

Probing Earthquake Faults with AI

A data driven approach

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LOS ALAMOS NATIONAL LABORATORY

With Chris Johnson, Bertrand Rouet-LeDuc, Claudia Hulbert, Kun Wang, Chris Marone and more.....



U.S. DEPARTMENT OF
ENERGY

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Science



CONTENTS

- Brief introduction to tectonics and earthquakes
- Brief introduction to supervised machine learning
- Probing faults and slips with machine learning
- Conclusions



Plate tectonics and the engine below

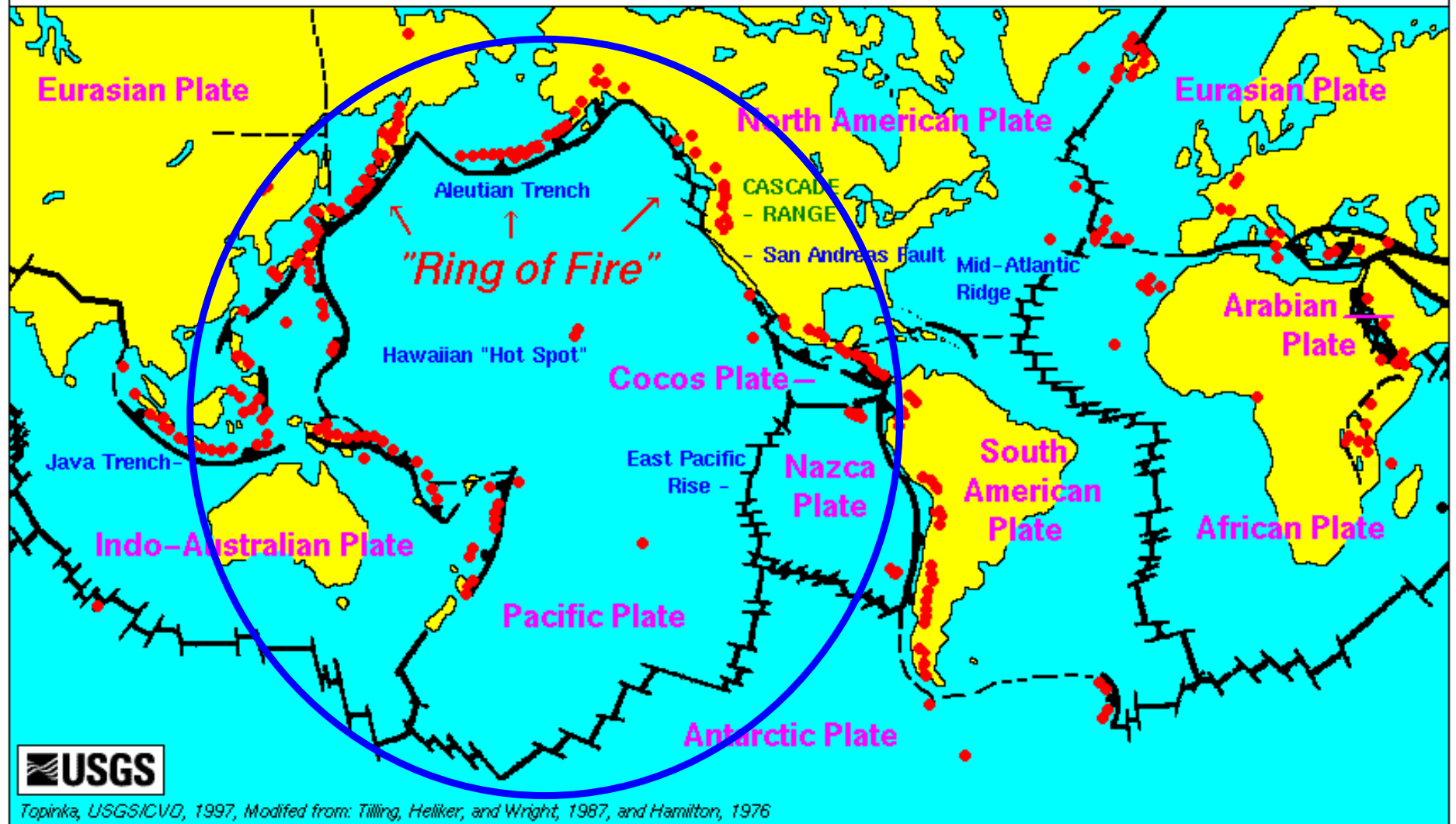


From the geo-Dharma

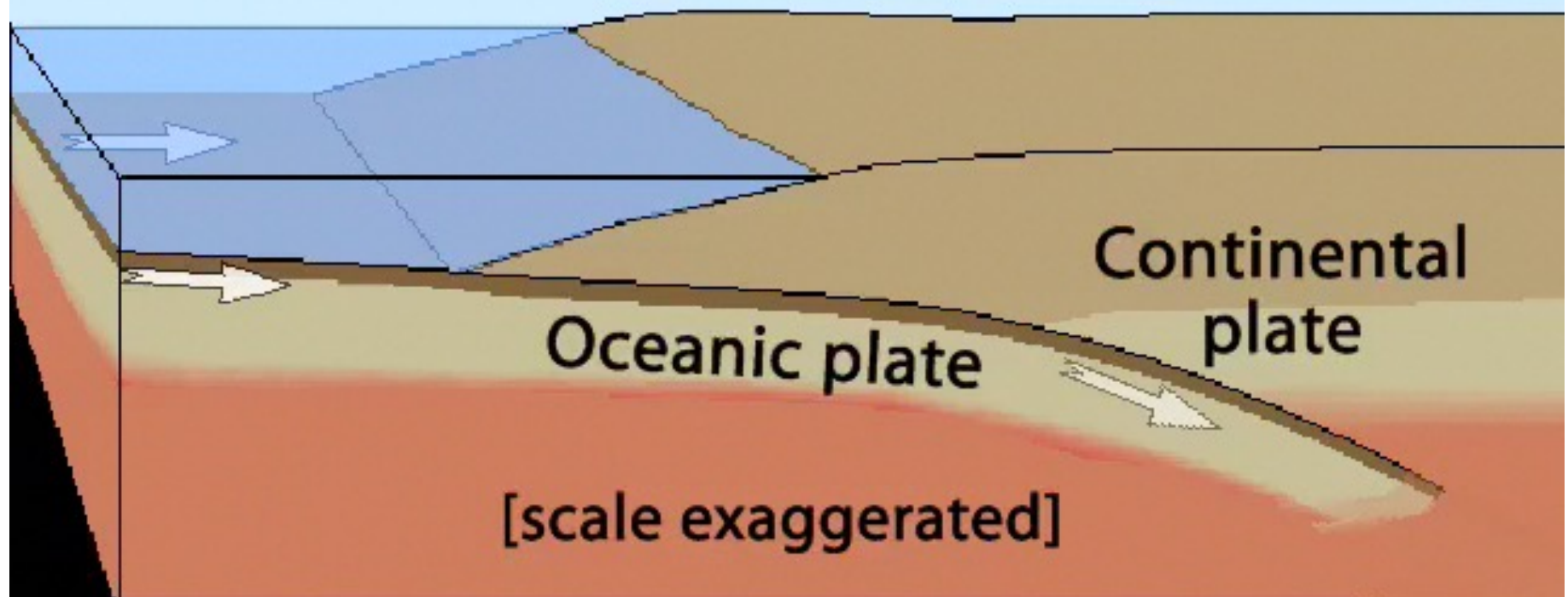
<https://www.youtube.com/watch?v=ryrXAGY1dmE>

the Ring of Fire driven by the mantle engine

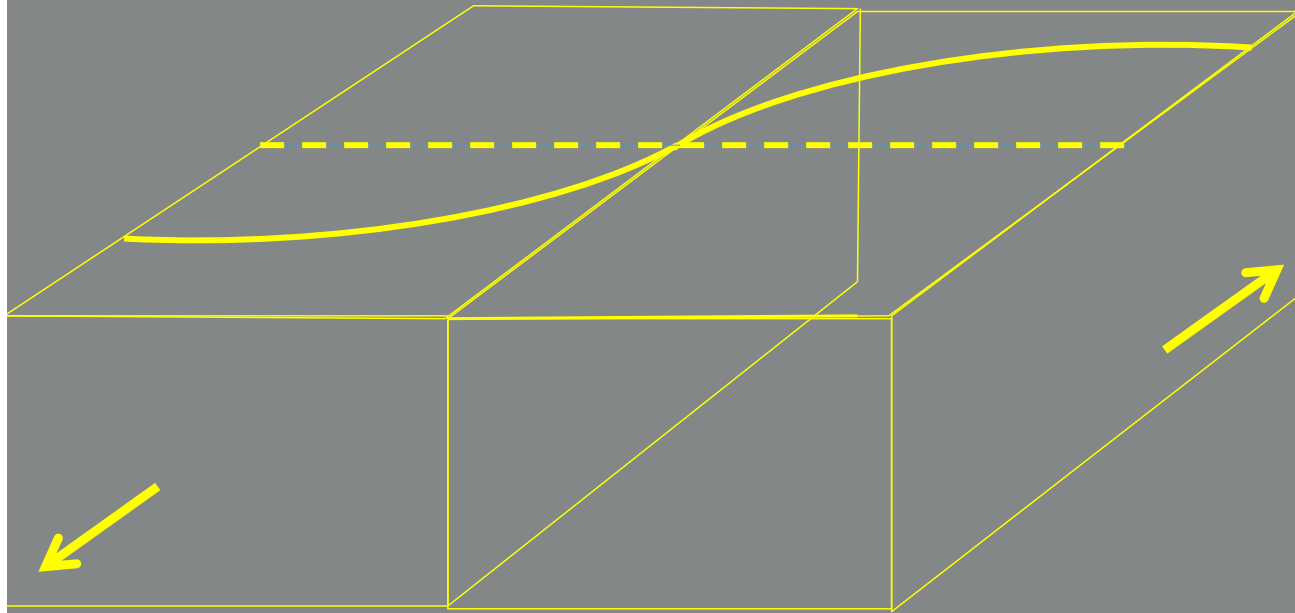
Active Volcanoes, Plate Tectonics, and the "Ring of Fire"



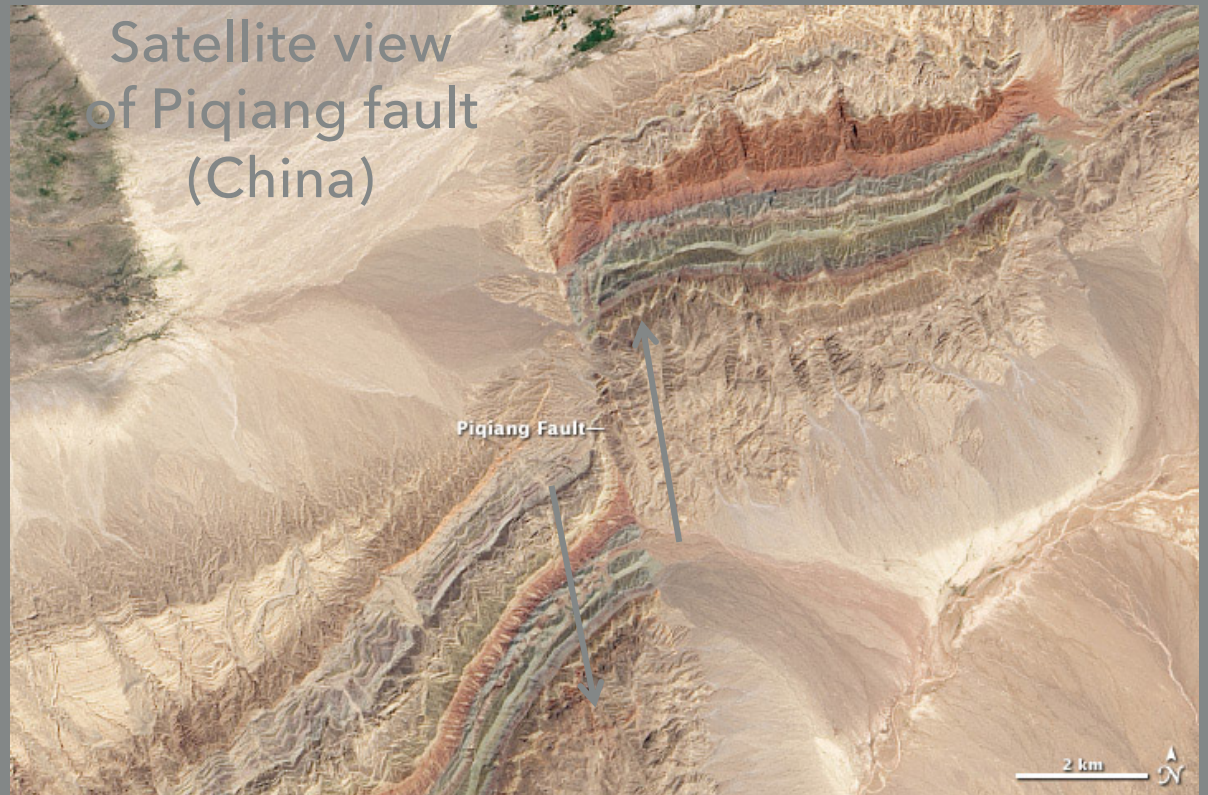
Elastic rebound in a subduction zone



strike-slip fault



Satellite view
of Piqiang fault
(China)

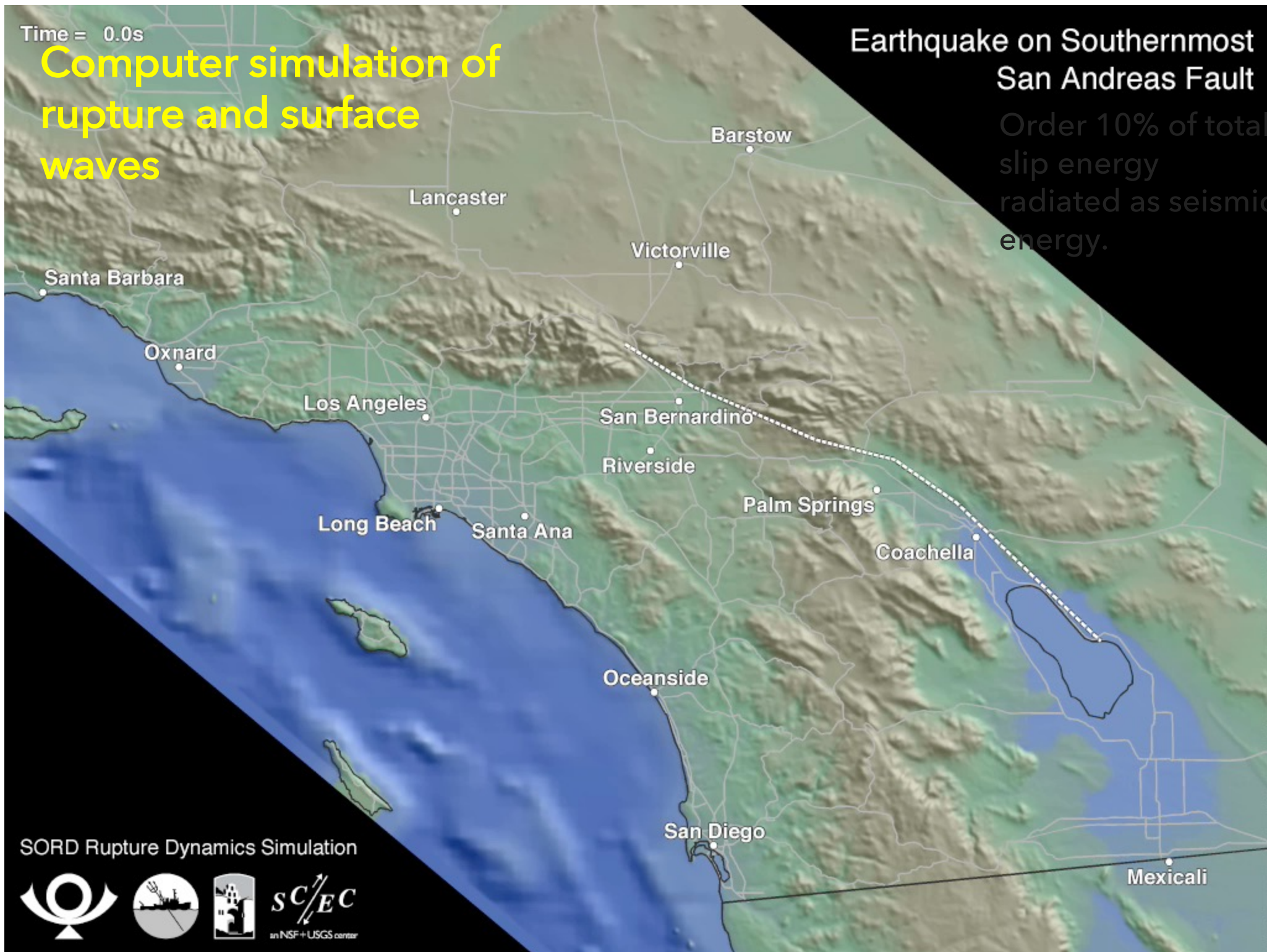


Time = 0.0s

Computer simulation of rupture and surface waves

Earthquake on Southernmost San Andreas Fault

Order 10% of total slip energy radiated as seismic energy.



