Early warning for great earthquakes from characterization of crustal deformation patterns with deep learning

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Showcasing work from:
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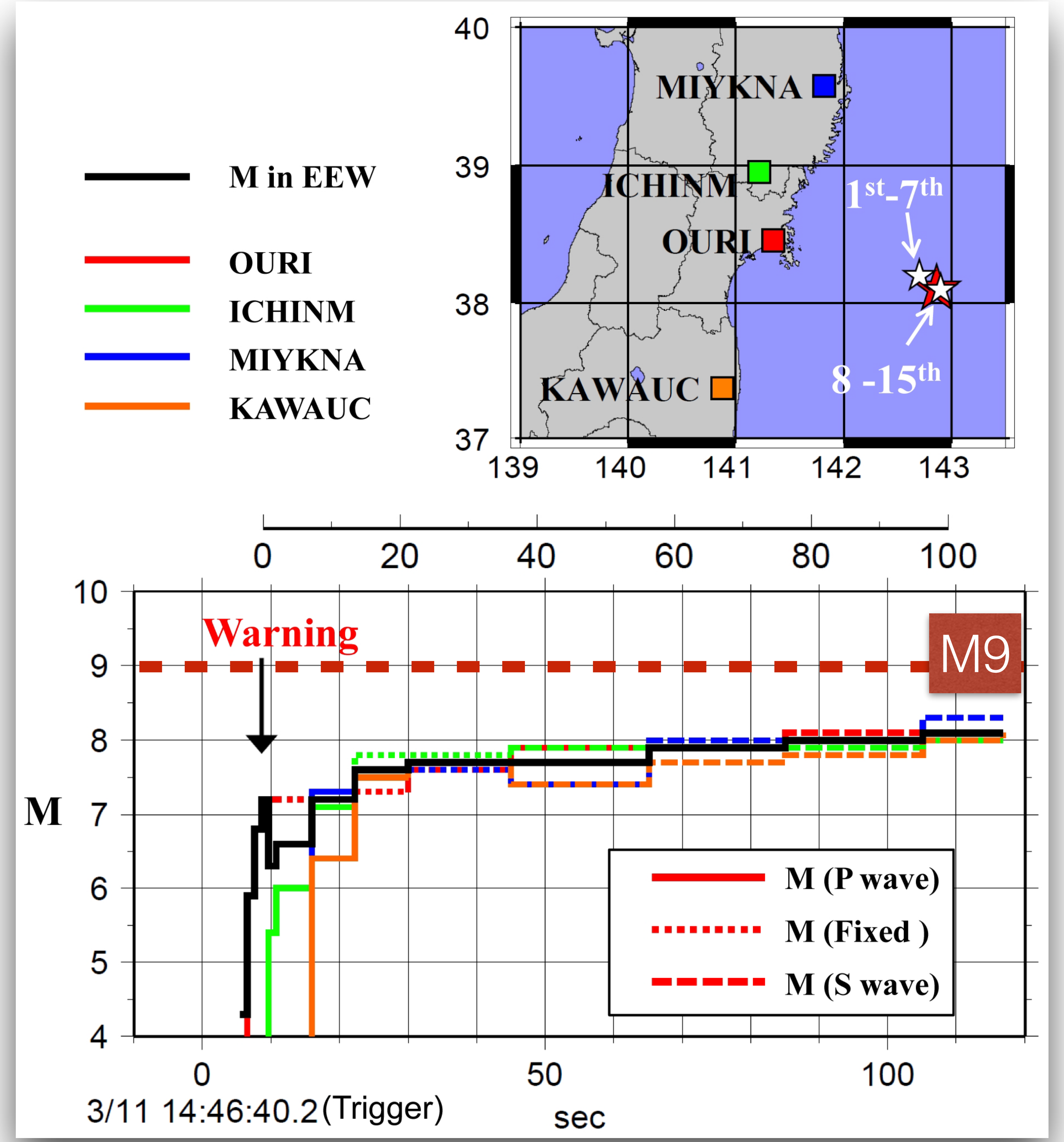
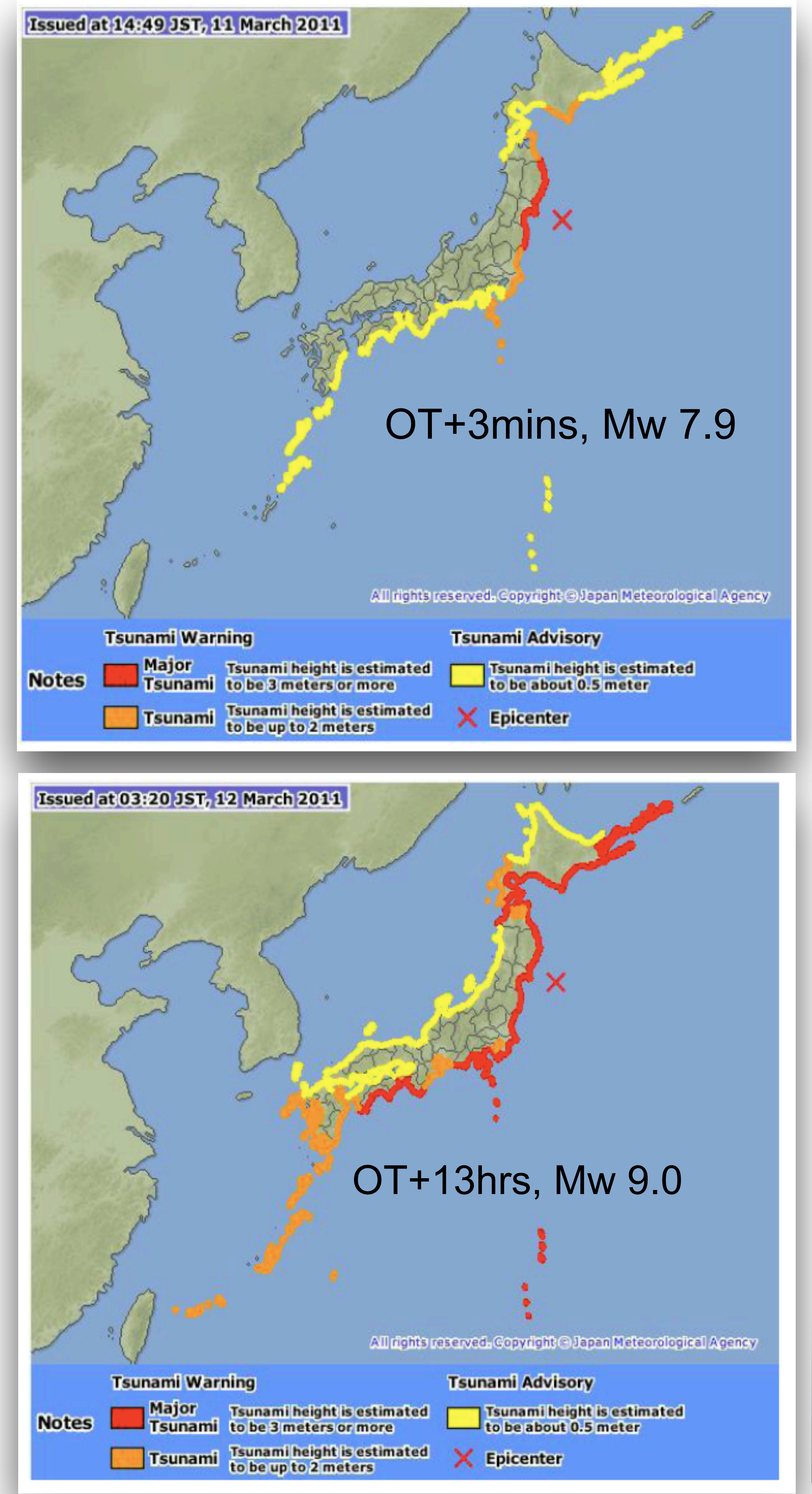
Image: Earthscope Consortium
All EEW/TEW systems operational today have issues with saturation at ~M7.5
And GNSS is a great fix but it needs help from ML
7 visible satellites
Wikipedia

The Tohoku Experience: Magnitude saturation

- Modern systems “saturate” at about M7.5



Hoshiba & Ozaki, 2014



Ozaki et al, 2011, EPS

Why?

