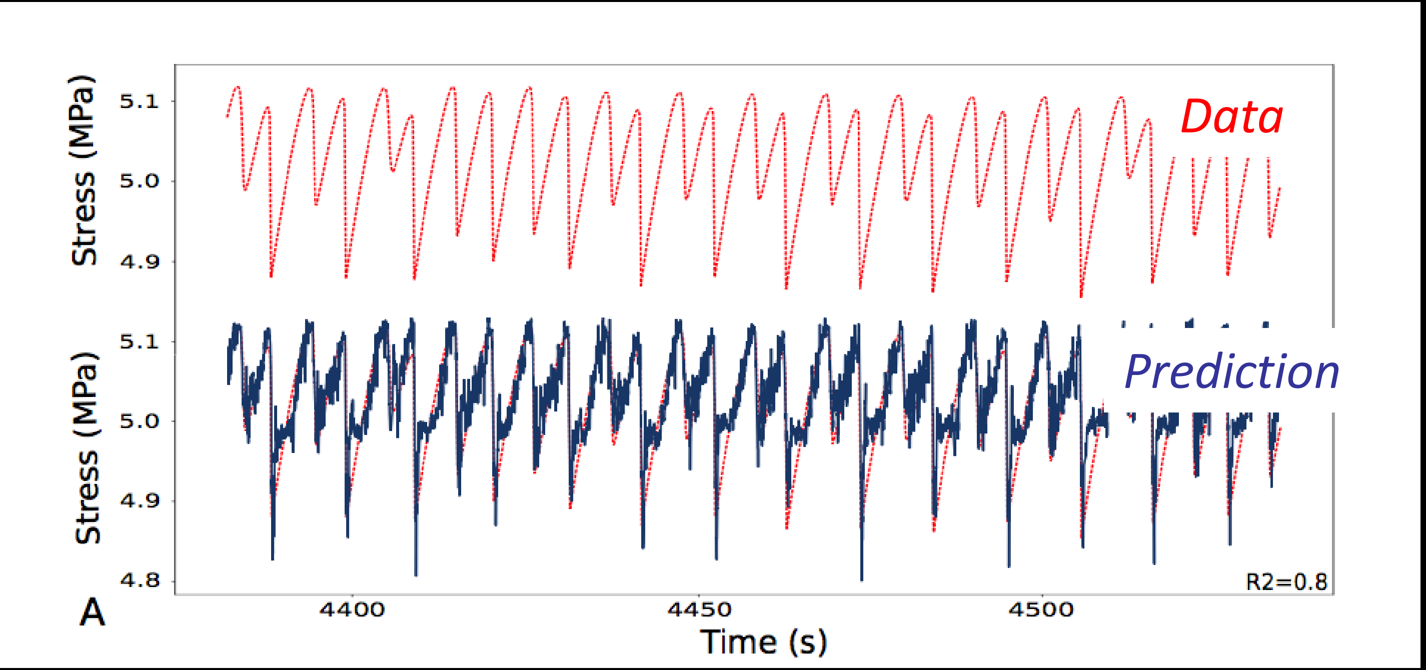
Shreedharan et al., JGR 2021

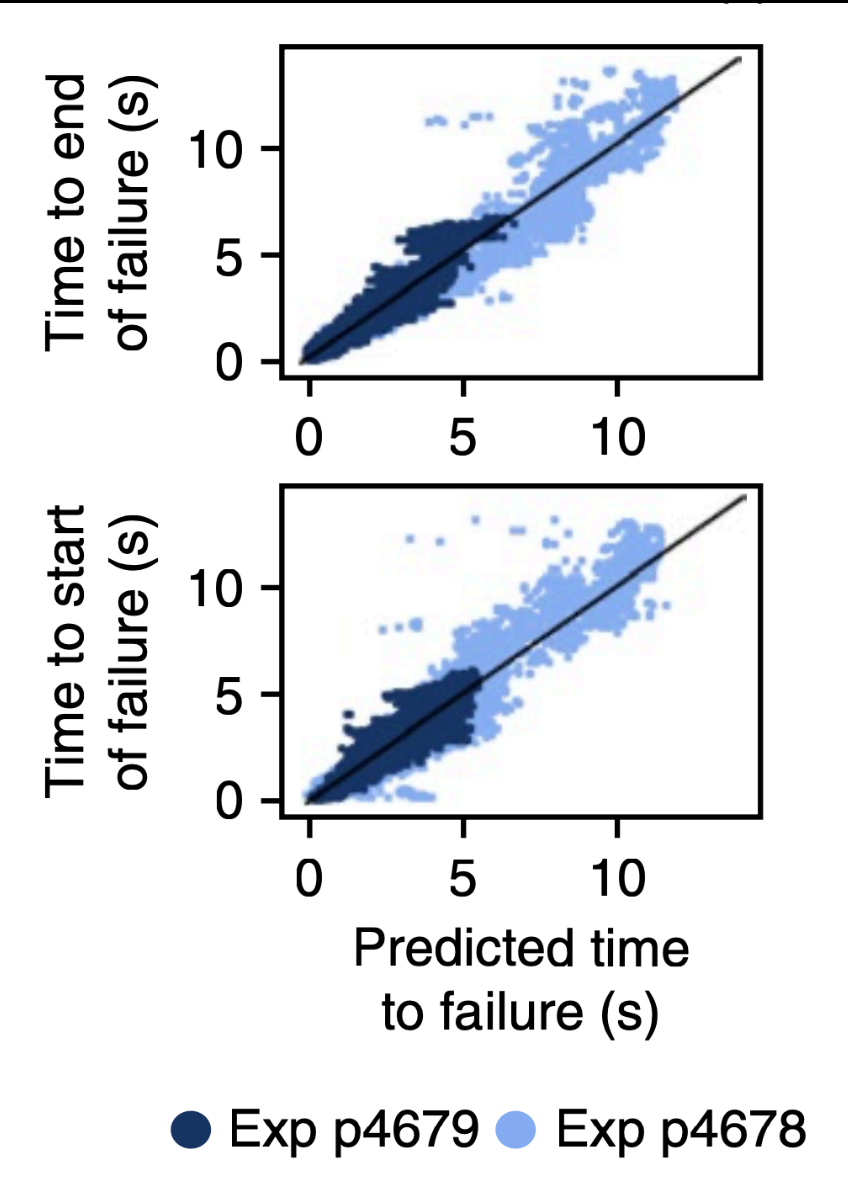
Labquake Prediction for the Full Spectrum of Slip Modes from slow to fast

nature geoscience
ARTICLES
https://doi.org/10.1038/s41561-018-0272-8
2019

Similarity of fast and slow earthquakes illuminated by machine learning

Claudia Hulbert[1]*, Bertrand Rouet-Leduc[1], Paul A. Johnson[1], Christopher X. Ren[1], Jacques Rivière[2], David C. Bolton[3] and Chris Marone[3]