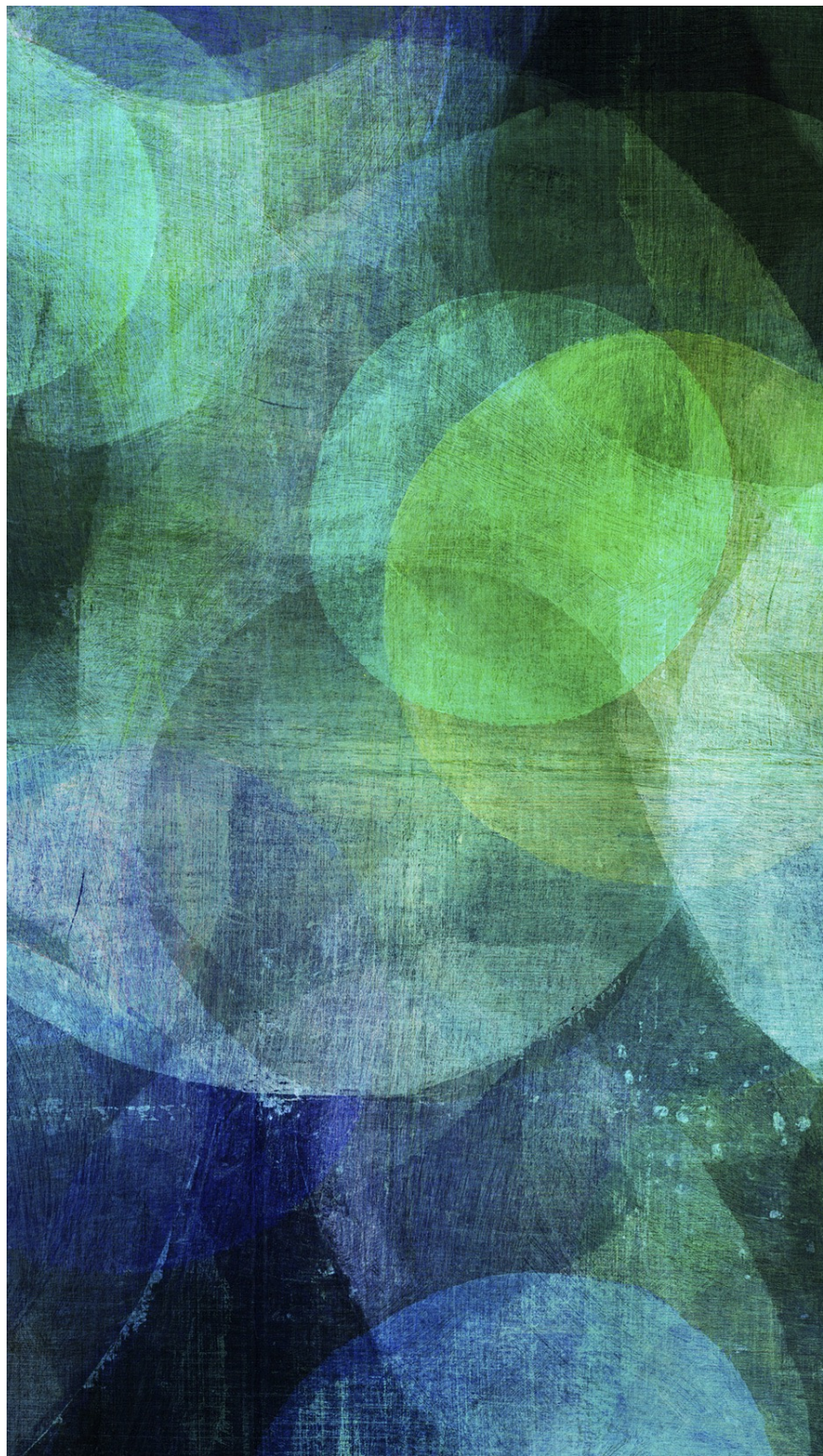
SORD Rupture Dynamics Simulation



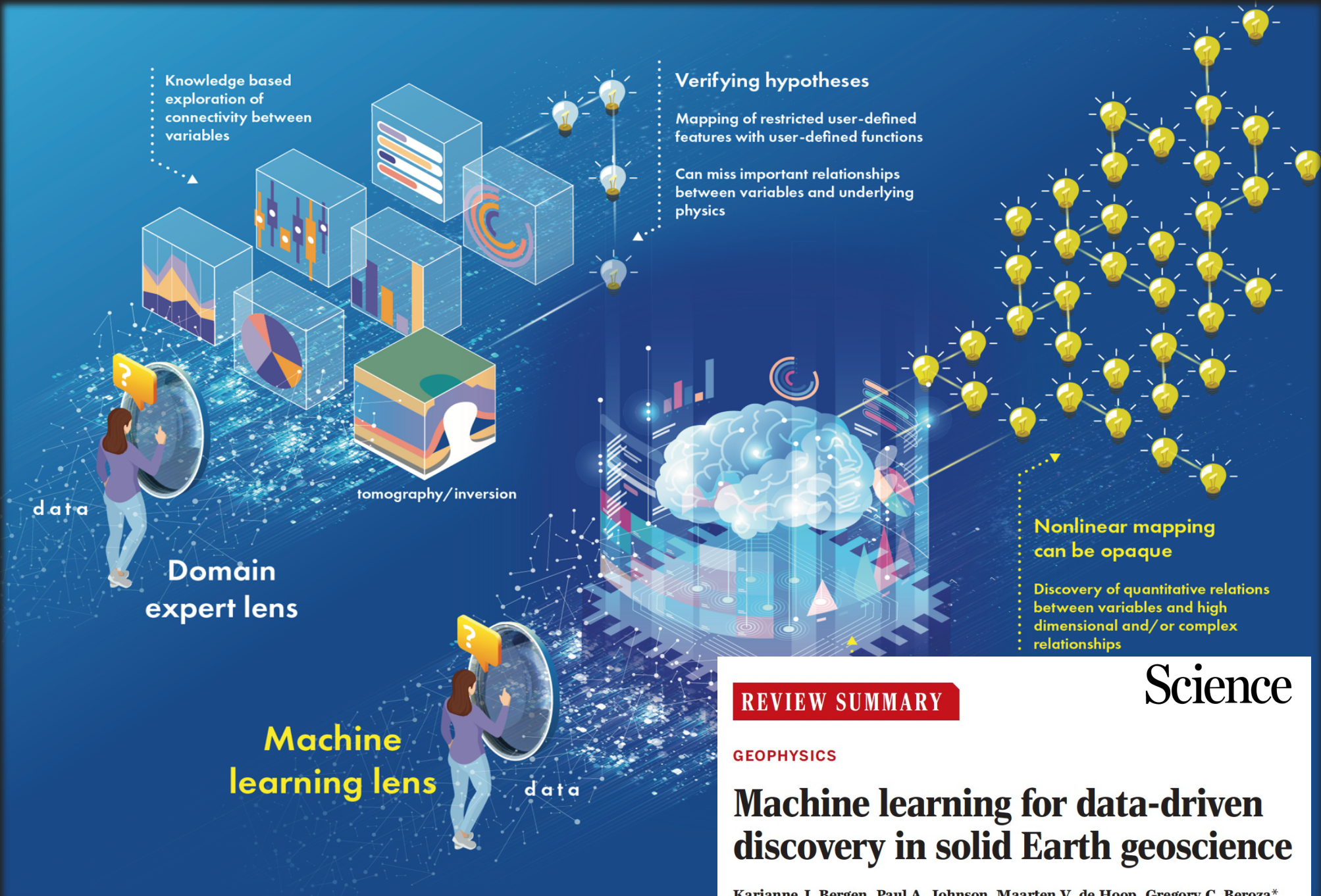
SC/EC
an NSF-USGS center



2011 M9.0 Japan earthquake (as experienced in Mukuhari, Japan)



The goal of machine learning is to learn from data and make accurate outcome predictions, without being explicitly programmed.



REVIEW SUMMARY

Science

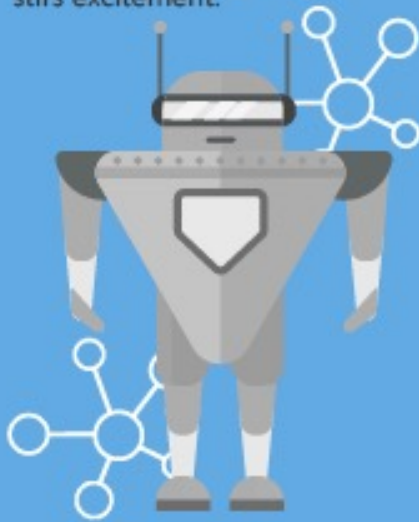
GEOPHYSICS

Machine learning for data-driven discovery in solid Earth geoscience

Karianne J. Bergen, Paul A. Johnson, Maarten V. de Hoop, Gregory C. Beroza*

ARTIFICIAL INTELLIGENCE

Early artificial intelligence stirs excitement.



MACHINE LEARNING

Machine learning begins to flourish.



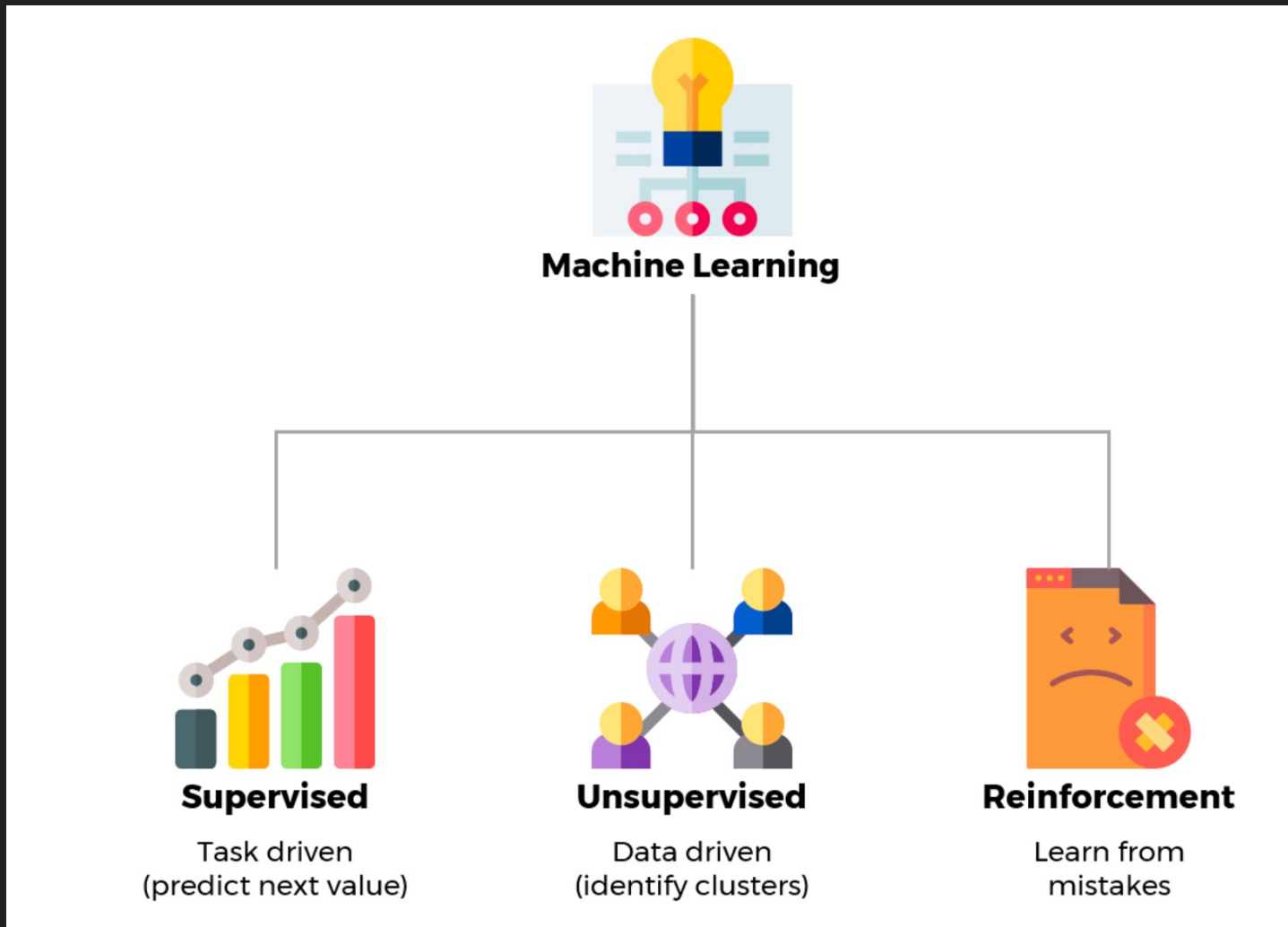
DEEP LEARNING

Deep learning breakthroughs drive AI boom.



Since an early flush of optimism in the 1950's, smaller subsets of artificial intelligence - first machine learning, then deep learning, a subset of machine learning - have created ever larger disruptions.

CATEGORIES OF MACHINE LEARNING

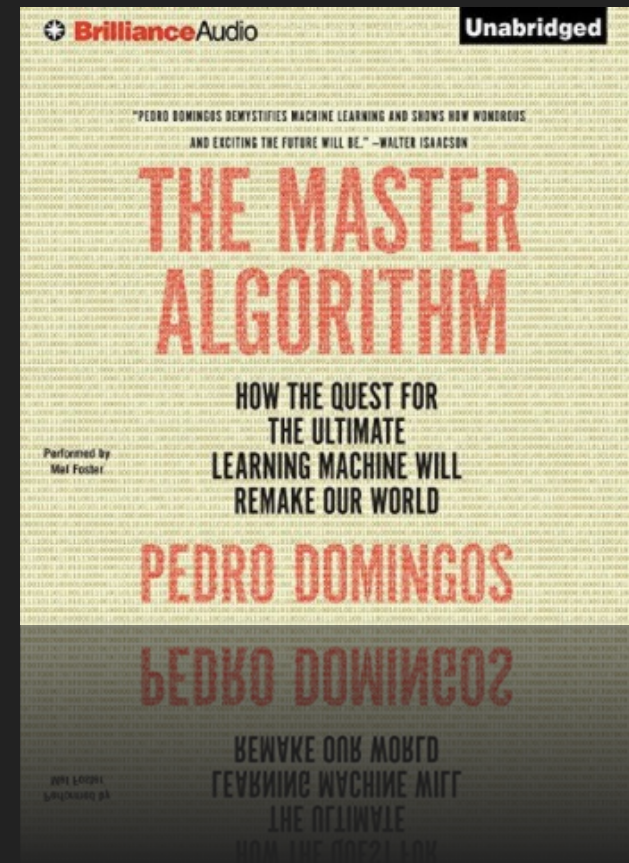


rule of thumb: only use machine learning when traditional programming methods are not effective/feasible for solving a particular problem.