- Physics:
  - Are ruptures deterministic?
- Sensors:
  - Inertial sensors are affected by baseline offsets (rotations)

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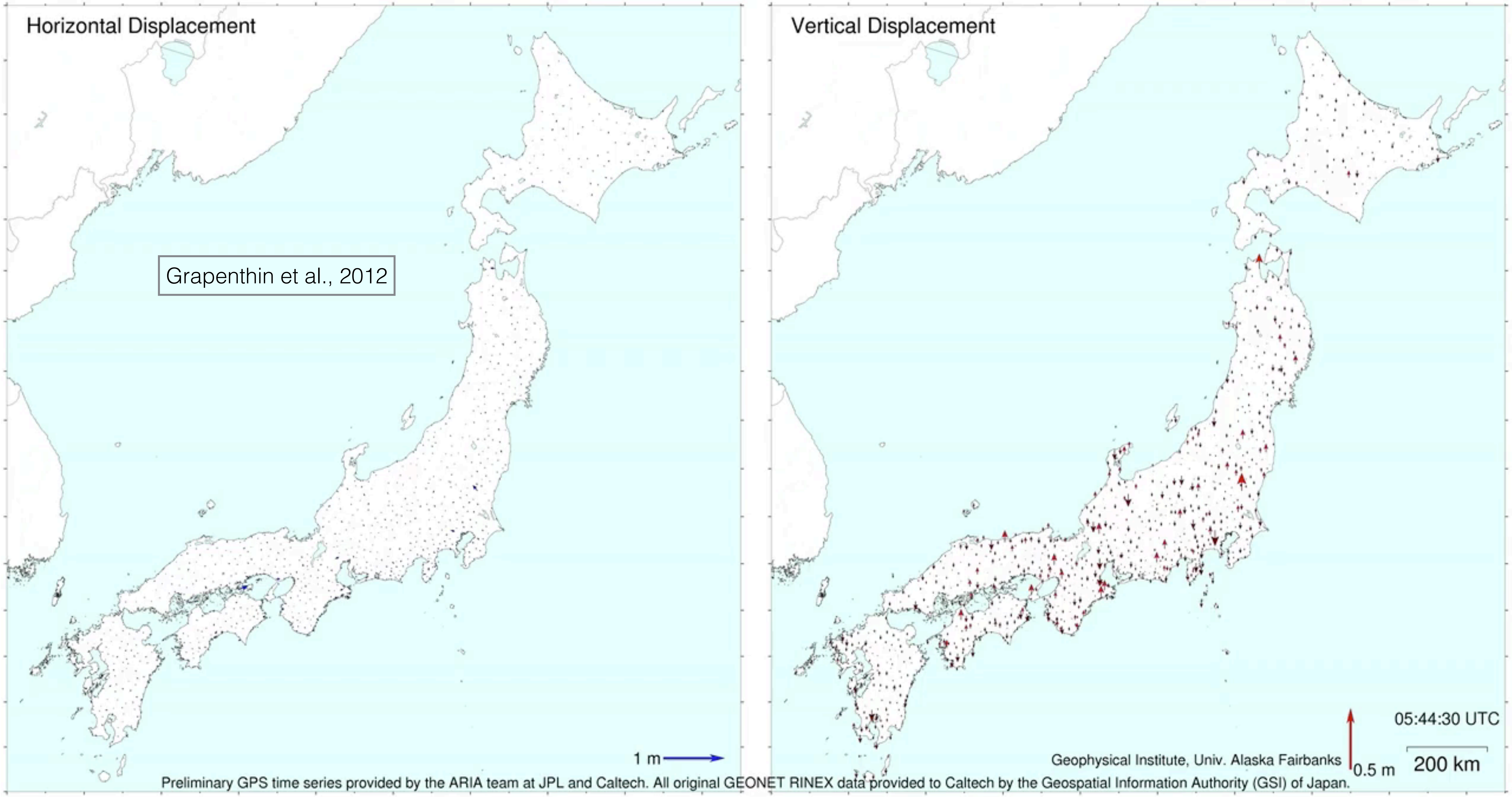
High-rate GNSS (GPS)