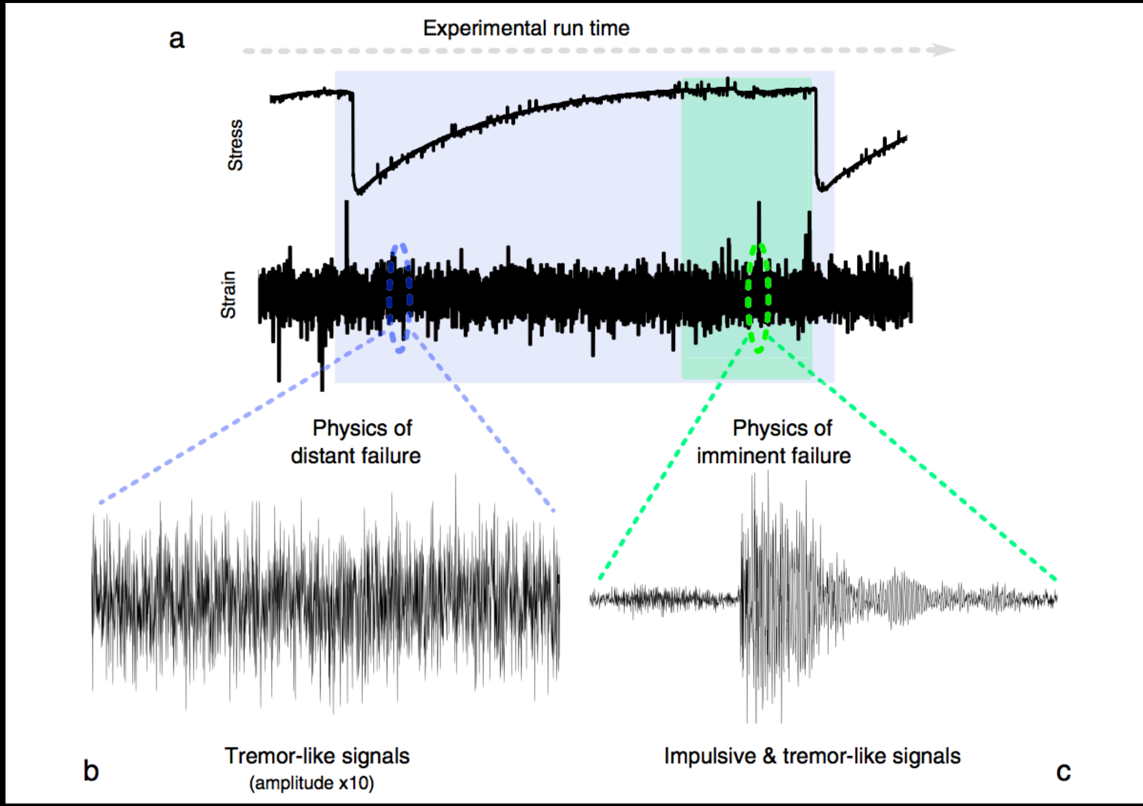


Hulbert et al., 2019

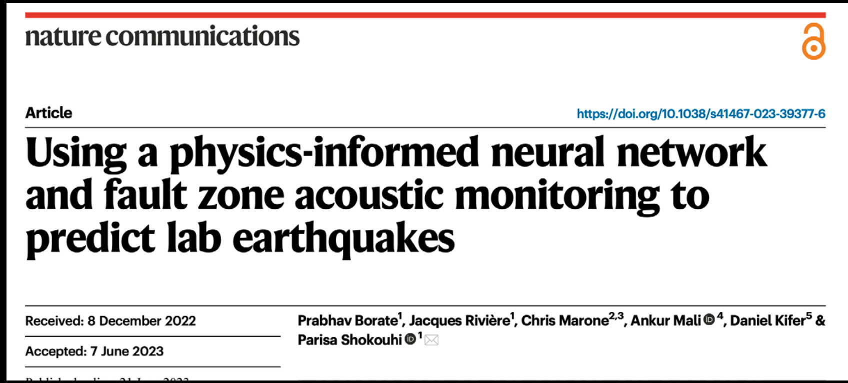
Labquake Prediction for the Full Spectrum of Slip Modes from slow to fast

Prediction

- Timing
- Size (stress drop, fault slip velocity)
- Fault Zone Stress
- ~~Location~~



Rouet-Leduc et al., 2017


nature communications

Article

https://doi.org/10.1038/s41467-023-39377-6

Using a physics-informed neural network and fault zone acoustic monitoring to predict lab earthquakes