[https://hethelinnovation.com/in-a-nutshell/machine-learning-in-a-nutshell.](https://hethelinnovation.com/in-a-nutshell/machine-learning-in-a-nutshell)

“People worry that computers will get too smart and take over the world—

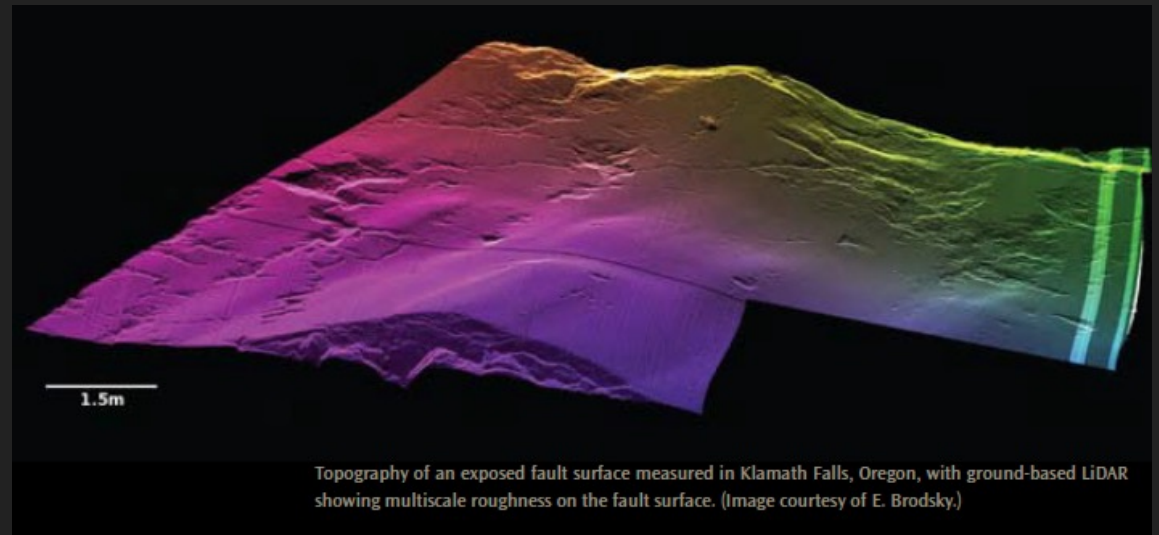
but the real problem is that they’re too stupid and they’ve already taken over the world.”



COMPLEXITY OF FAULTING

How to capture the controlling physics of such a complex system?

Can new data analyses approaches help?



courtesy E. Brodsky



HOW DO EARTHQUAKES EVOLVE?

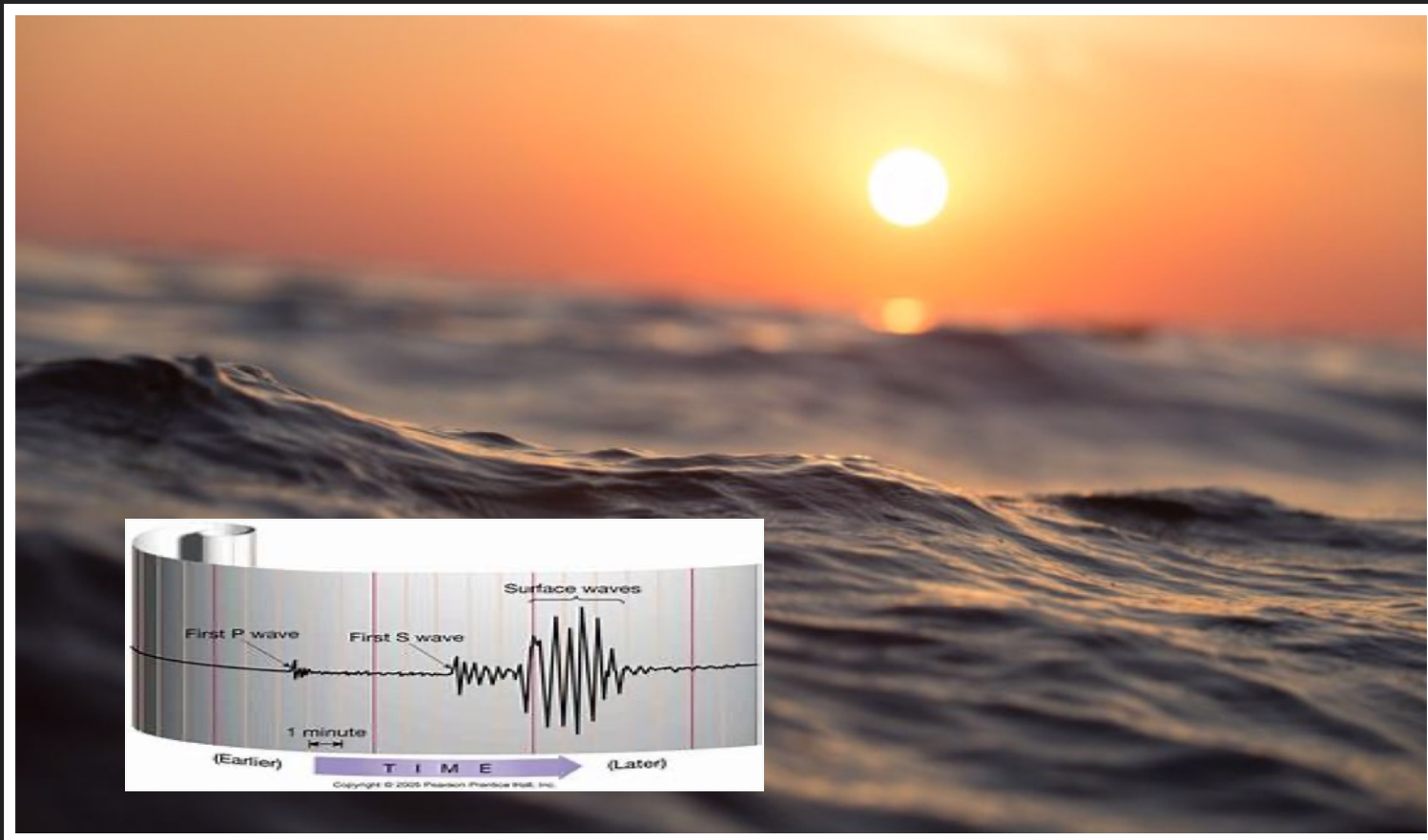
Data driven approach

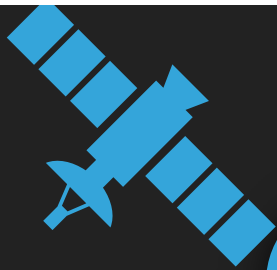
**answers we seek hidden in existing
data**

THE NOISE IS THE SIGNAL

Is there information regarding fault slip contained in the sea of background seismic noise?

A quick summary of work to date





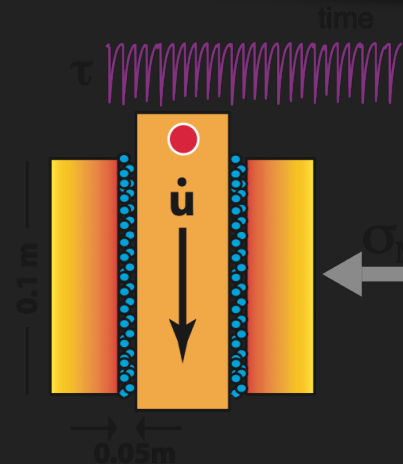
INSAR, GPS

PROBING FAULT PHYSICS
USING EARTHQUAKE
CATALOGS



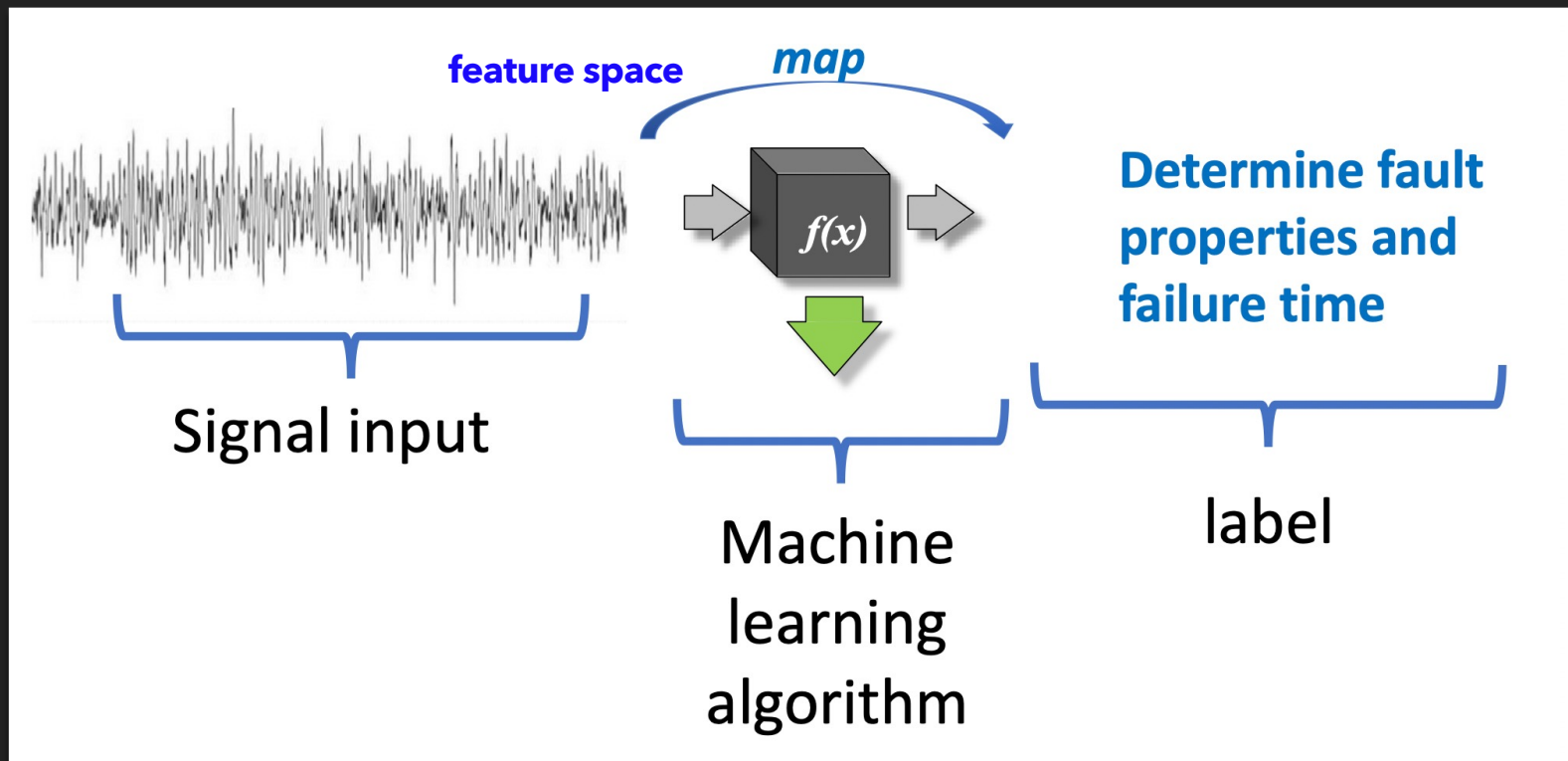
PROBING FAULT PHYSICS
APPLYING CONTINUOUS
SEISMIC DATA

Laboratory
experiments



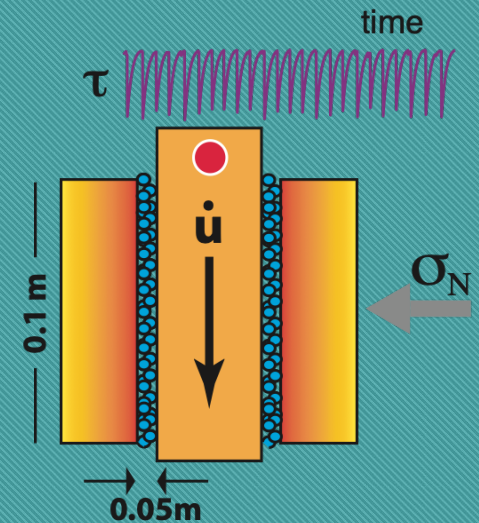
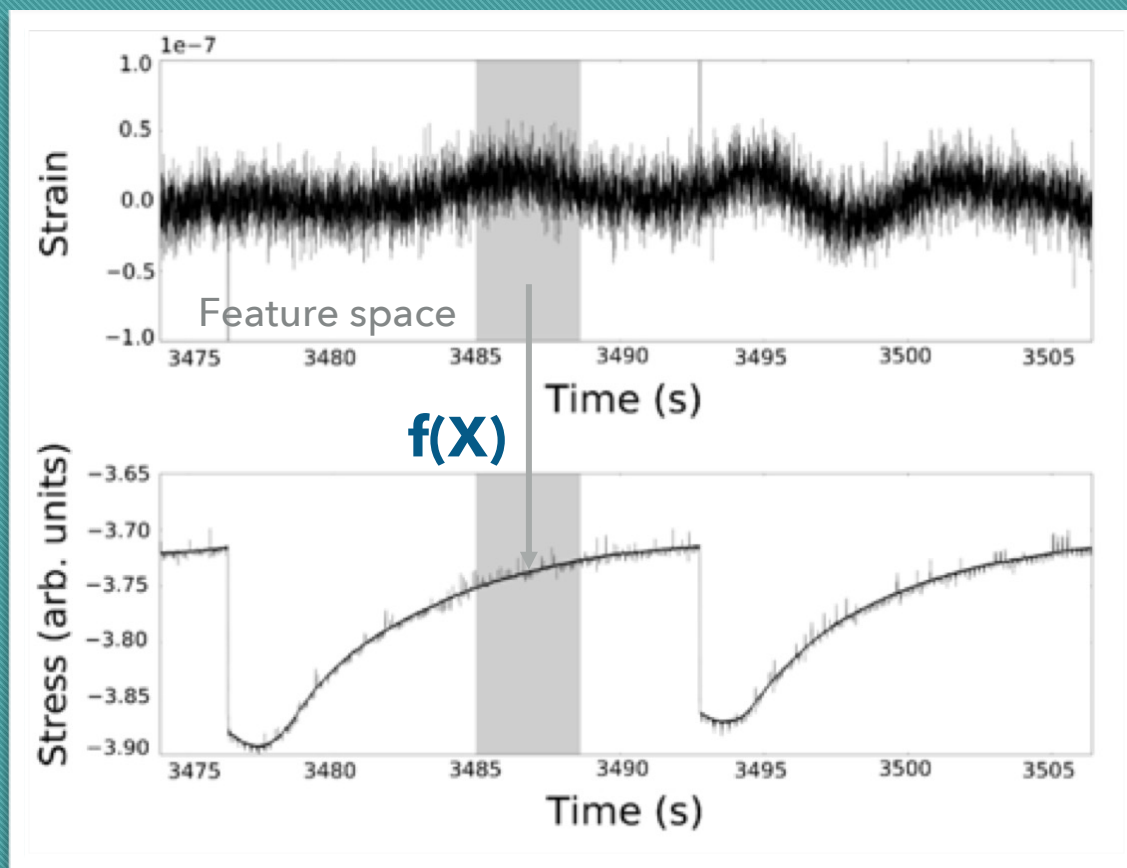
SUPERVISED LEARNING APPROACH IN A NUTSHELL