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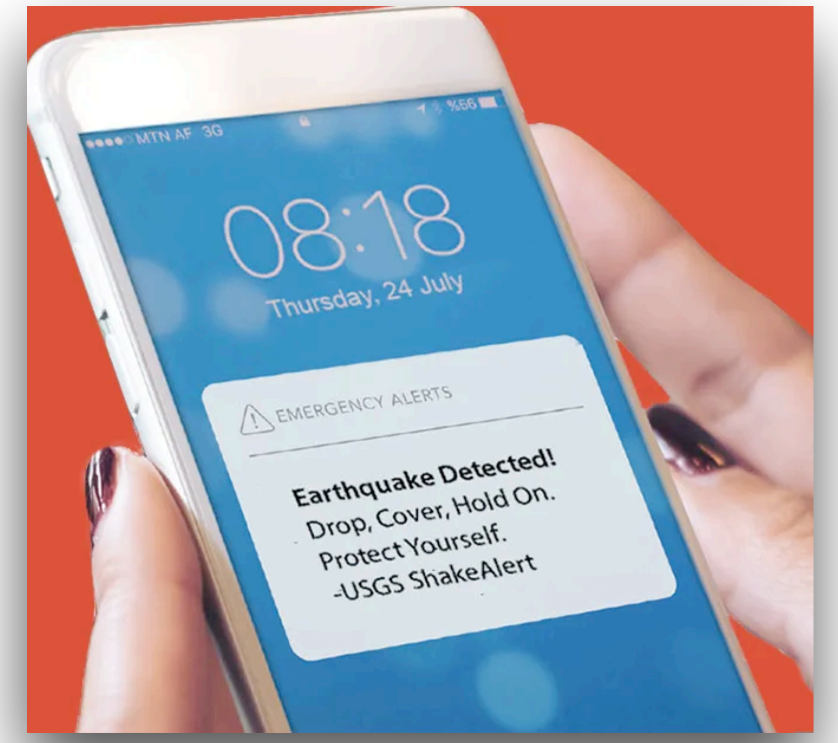
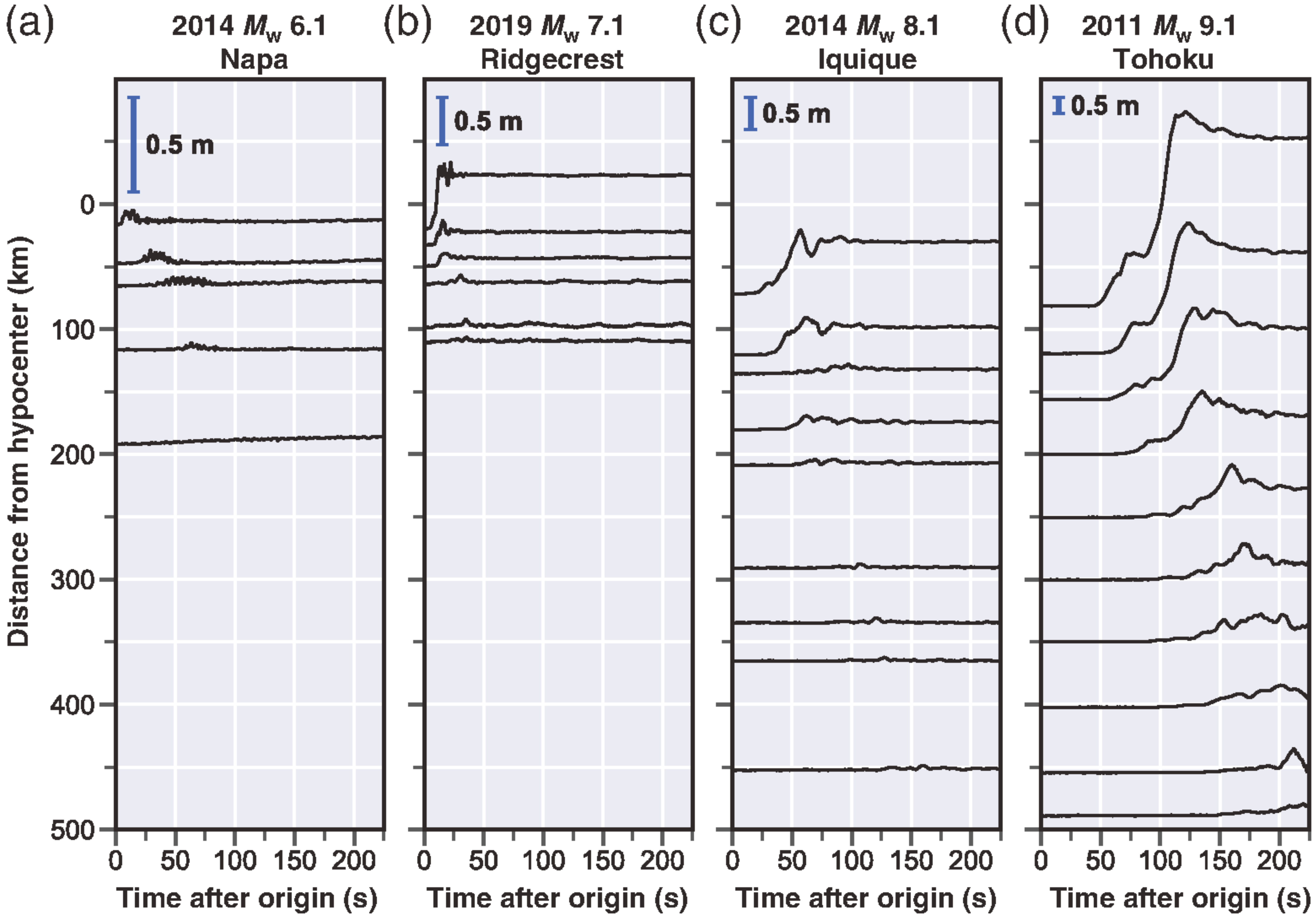
A HR-GNSS workflow

- GNSS is a **frontline** instrument in earthquake and tsunami early warning
  - It's already in ShakeAlert
  - It's in testing at NOAA



High-rate GNSS (GPS)

- There are two issues, both can be fixed with ML
  - **RT-GNSS is noisy** (2-5cm)
  - Big EQs are complex (i.e. not point sources), **traditional algorithms don’t work very well**



Goldberg et al, 2021

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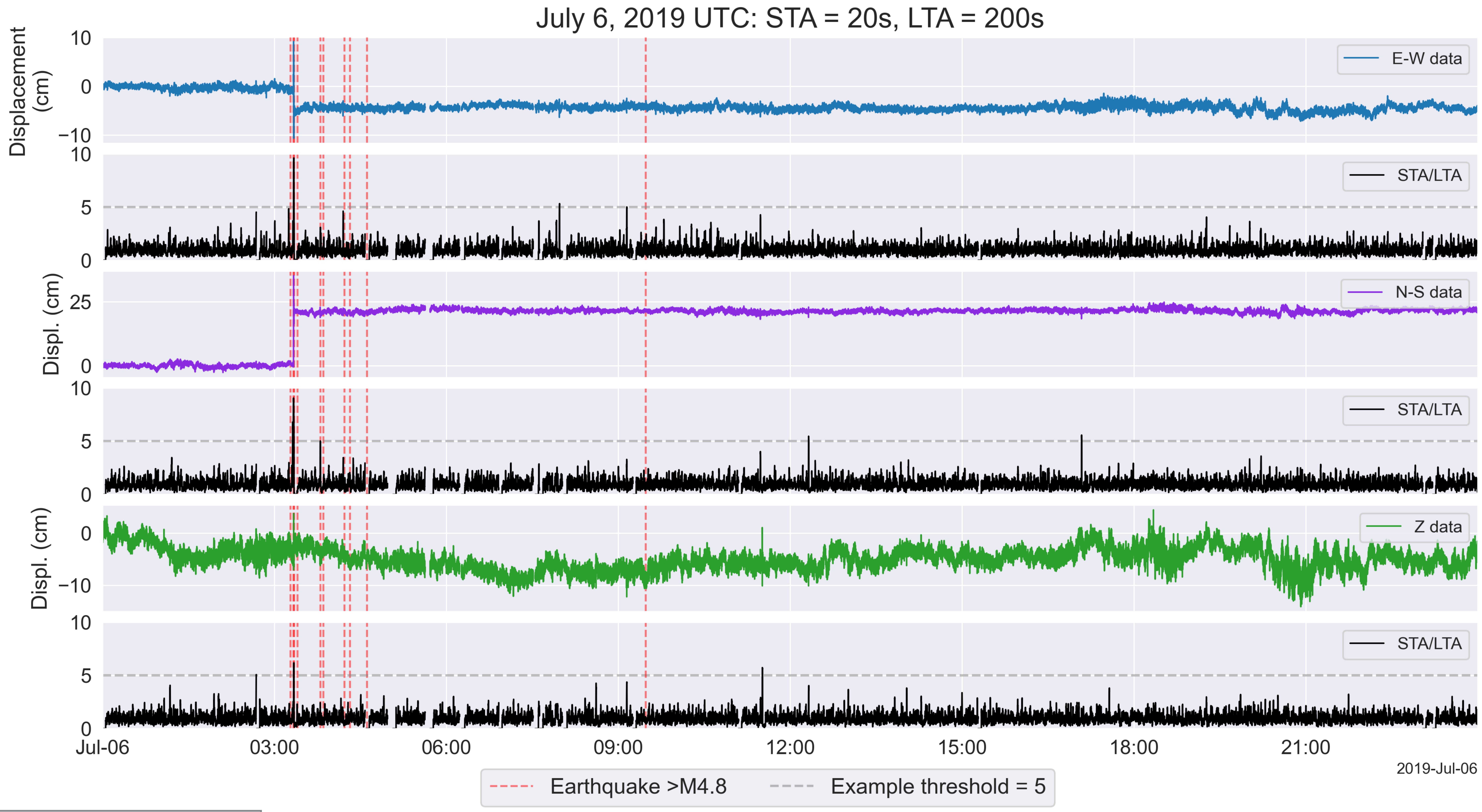
GNSS is noisy