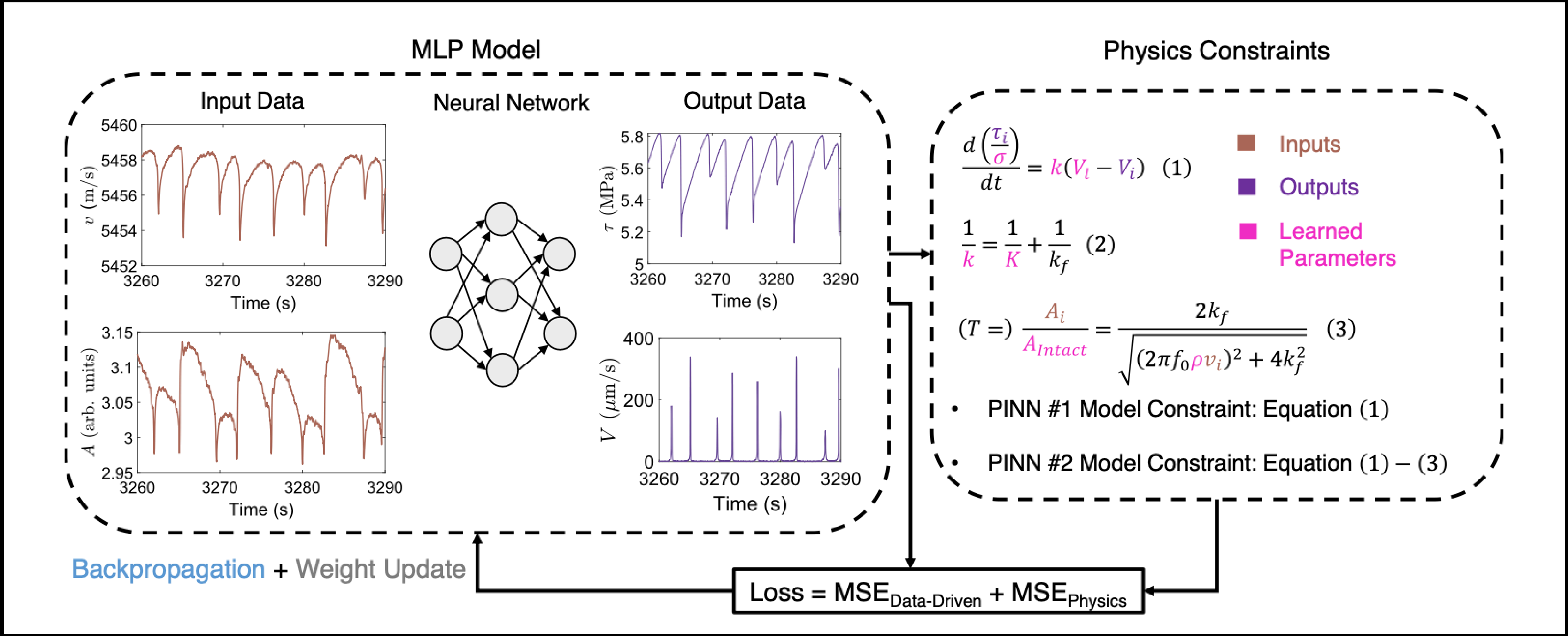
Received: 8 December 2022

Accepted: 7 June 2023

Prabhav Borate[1], Jacques Rivière[1], Chris Marone[2,3], Ankur Mali[4], Daniel Kifer[5] & Parisa Shokouhi[1]

Loss function based on

- Fault zone elastic parameters (V_p, $V_p Amplitude$)
- RSF: relating fault zone slip velocity to local stiffness and frictional shear strength