SUPERVISED LEARNING INVOLVES A TRAINING PROCEDURE TO BUILD THE MODEL, THEN VALIDATION AND TESTING, IN THE FORM OF A REGRESSION

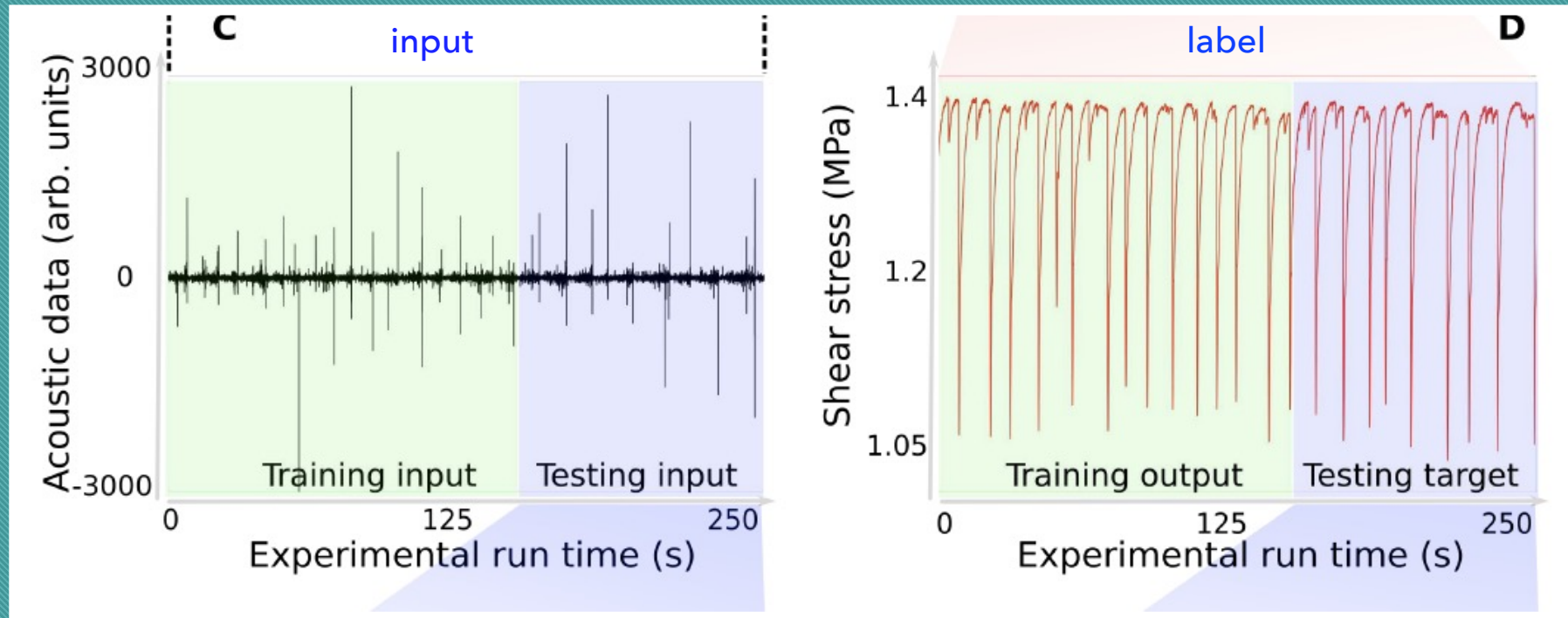


DATA

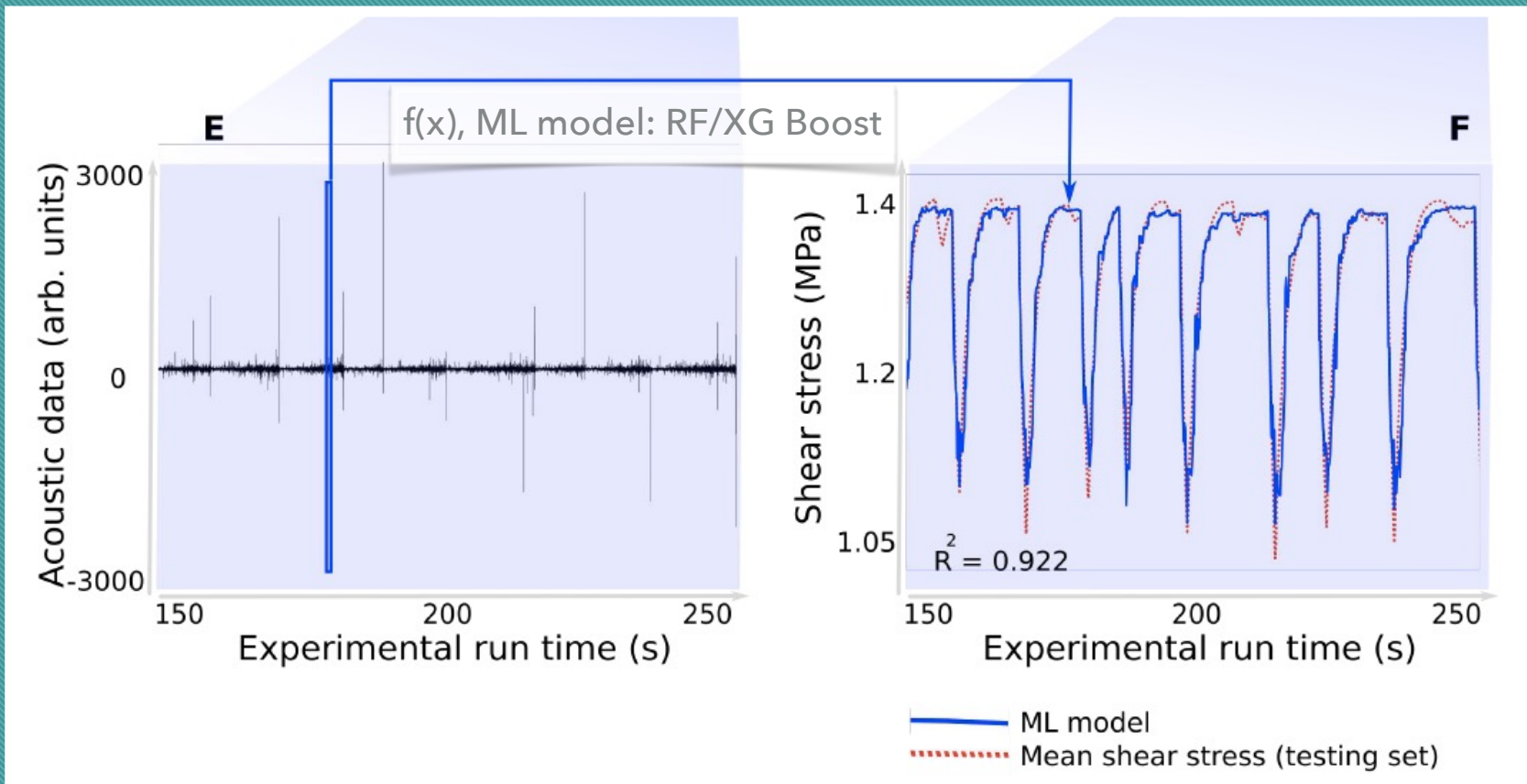
LEARNING THE FAULT PHYSICS USING THE RECORDED ACOUSTIC SIGNAL



ML PROCEDURE

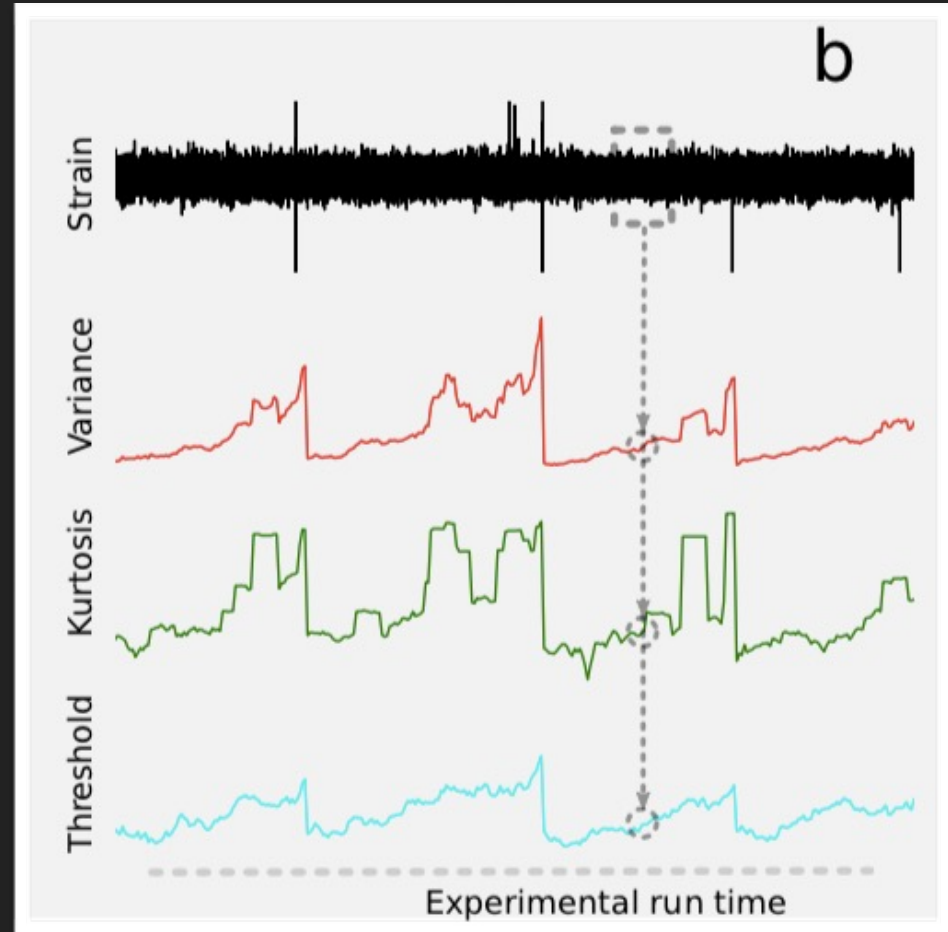
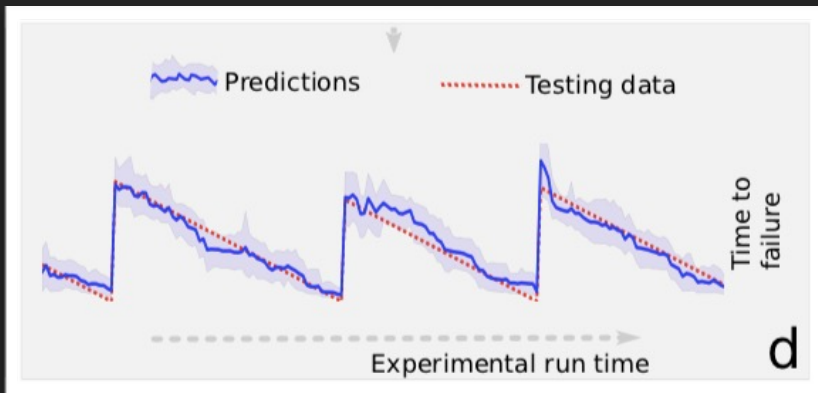
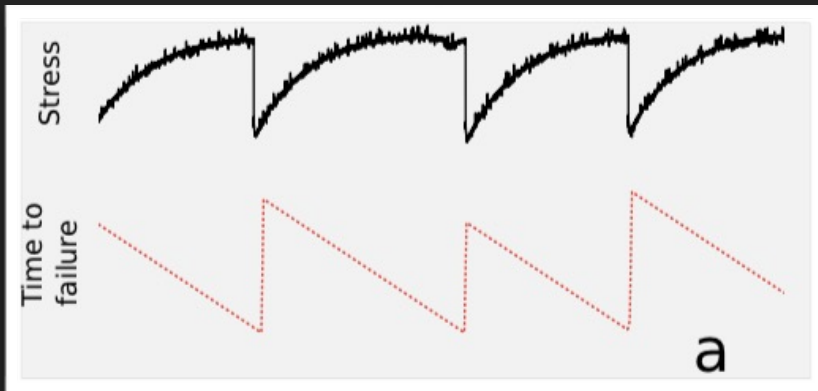


RESULT



The continuous signal contains a fingerprint of the instantaneous behavior of the fault at all times

TIMING FORECASTING



KAGGLE COMPETITION ON TOPIC OF LABORATORY EARTHQUAKE PREDICTION



Research Prediction Competition

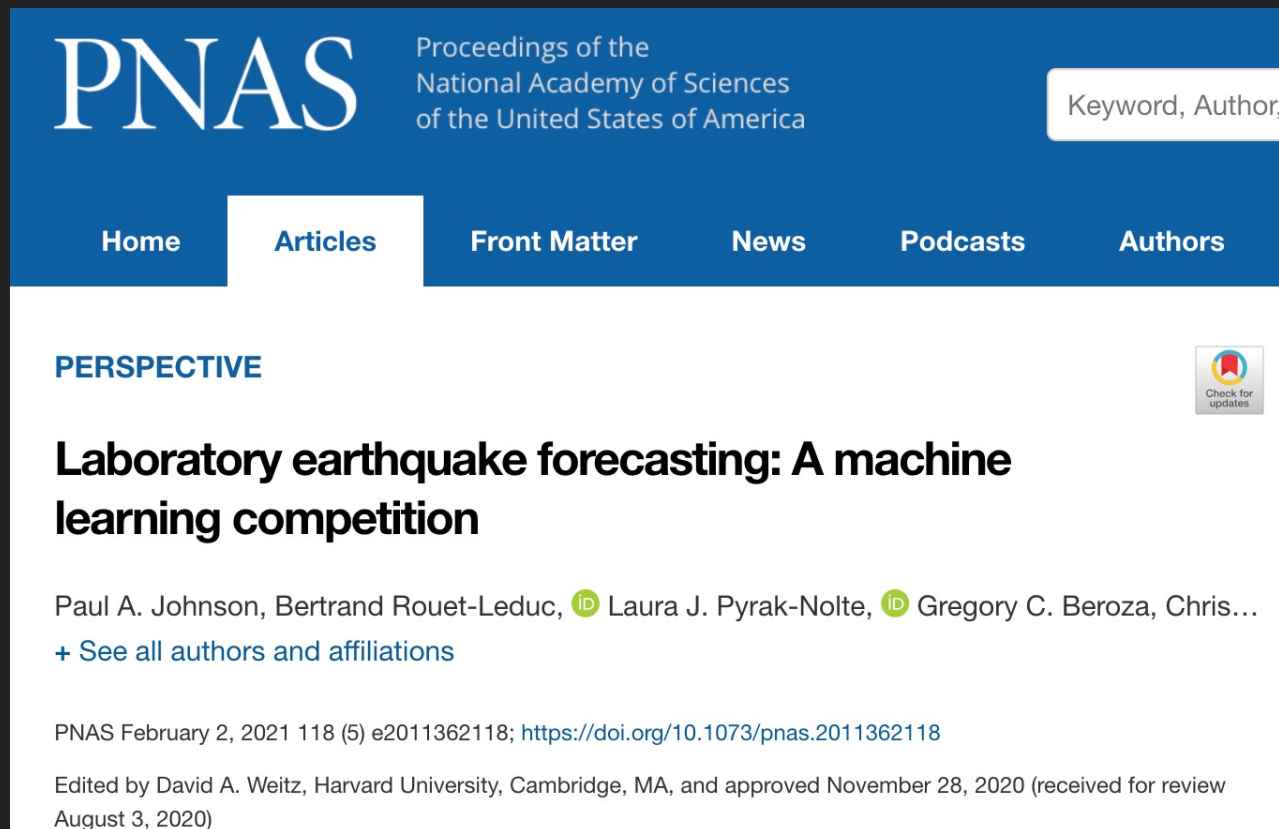
LANL Earthquake Prediction

Can you predict upcoming laboratory earthquakes?