Dybing et al., in prep

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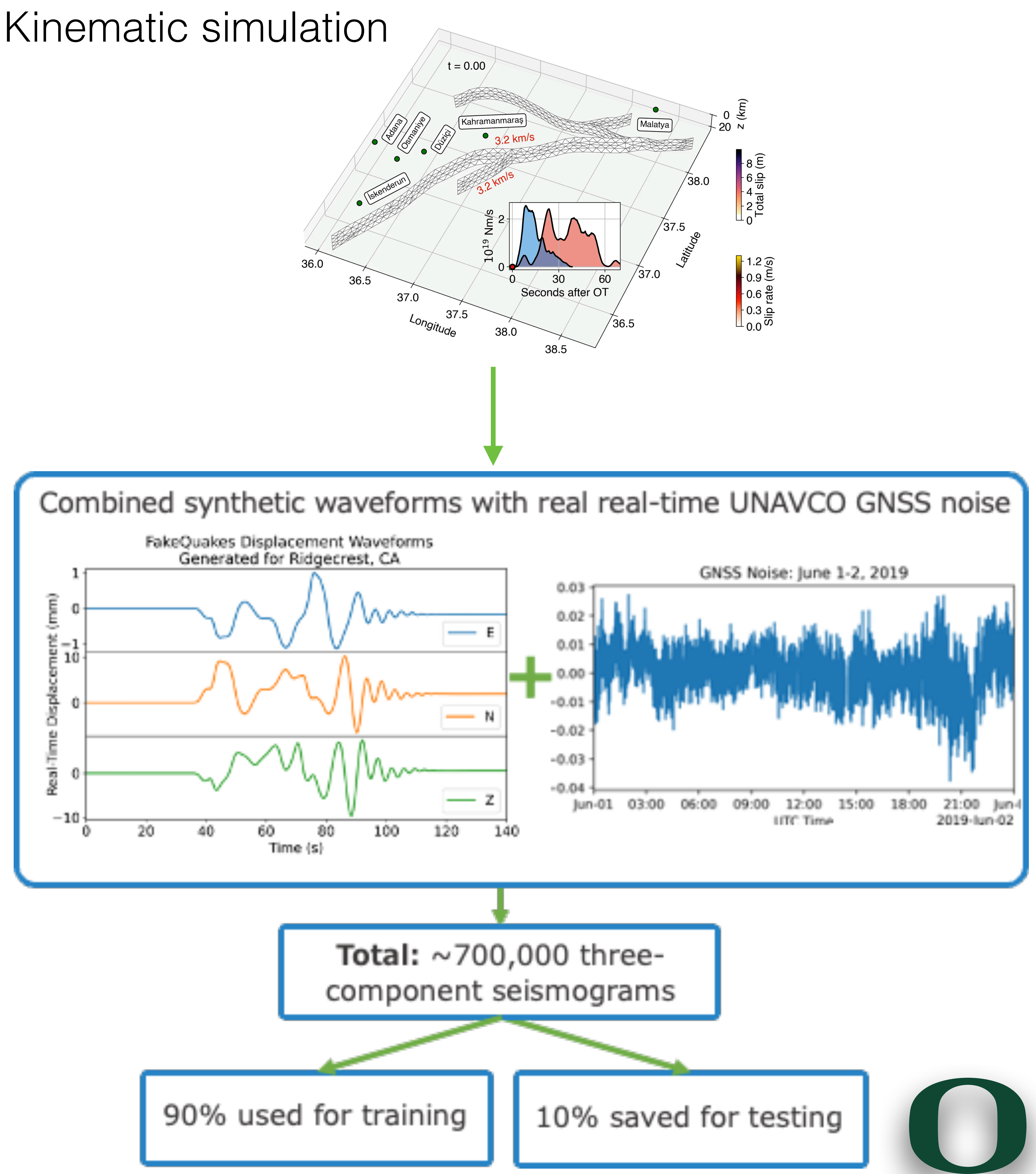
A U-net picker for RT-GNSS

- Because of the amount of noise at present **GNSS is only used if there's an external trigger** by the seismic network
- That's an ok stop-gap but ti **does not guarantee good quality data**
- We built an **ML GNSS picker** to remove the seismic dependency
- U-net convolutional neural network model architecture (Ronneberger et al., 2015)



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Don’t let the noisy data through

- Predicts **EARTHQUAKE**: model produces a Gaussian at its chosen P-wave arrival time
- Predicts **NOISE**: model produces zeros (or small numbers close to zero)

Dybing et al., in prep

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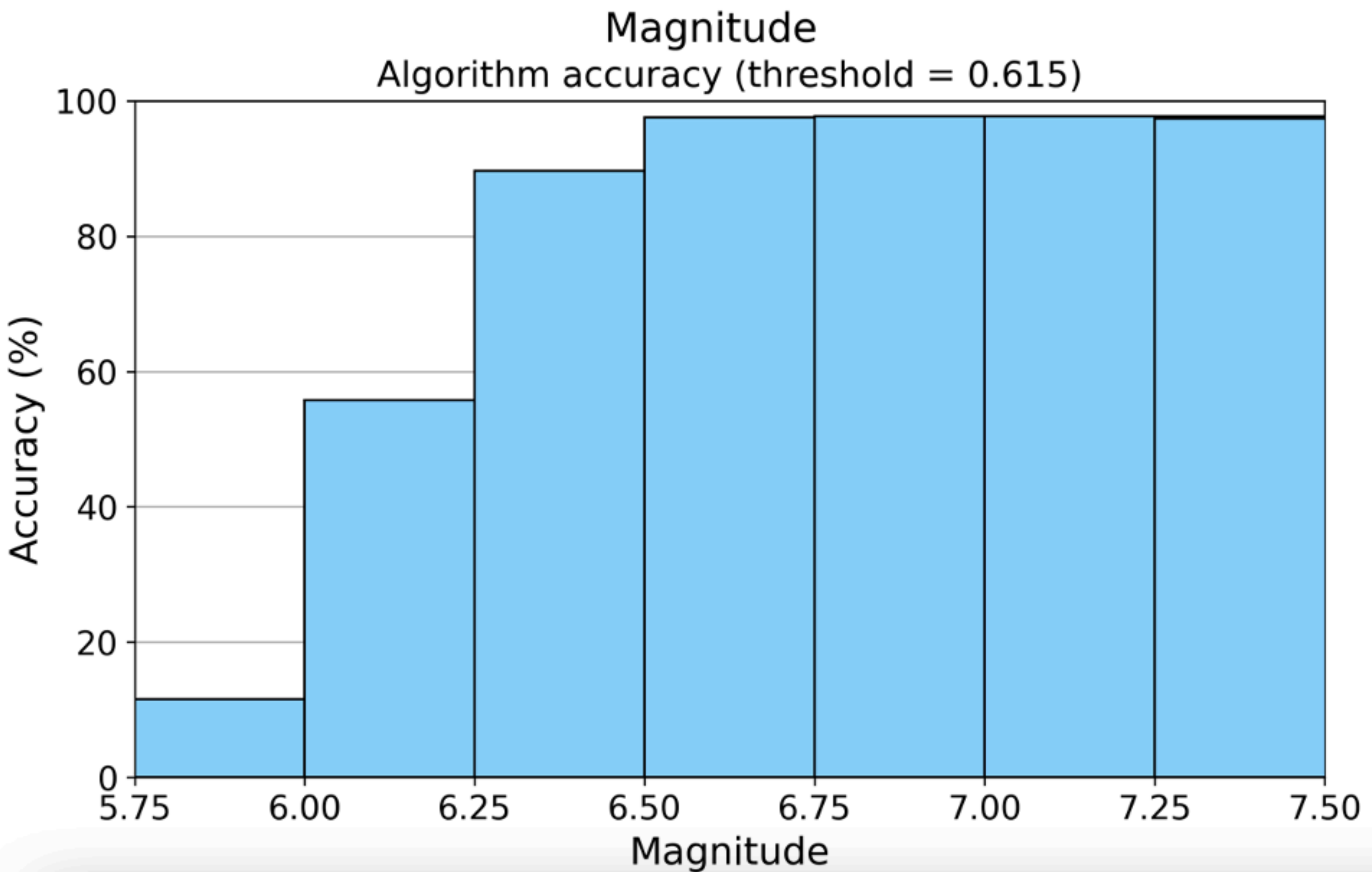