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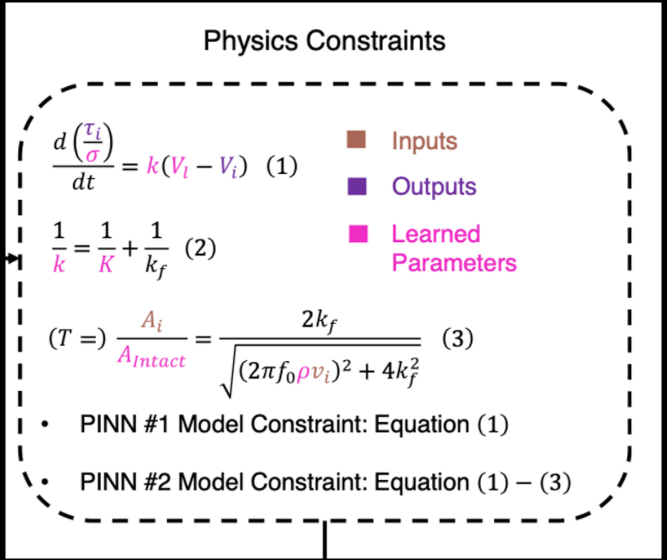
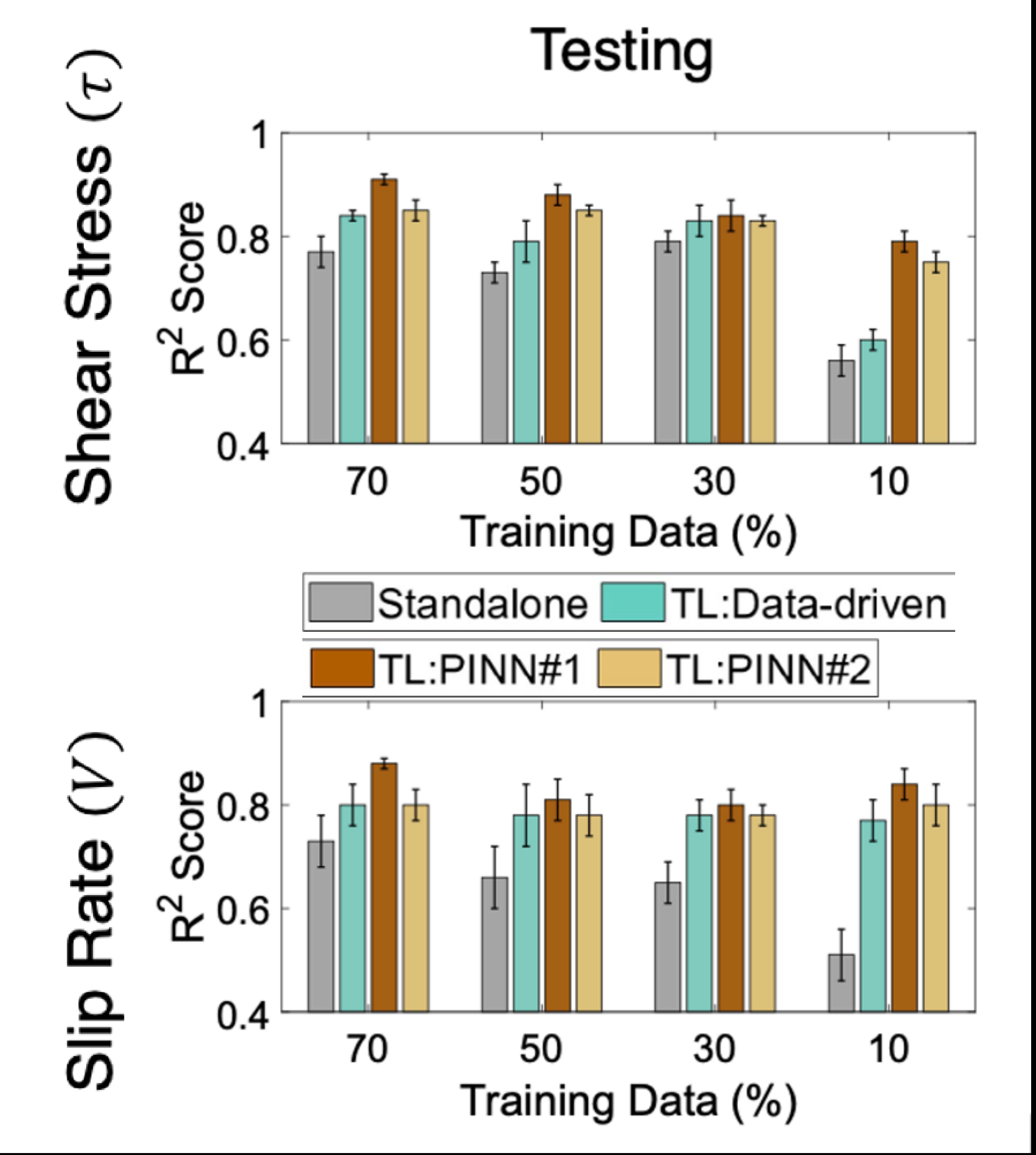
Loss function based on

- Fault zone elastic parameters (V_p, $V_p Amplitude$)
- RSF: relating fault zone slip velocity to local stiffness and frictional shear strength

$$L_1(\theta) = \frac{1}{N}\sum_{i=1}^{N}\left(\tau_i(u_i) - \hat{\tau}_i(u_i;\theta)\right)^2 + \frac{1}{N}\sum_{i=1}^{N}\left(V_i(u_i) - \hat{V}_i(u_i;\theta)\right)^2 + \frac{1}{N}\sum_{i=1}^{N}\left(\hat{f}_1(u_i;\theta)\right)^2$$