\$50,000
Prize Money

Los Alamos National Laboratory · 4,516 teams · 3 years ago

The banner features a blue background with a yellow seismic waveform. A search icon is in the top left, and a 'Prize Money' badge is on the right. The Los Alamos National Laboratory logo is in the bottom left.





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PERSPECTIVE

Laboratory earthquake forecasting: A machine learning competition

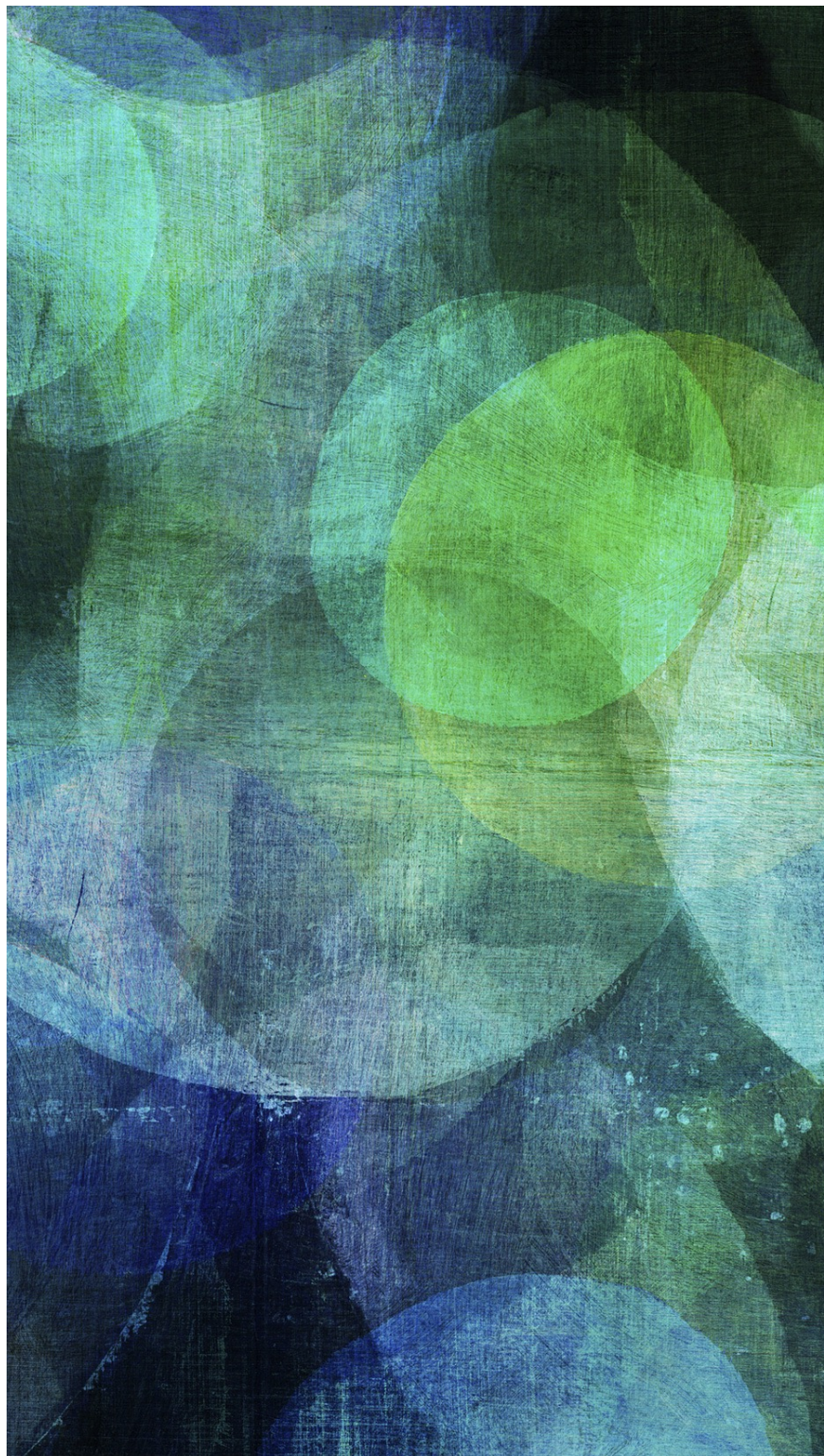
Paul A. Johnson, Bertrand Rouet-Leduc,  Laura J. Pyrak-Nolte,  Gregory C. Beroza, Chris...

+ See all authors and affiliations

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The article page has a blue header with the PNAS logo and a search bar. A navigation menu is below the header. The article title is in large bold font, followed by the authors' names with ORCID icons. A 'Check for updates' button is in the top right. The publication details and editor information are at the bottom.



Episodic slow slip and tremor in Cascadia

TEXT

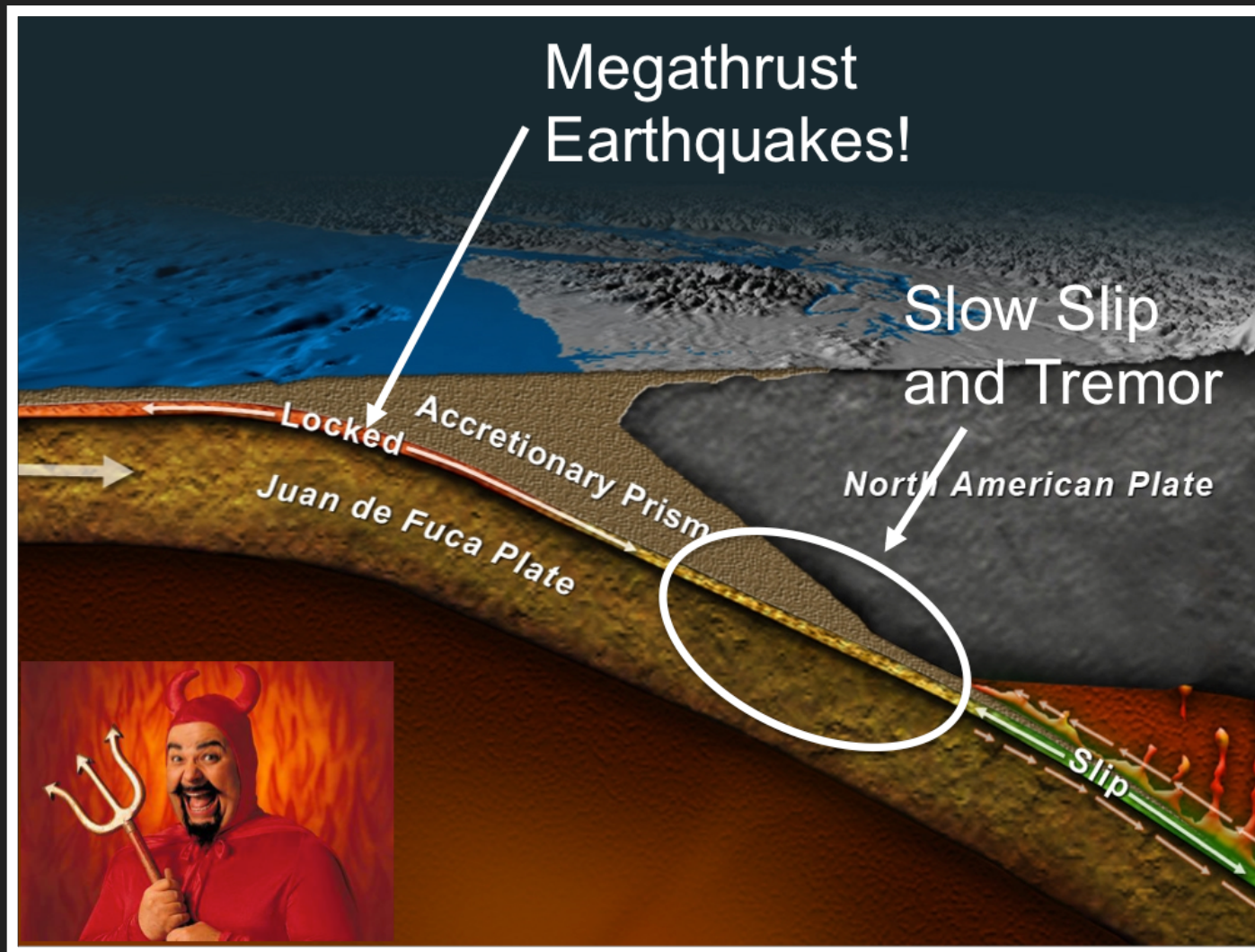
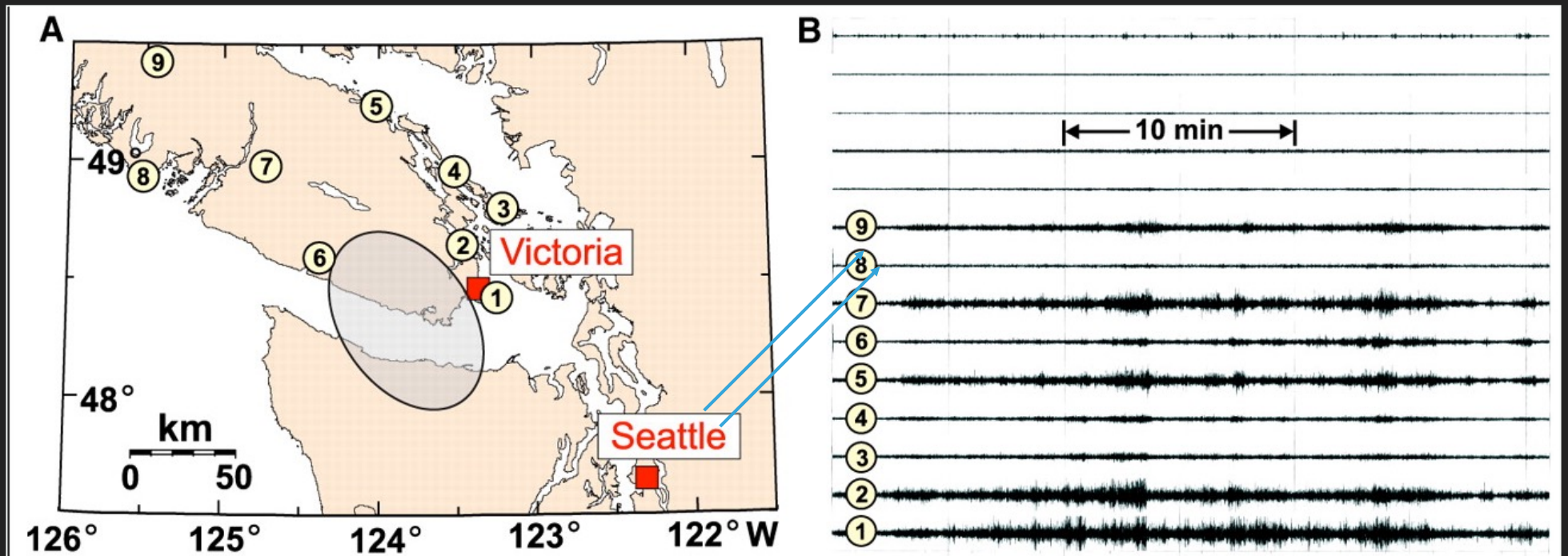


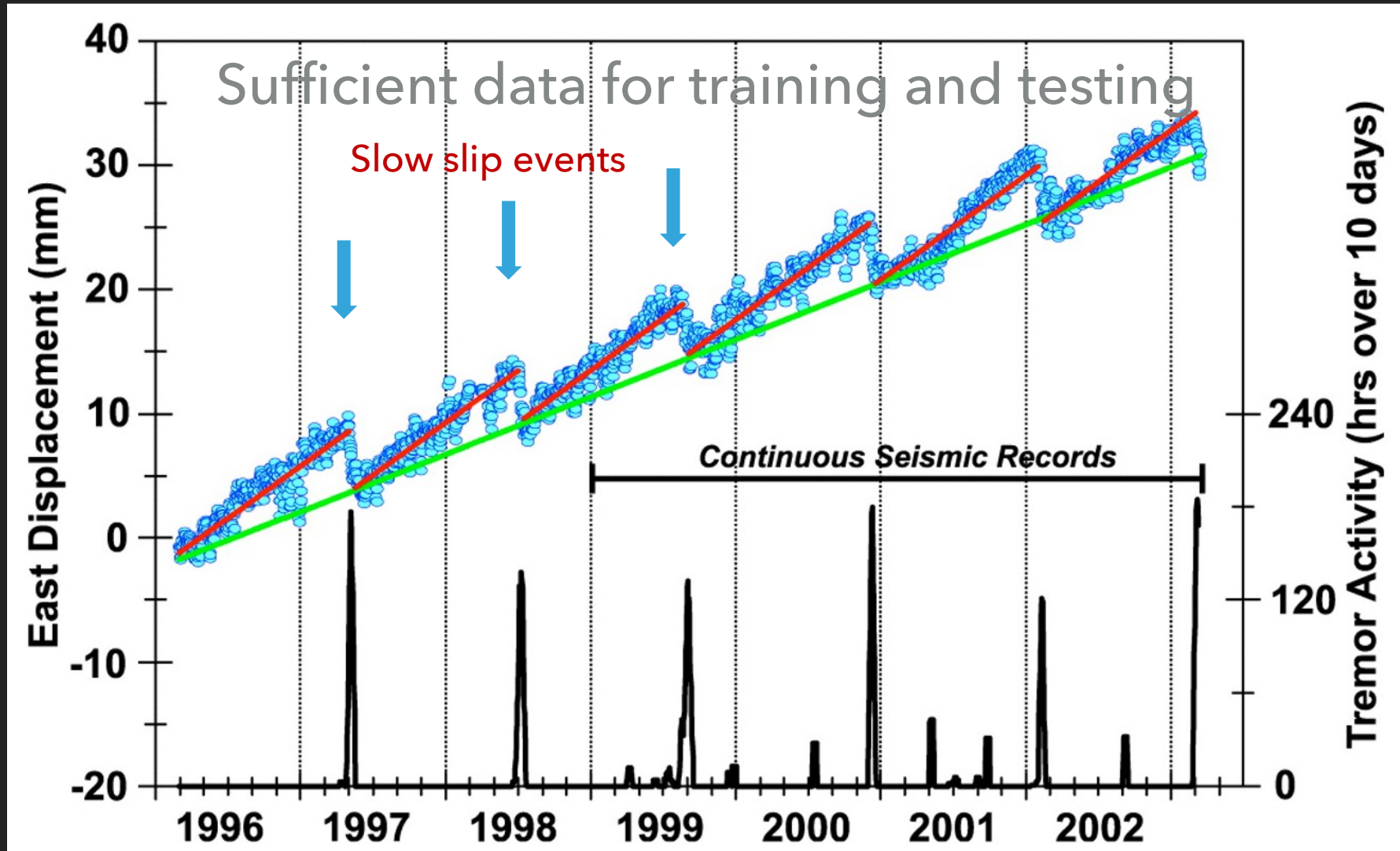
Figure courtesy Gina Schmalzle

<http://geodesygina.com/tag/cascadia-subduction-zone.html>

TREMOR VICTORIA BRITISH COLUMBIA (CANADA)