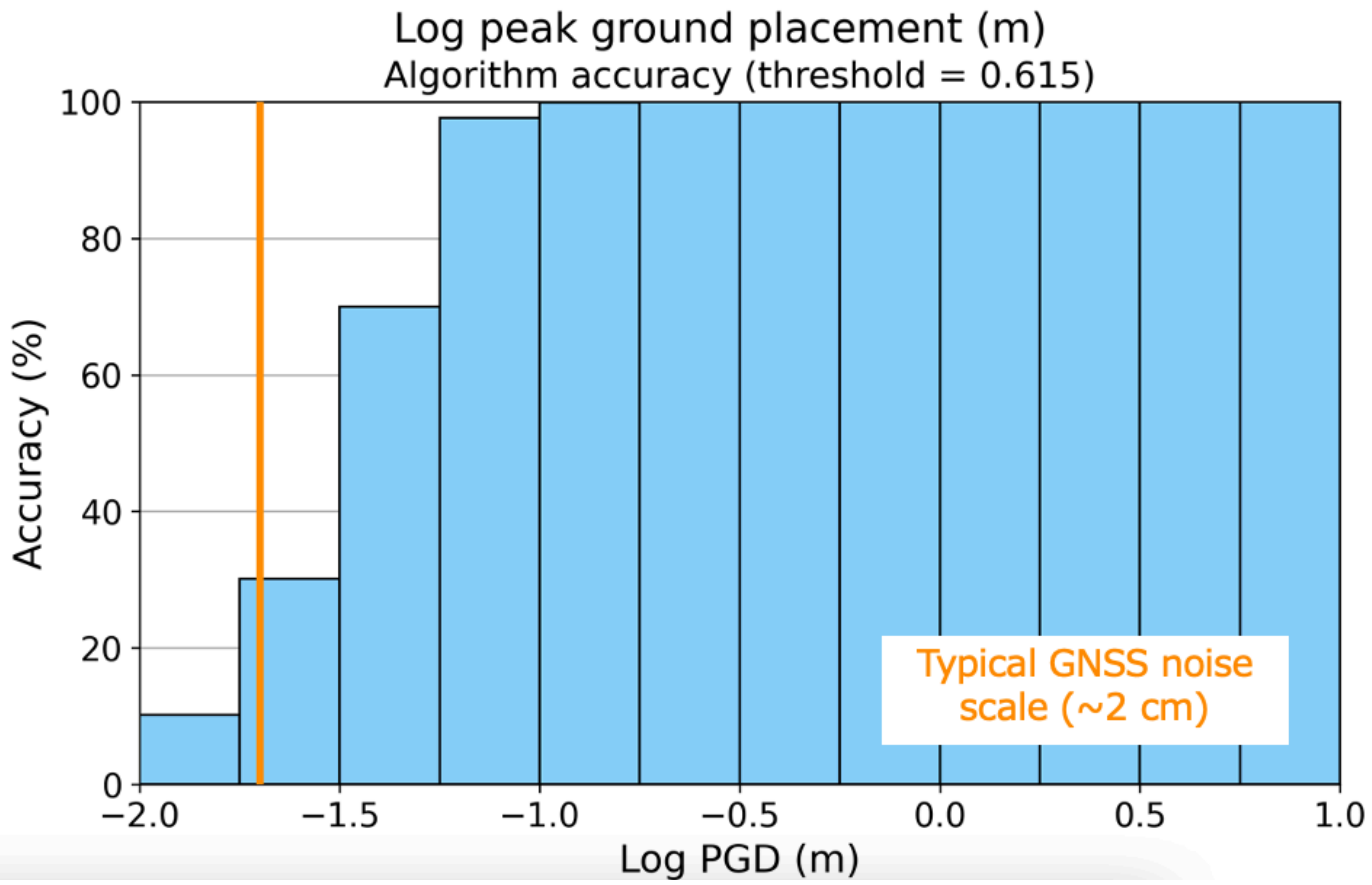

Dybing et al., in prep

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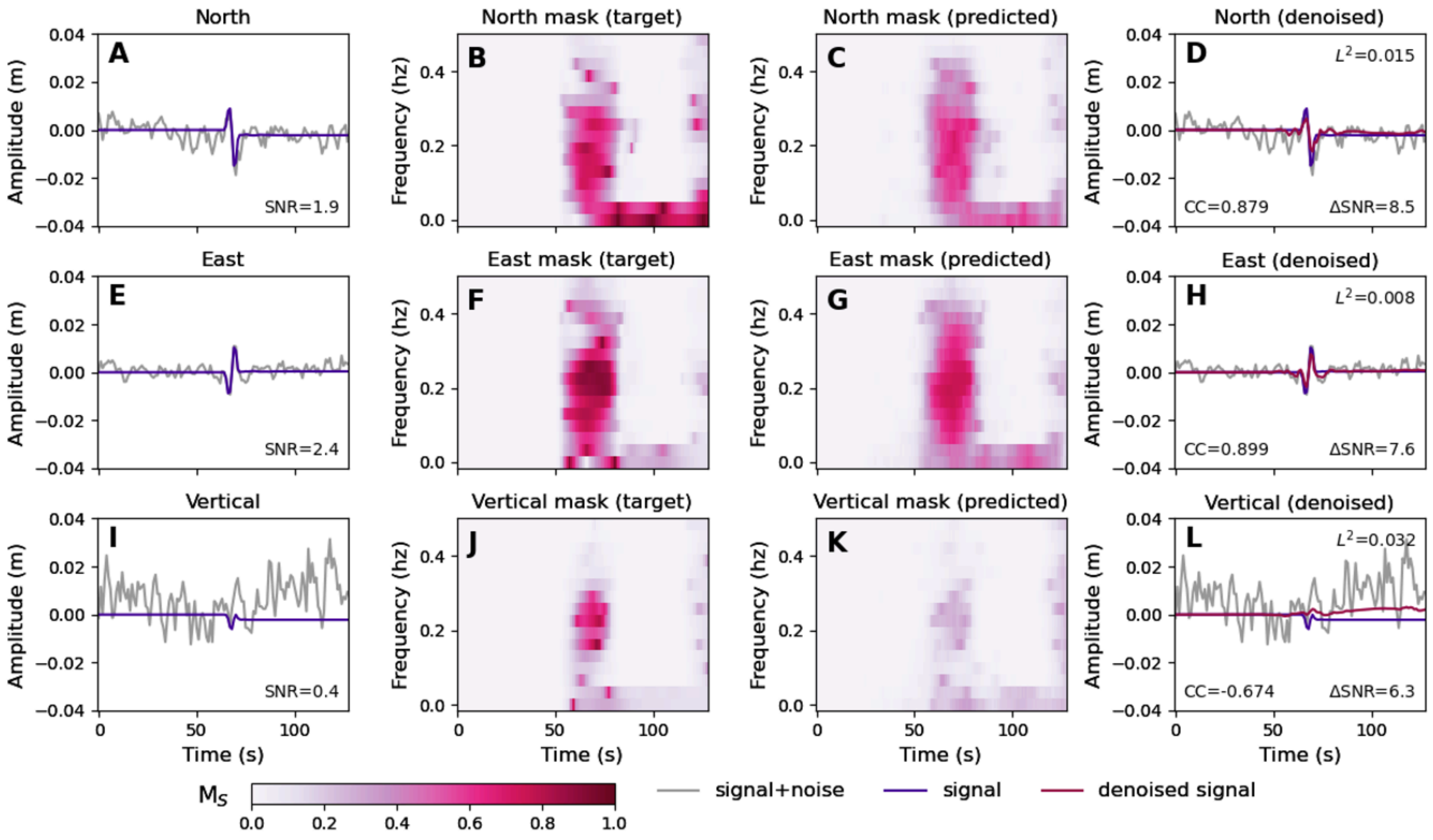
De-noise it if you can: Single stations approaches