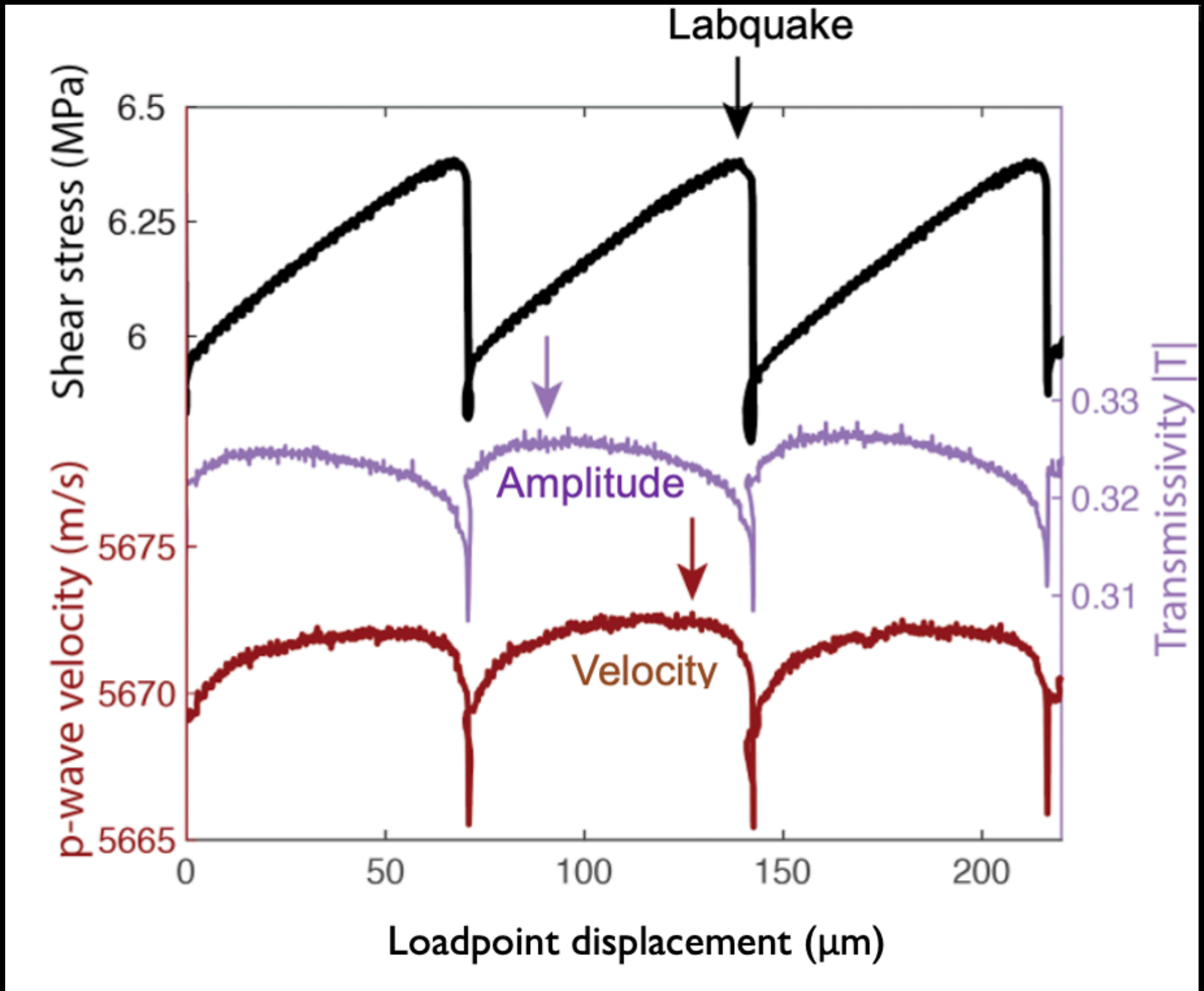


Explainable Machine Learning: Generalizable Models



Borate et al. Nat. Comm. 2023

Explainable Machine Learning
Lab Earthquake Prediction and Rate/State Friction



Shreedharan et al., JGR 2021