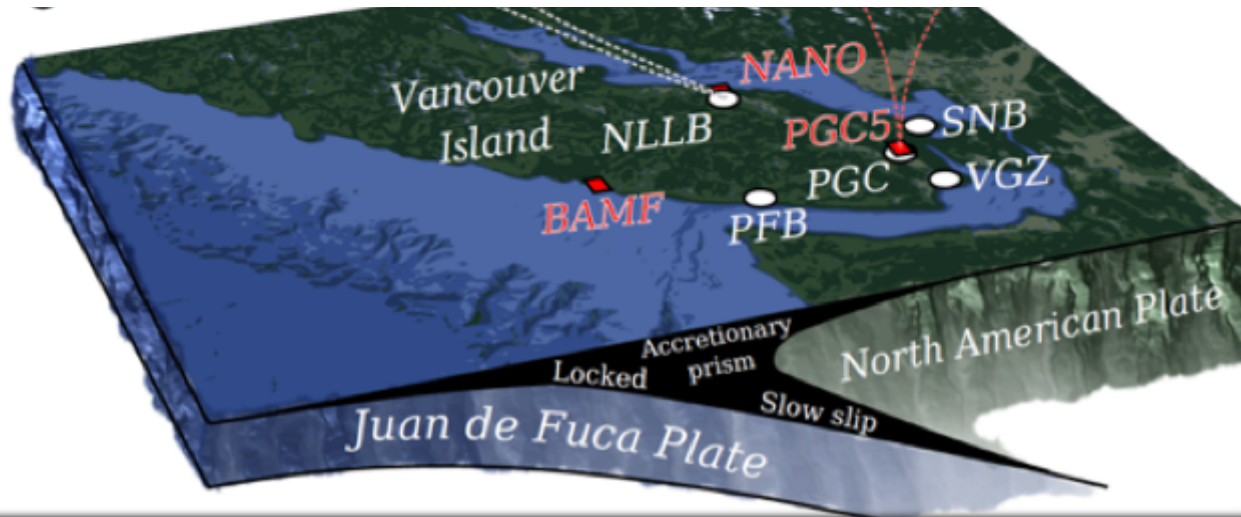
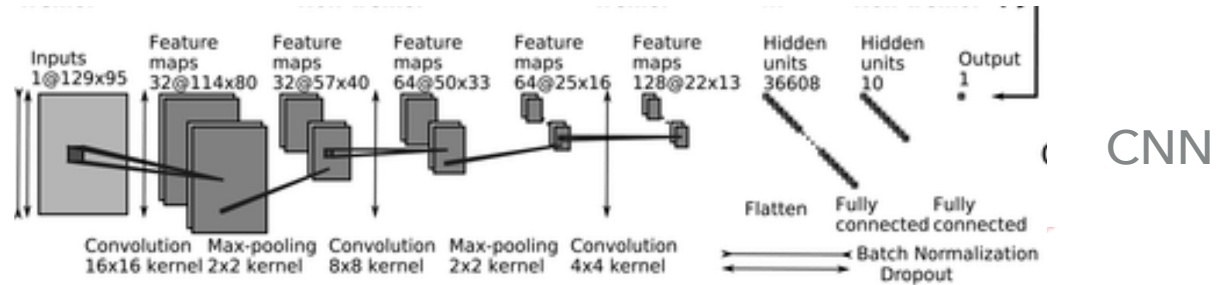


THE FAMOUS FIGURE



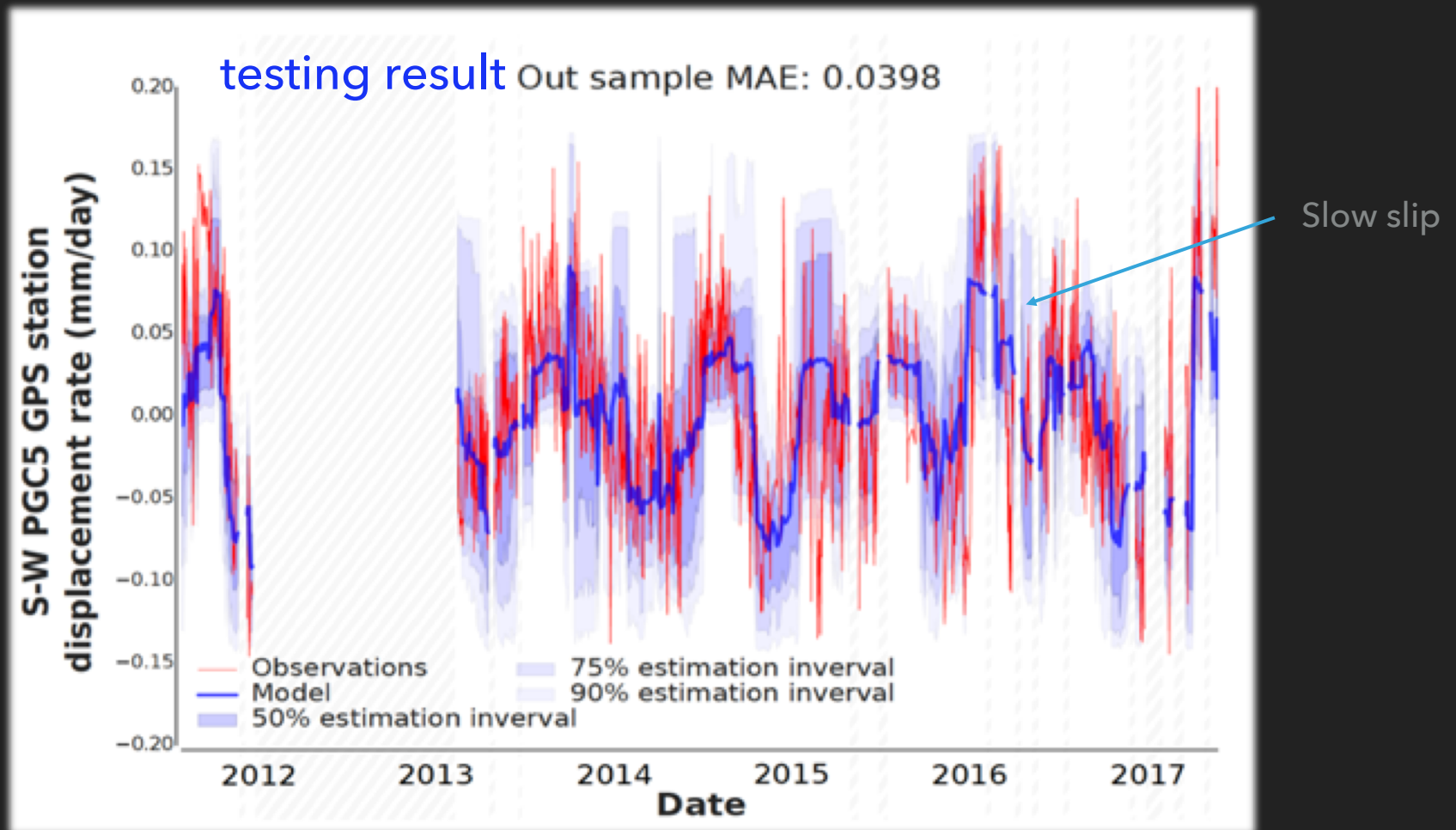
ML DATA SETS AND MODELS FOR CASCADIA

- Model input: continuous seismic data
- Model output: continuous Global Positional Satellite (GPS) displacement rate
- Models: XG Boost and and deep learning (autoencoder)



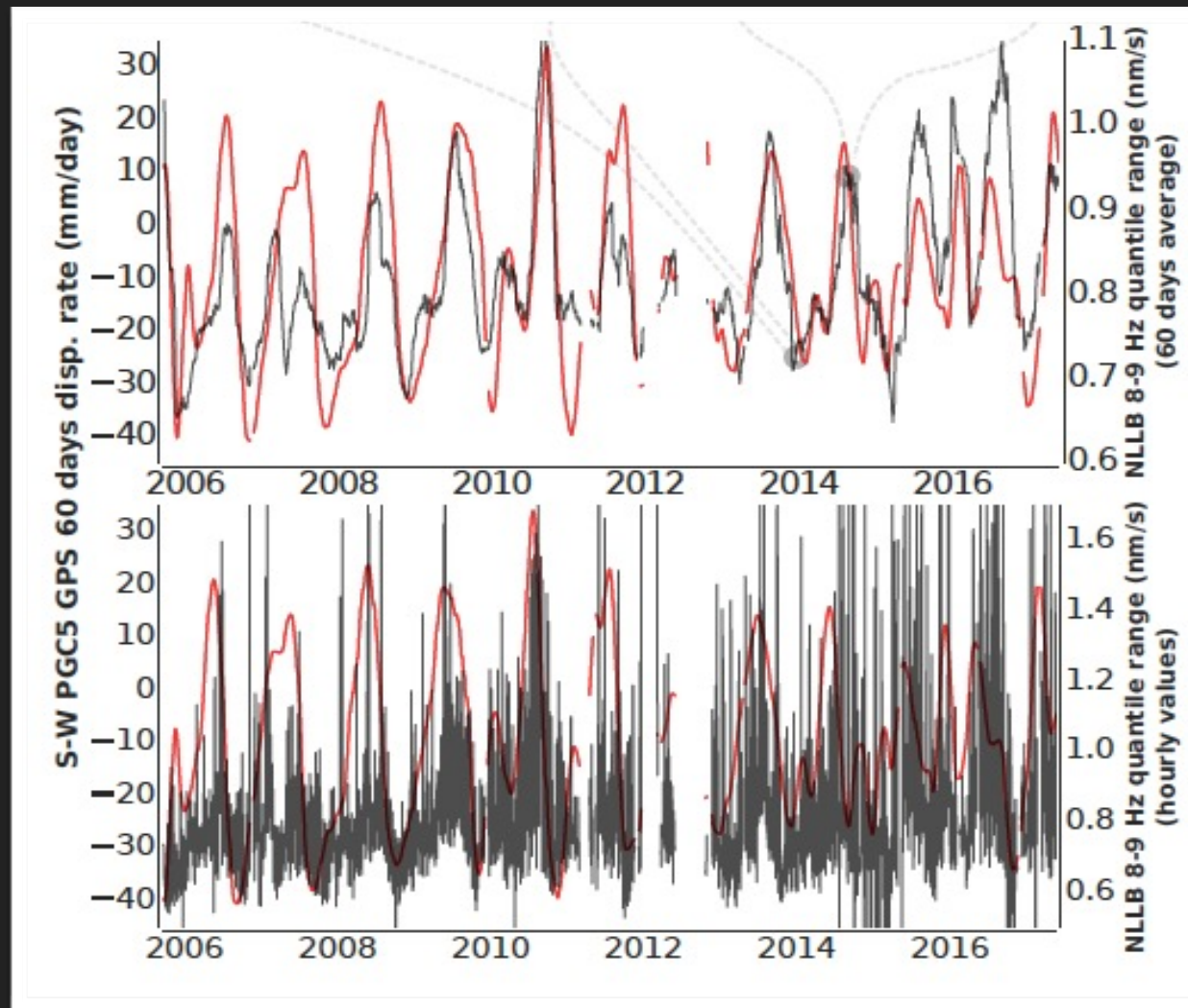
CASCADIA: MODEL OUTPUT

SAME APPROACH: MODEL PREDICTS SURFACE DISPLACEMENT RATE AT ALL TIMES

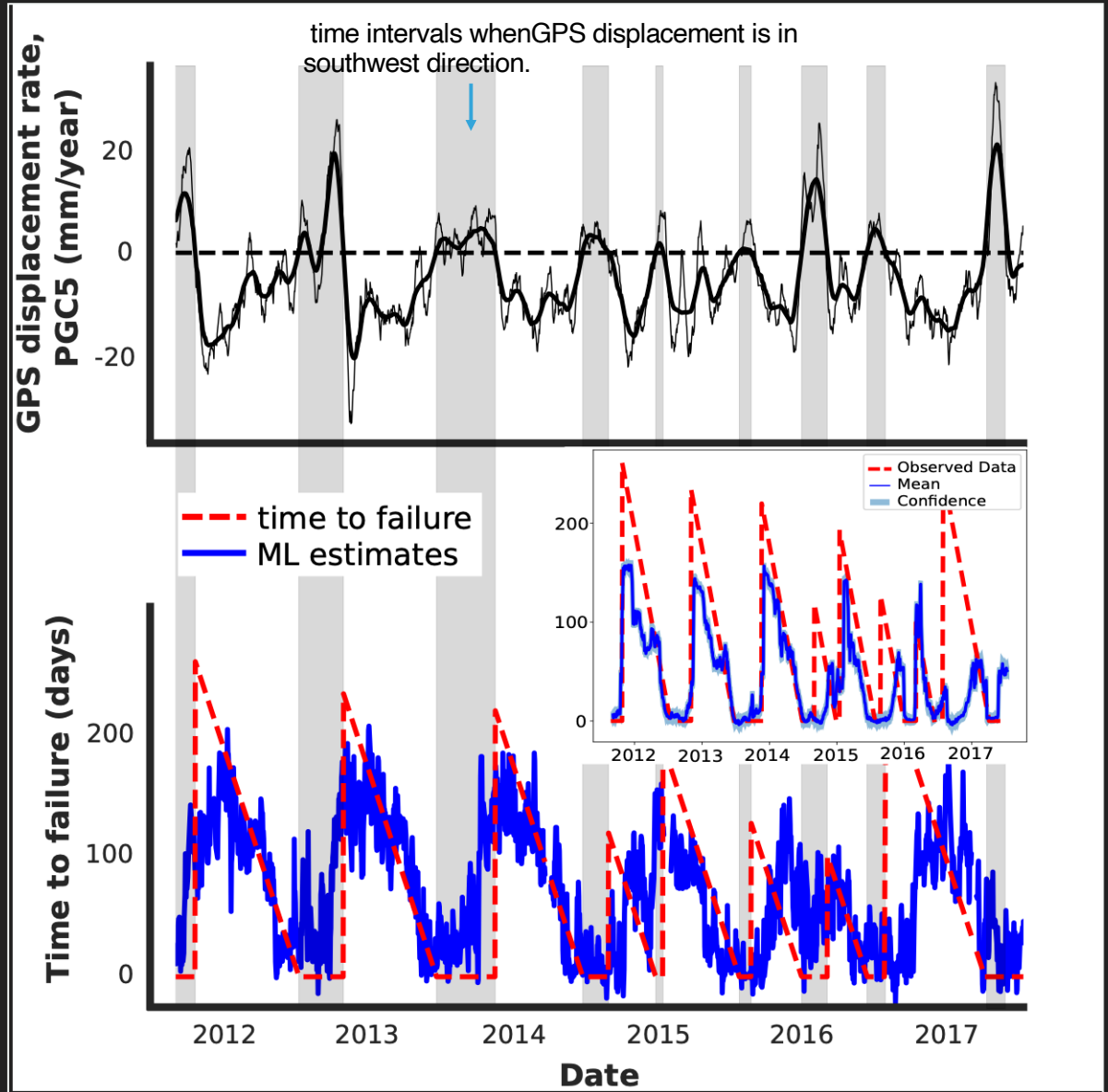
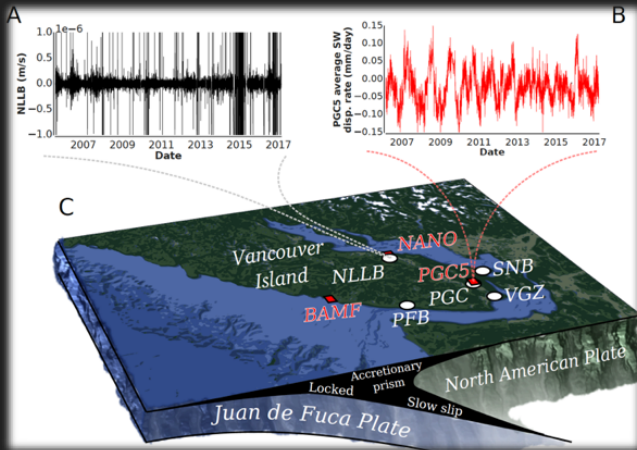


STATISTICS

MOST IMPORTANT SIGNAL STATISTIC: INTERQUARTILE RANGE (ENERGY)