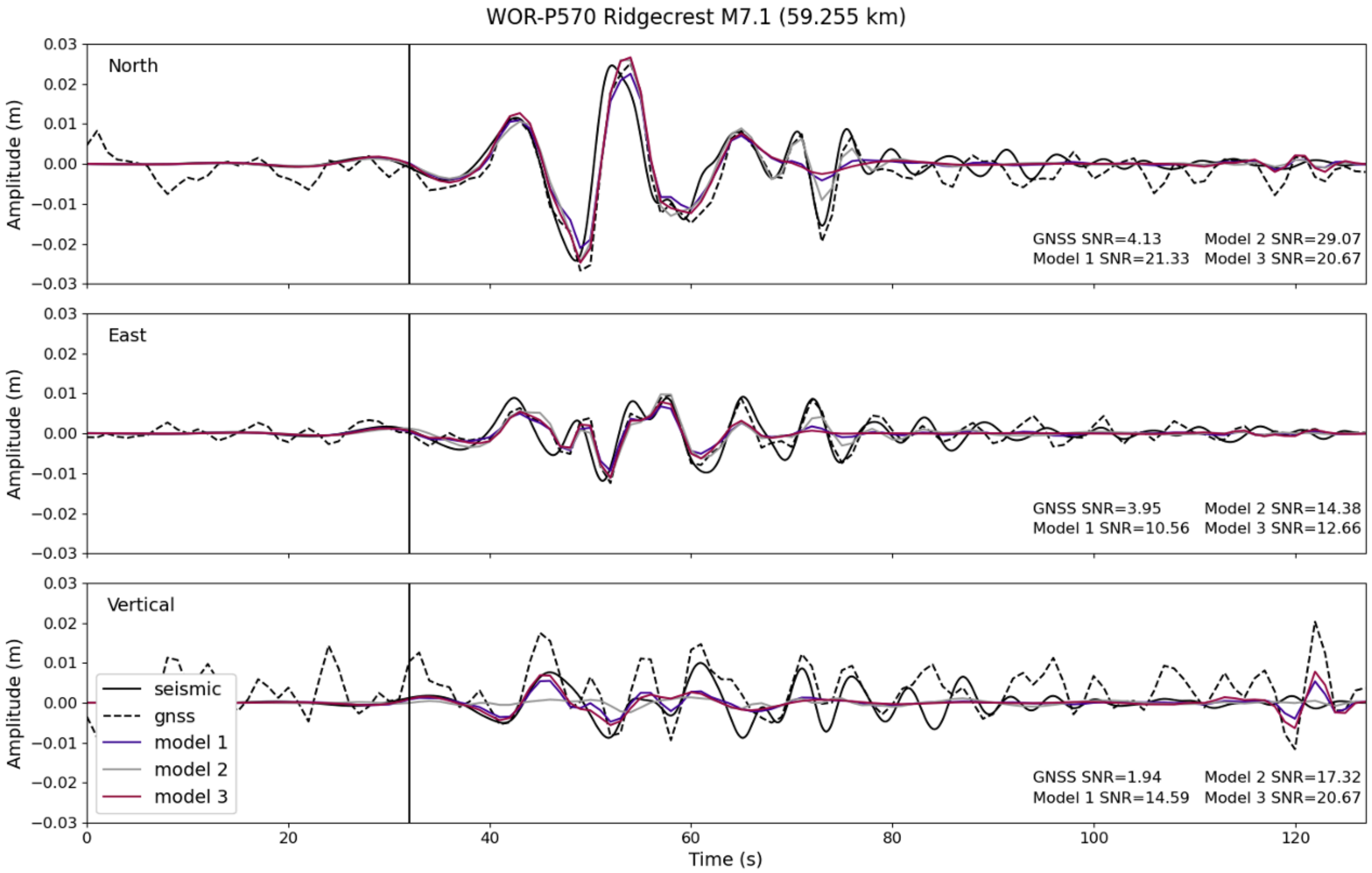
- Same **synthetic displacement waveforms + real noise** used for training picker
- CNN architecture similar to **Deep Denoiser** (Zhu and Beroza, 2019) but using three-component GNSS data
- Uses frequency domain information to **identify and remove the noise spectrum** while leaving the signal spectrum



Thomas et al, Seismica, 2023

De-noise it if you can: Single stations approaches

- Figure shows data from the **M7.1 Ridgecrest** EQ, including integrated strong motion data, recorded and denoised GNSS
- Denoising **before** the P-wave works well
- Struggles with the coda
- **Missing basin/site effects** in synthetic training data – only 1D velocity model used