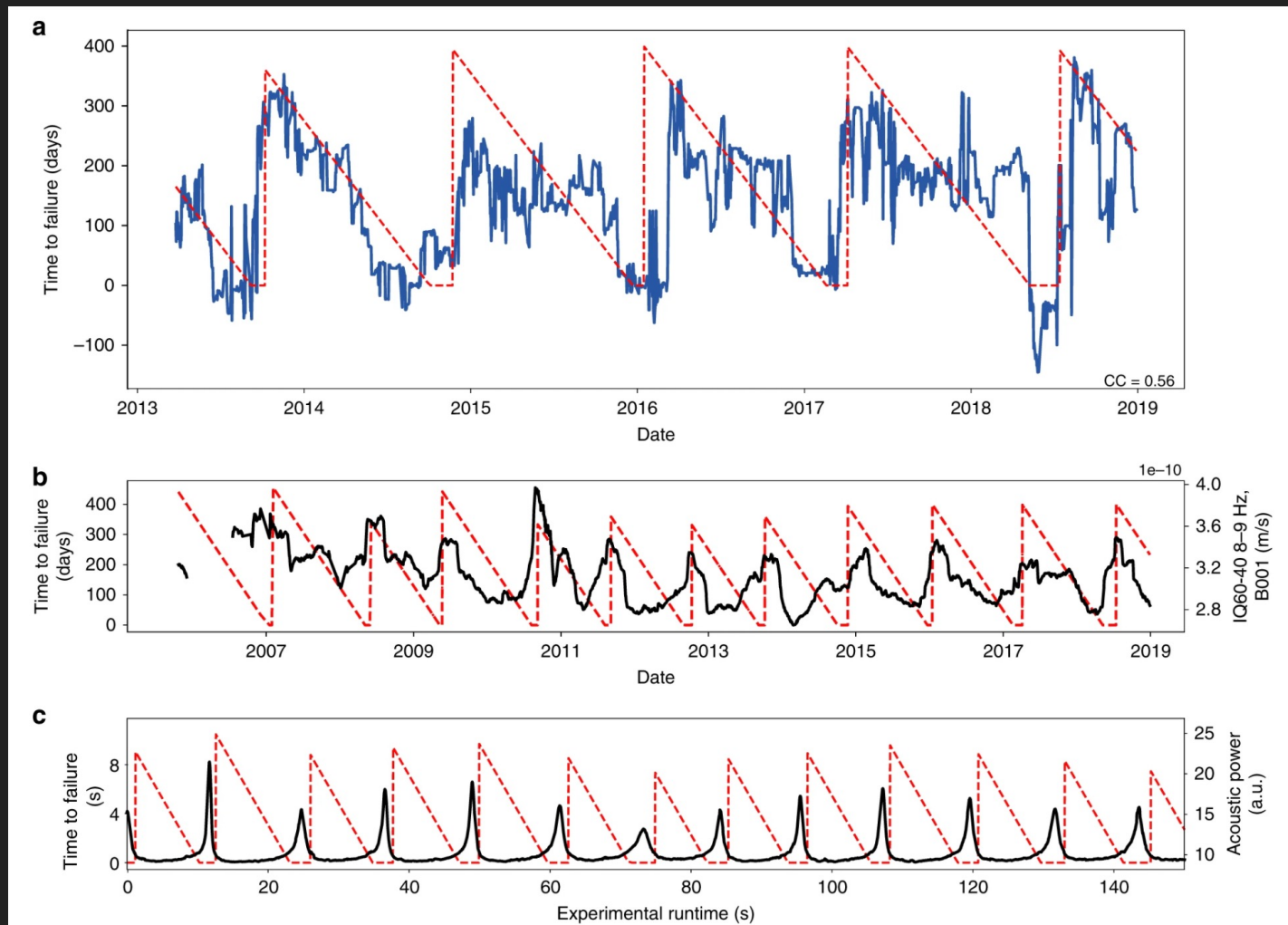


FORECASTING FAILURE TIME

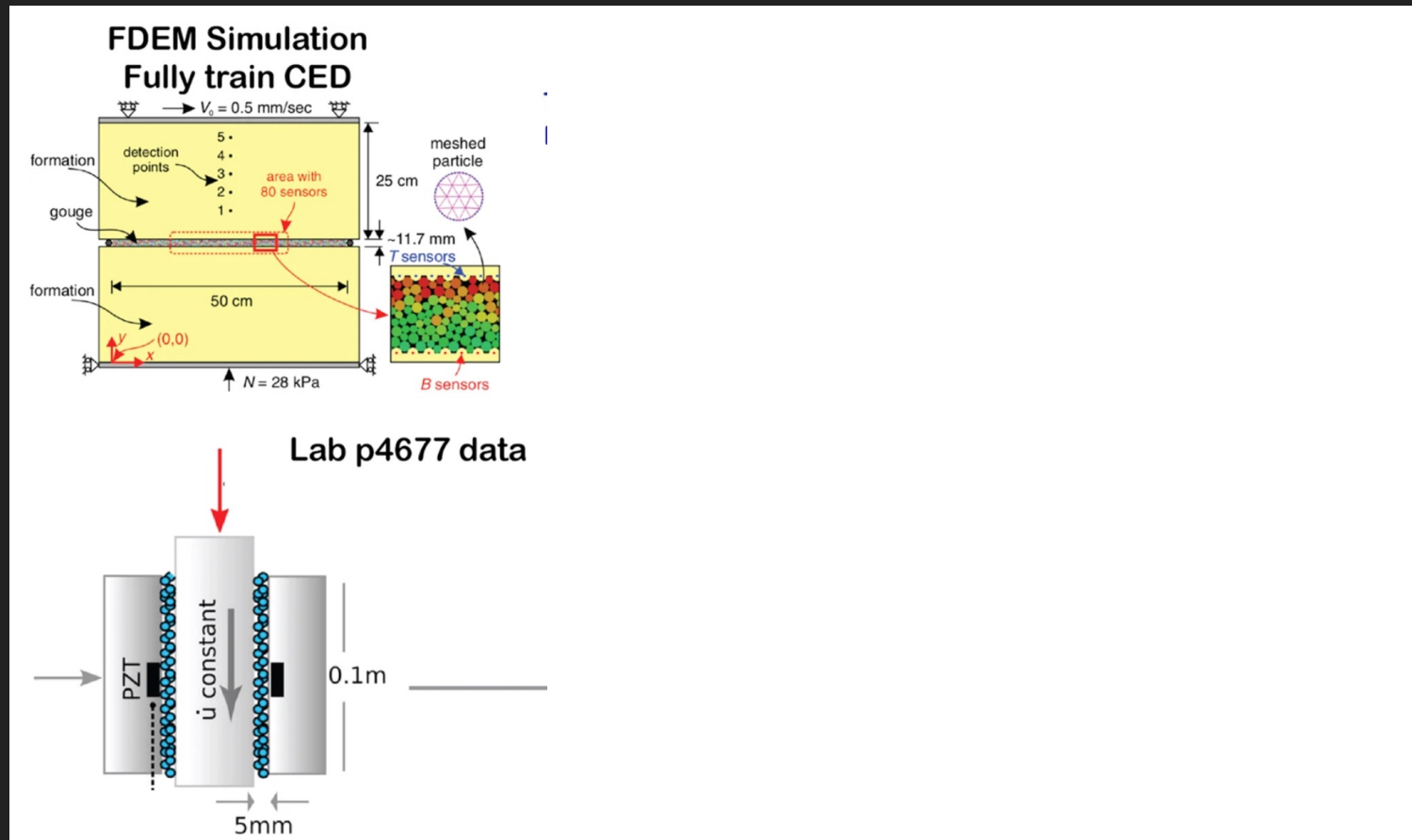


IMPORTANT FEATURE AND COMPARISON TO LAB

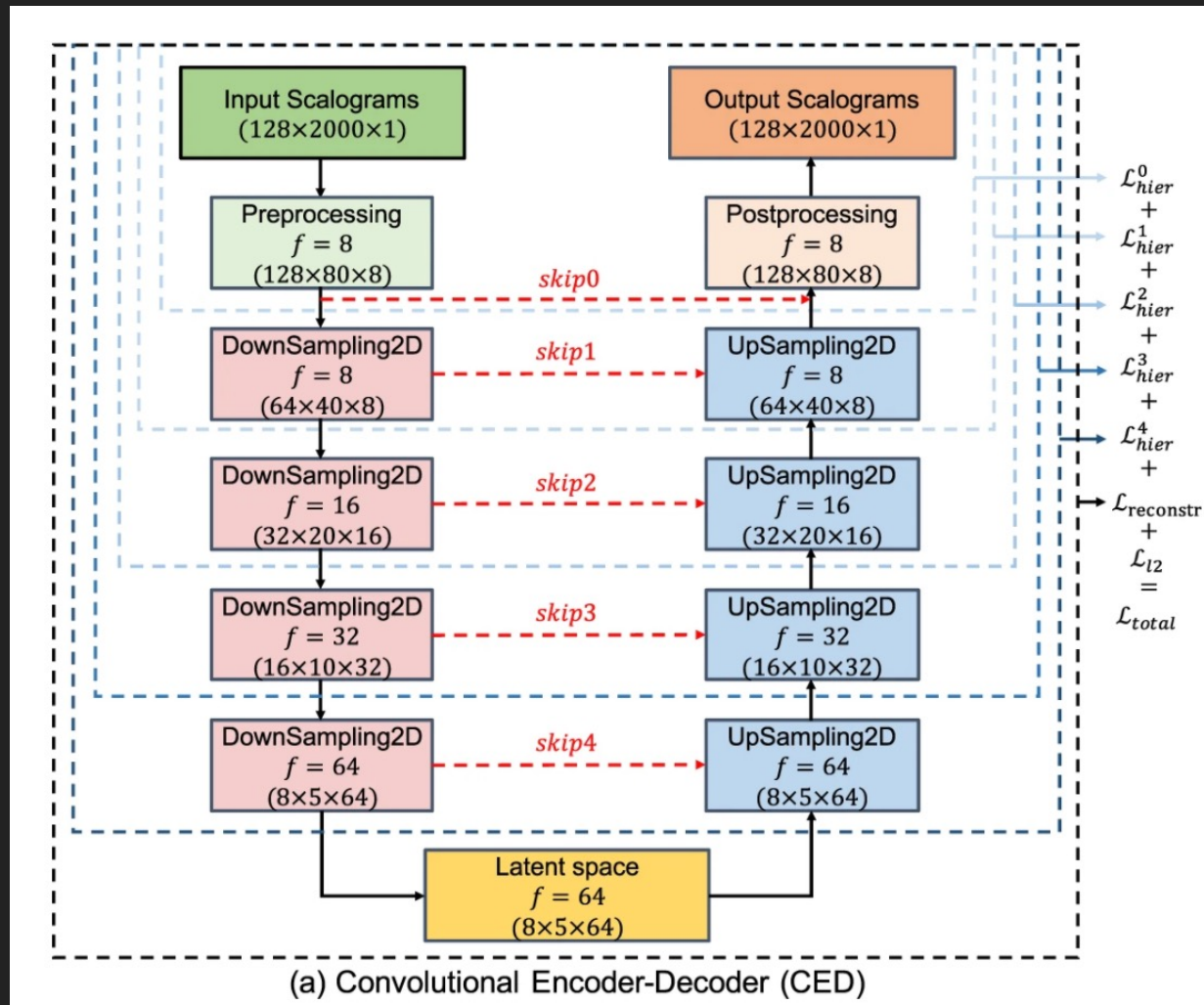
Energy related features in lab and in Earth



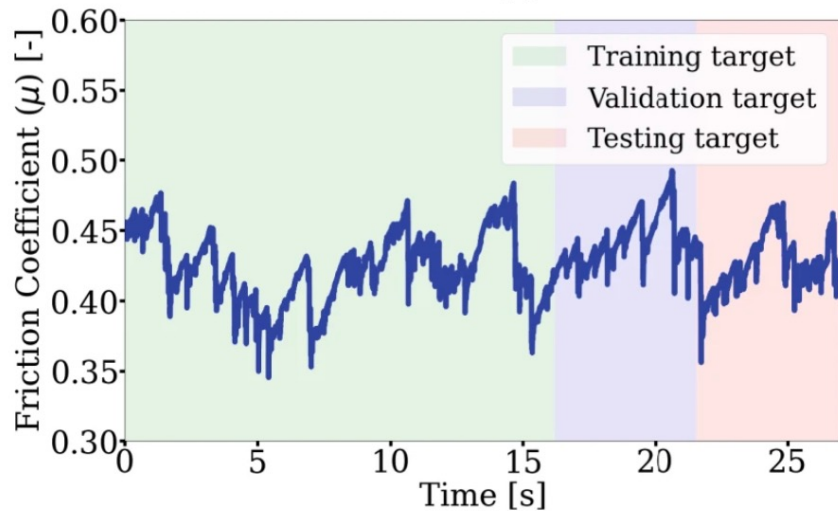
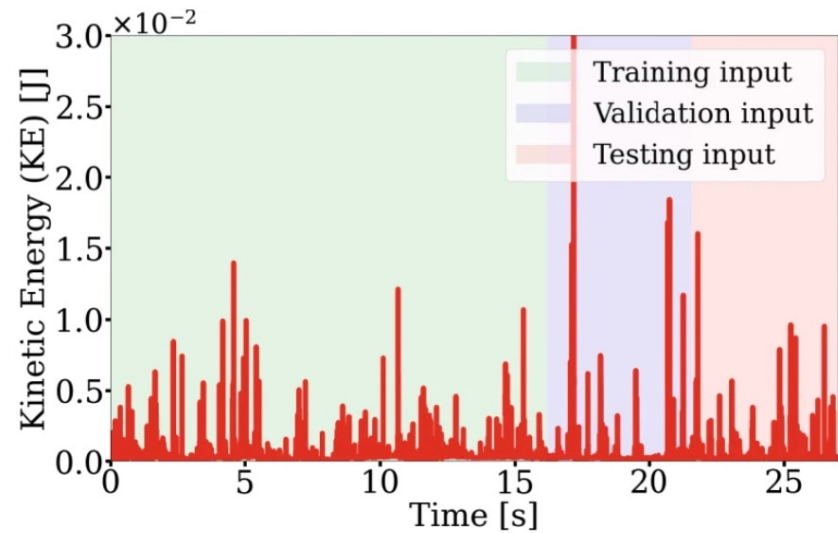
ATTACKING THE CHALLENGING PROBLEM IN EARTH



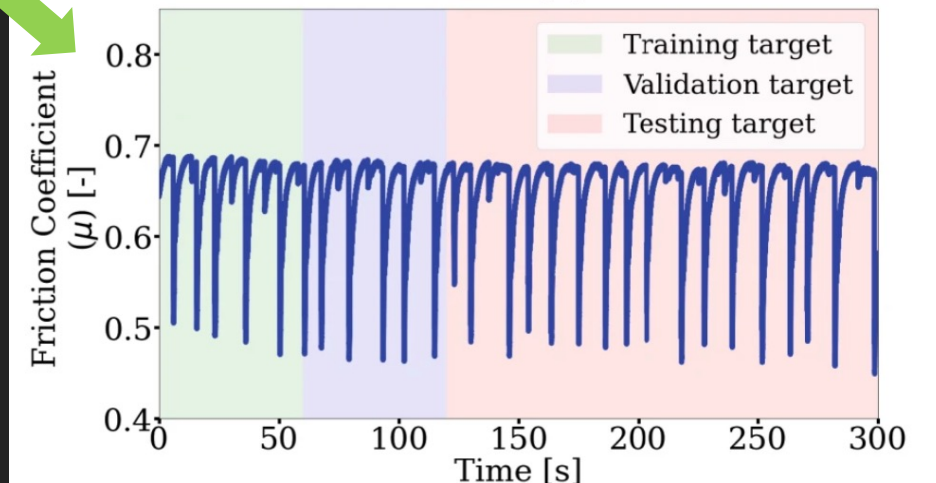
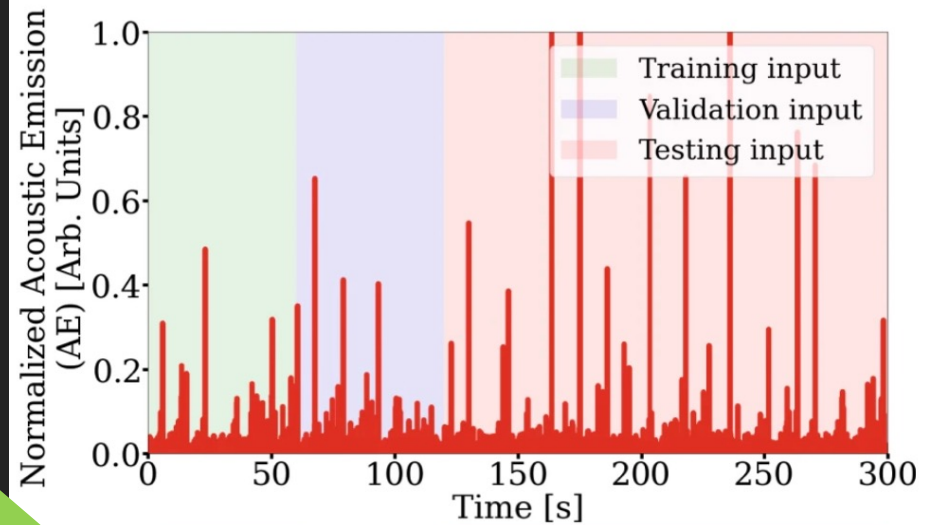
ENCODER-DECODER MODEL