Thomas et al, Seismica, 2023

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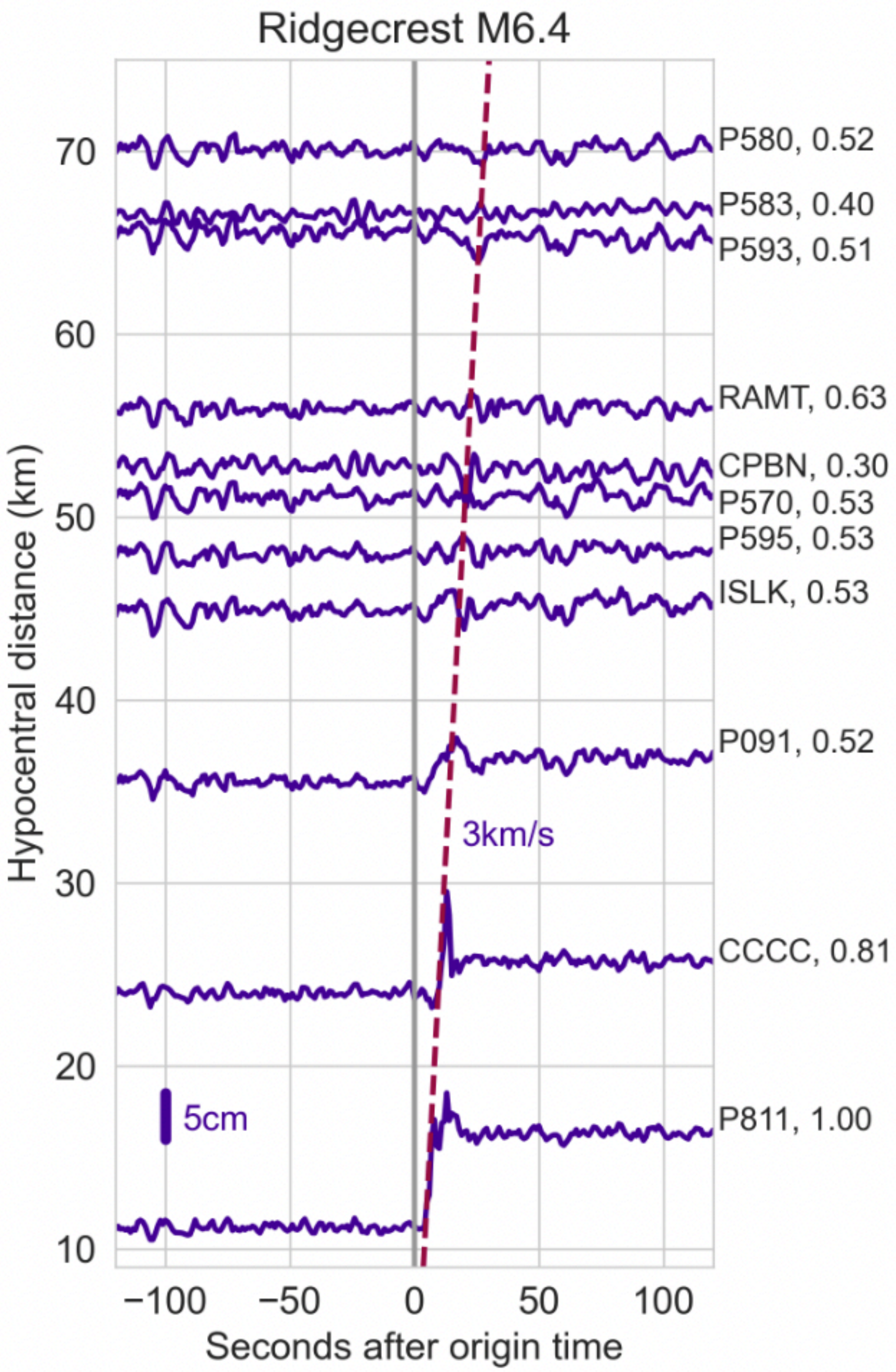
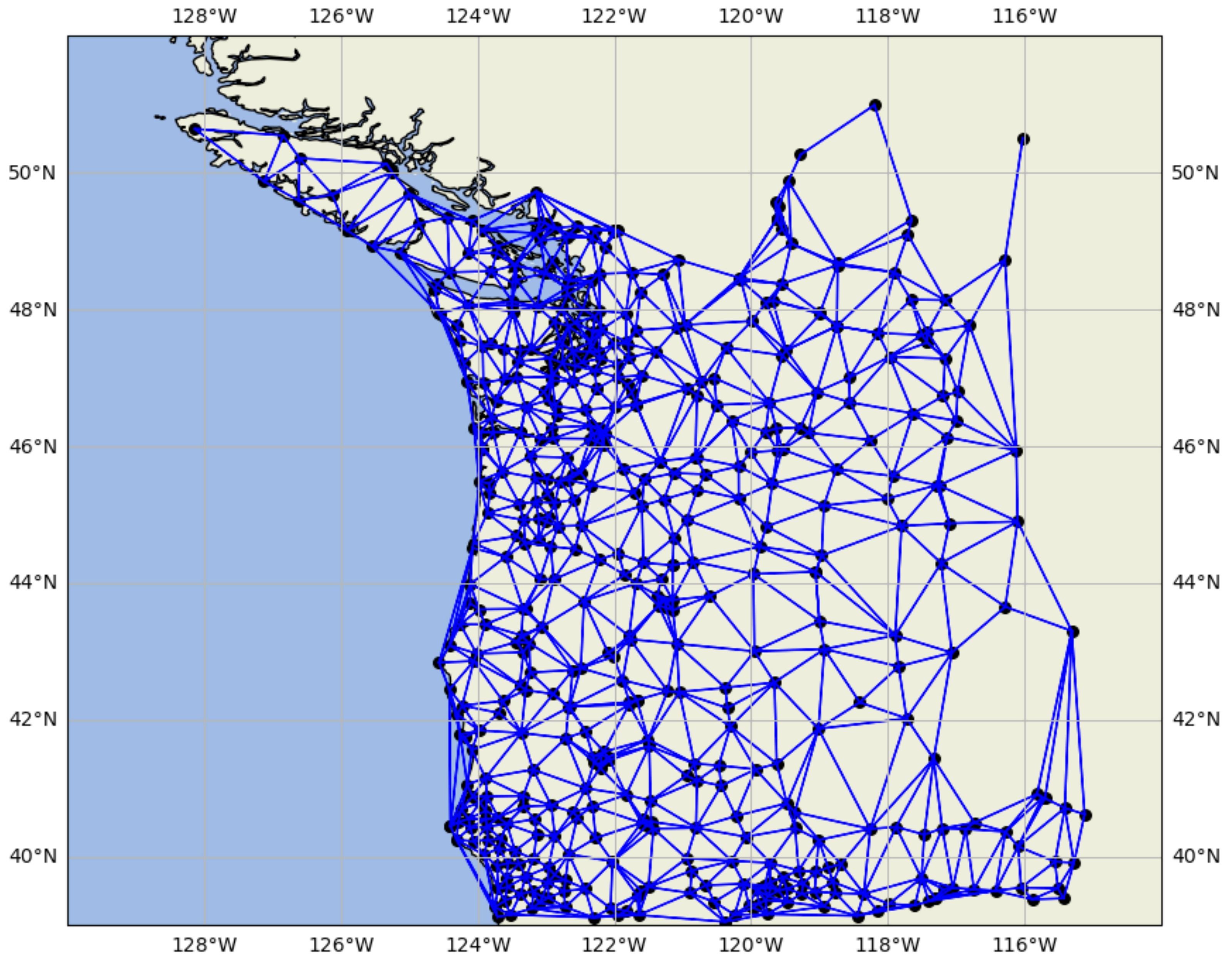
De-noise it if you can: Take advantage of network correlations

- There is a lot of **"network" or correlated noise** in GNSS
- We are building a **graph neural network** algorithm to take advantage of this
  - Message passing layer to exchange info between stations
  - Prediction per station
- Of use for **daily and sub-daily** positions