MODEL INPUT AND OUTPUT DATA SETS



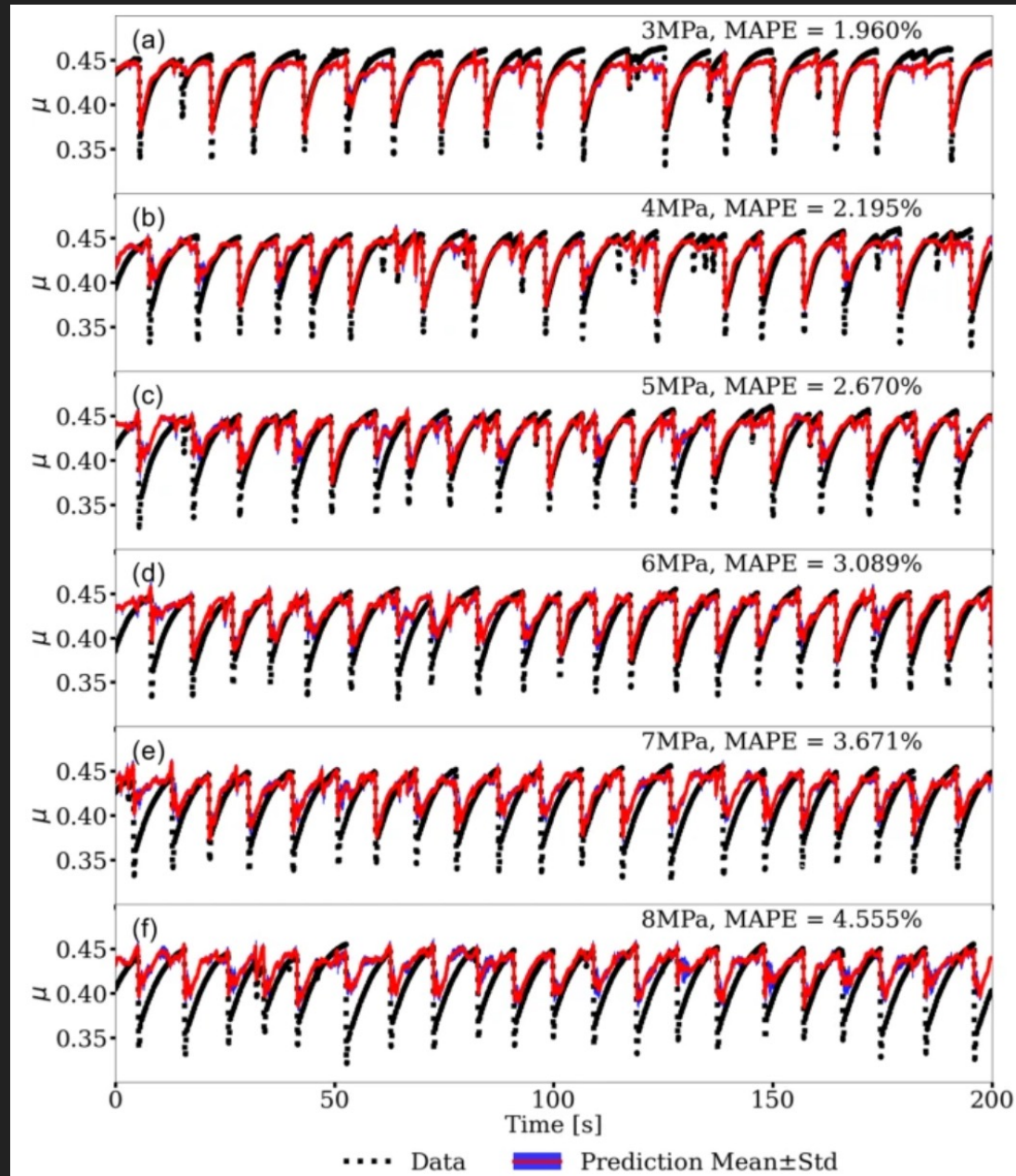
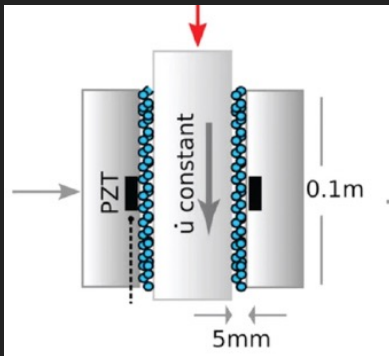
(a) FDEM simulation data



(b) p4677 experimental data

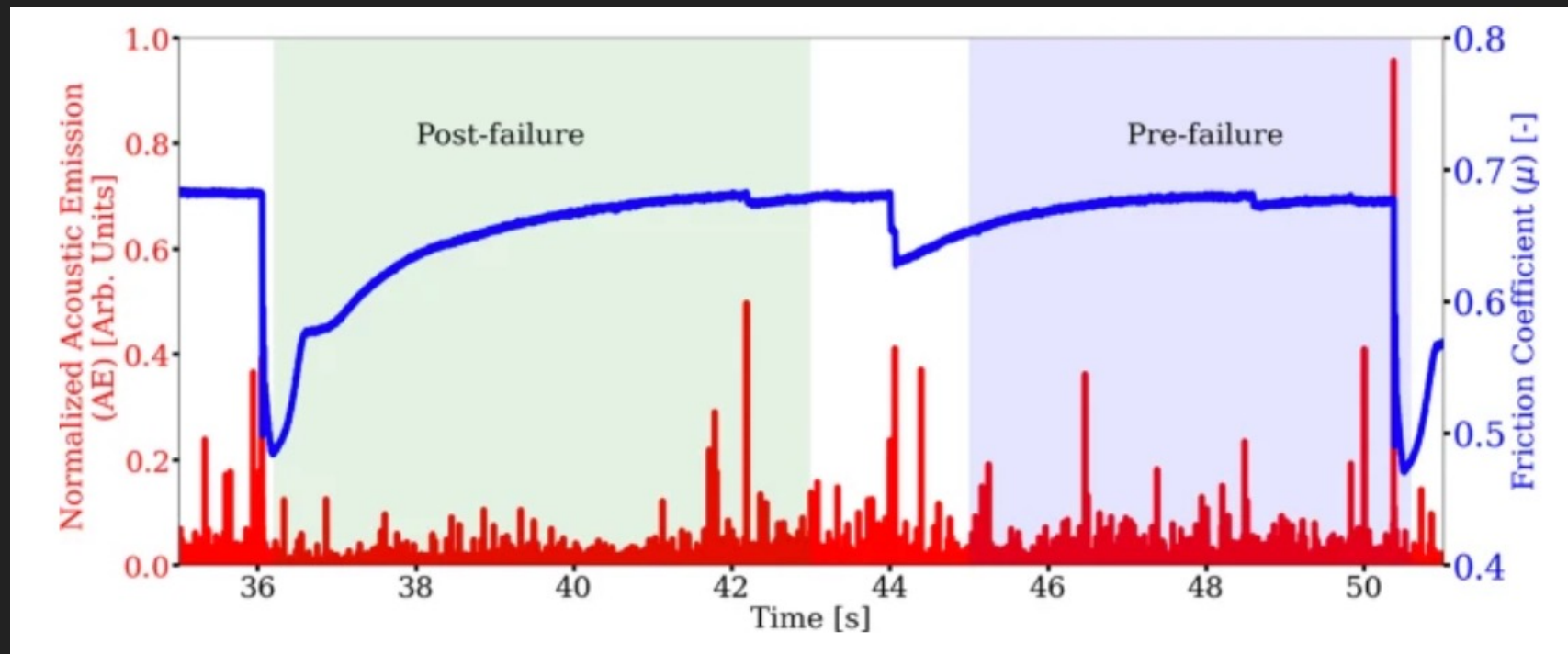
MODEL PREDICTIONS USING MODEL TRAINED ON SIMULATIONS

Model tested on a different laboratory experiment, conducted at 6 different applied loads.

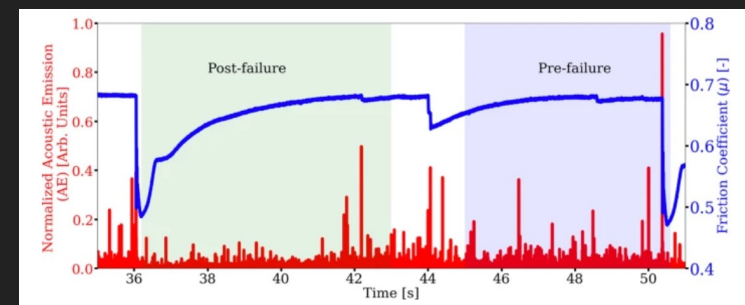
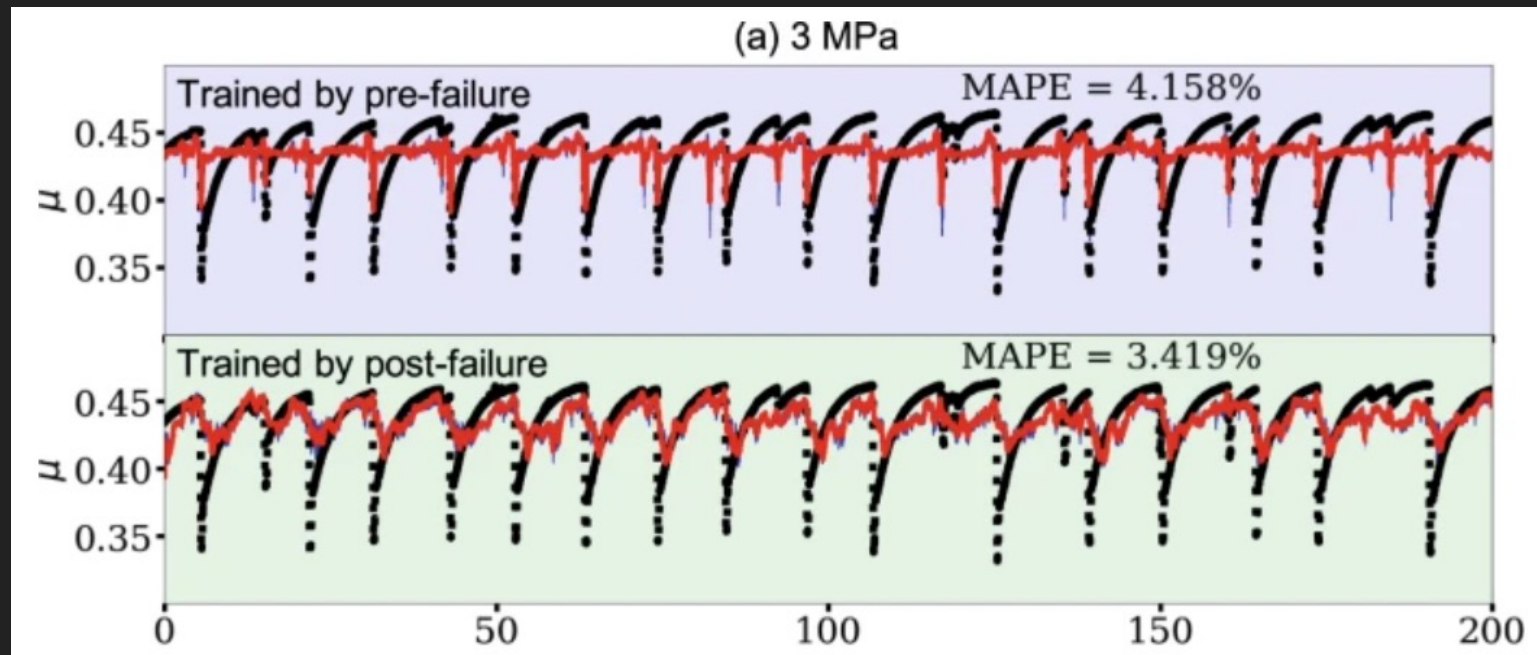


CROSS TRAINING WITH GOAL OF DEVELOPING AN APPROACH FOR FAULTS IN EARTH

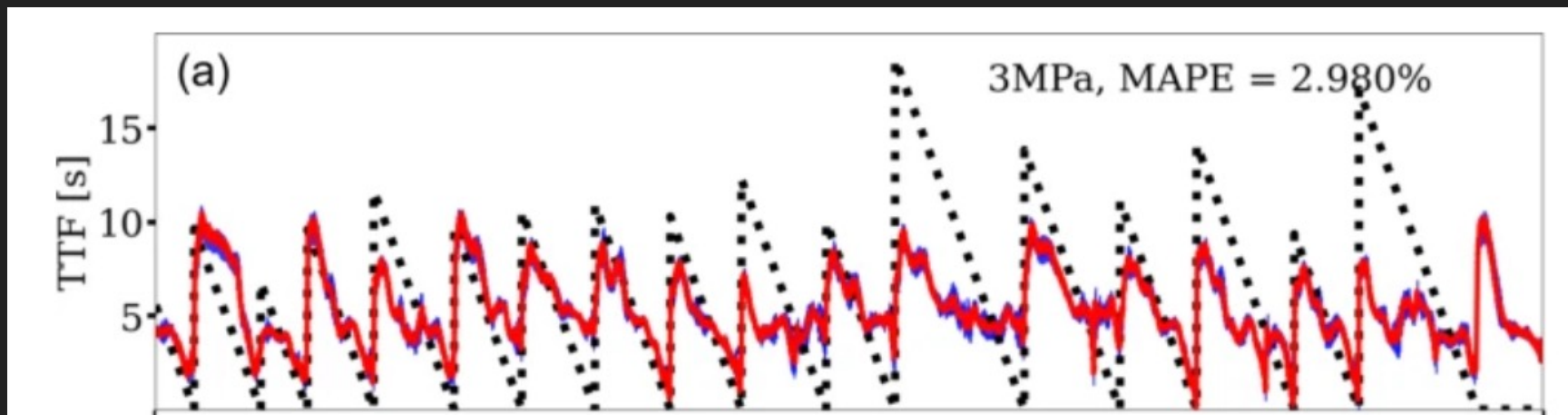
USING TRAINED MODEL, AND RETRAIN ONLY THE LATENT SPACE



CROSS-TRAINED ENCODER-DECODER MODEL PREDICTIONS



CROSS-TRAINED ENCODER-DECODER MODEL PREDICTIONS: TIME-TO-FAILURE



2-PRONGED APPROACH TO SEISMOGENIC FAULTS IN EARTH

- ▶ Train on simulations of earth faults and test on actual faults, using seismic data as input and surface displacement as target
- ▶ Use a frictional model in the deep learning model with the same input and target.



<https://epod.usra.edu/blog/2006/11/elkhorn-scarp-along-san-andreas-fault.html>



TAKE HOME MESSAGE

**THE 'NOISE' IS THE
SIGNAL GIVING INSIGHT
IN TO FAULT PHYSICS.**

ML TOOLS REVEAL IT.