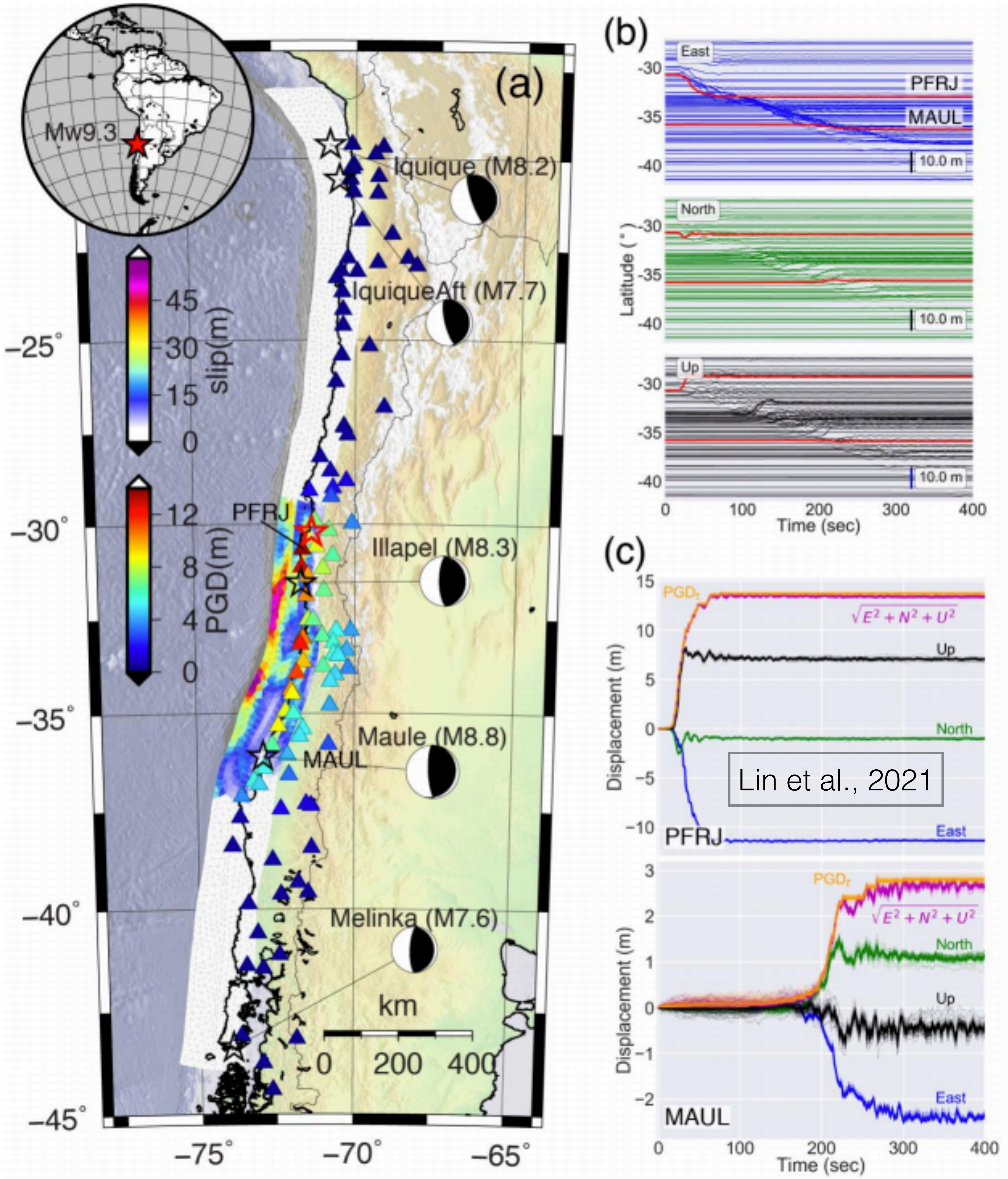
Thomas et al., 2023

Bachelot et al., in prep

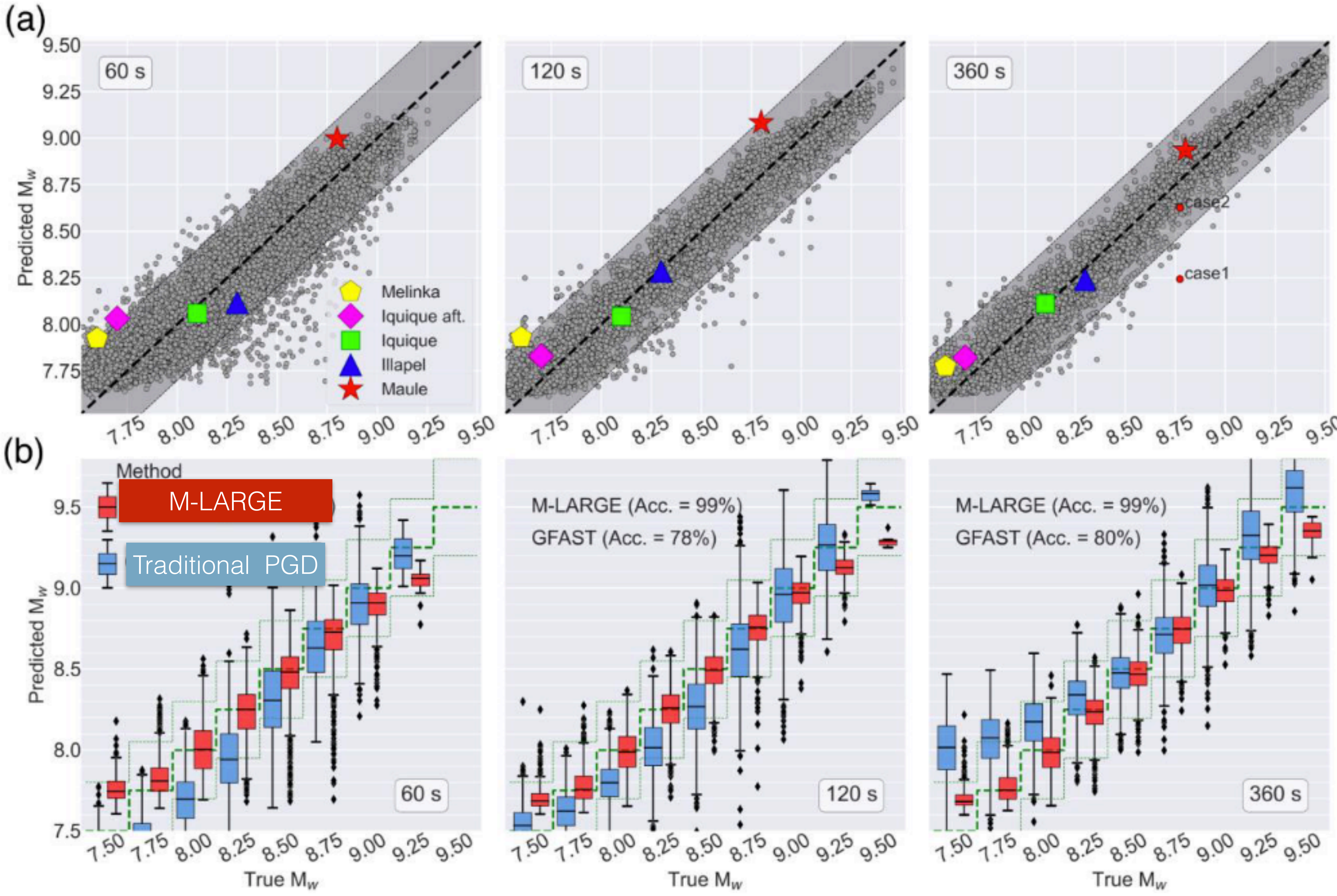


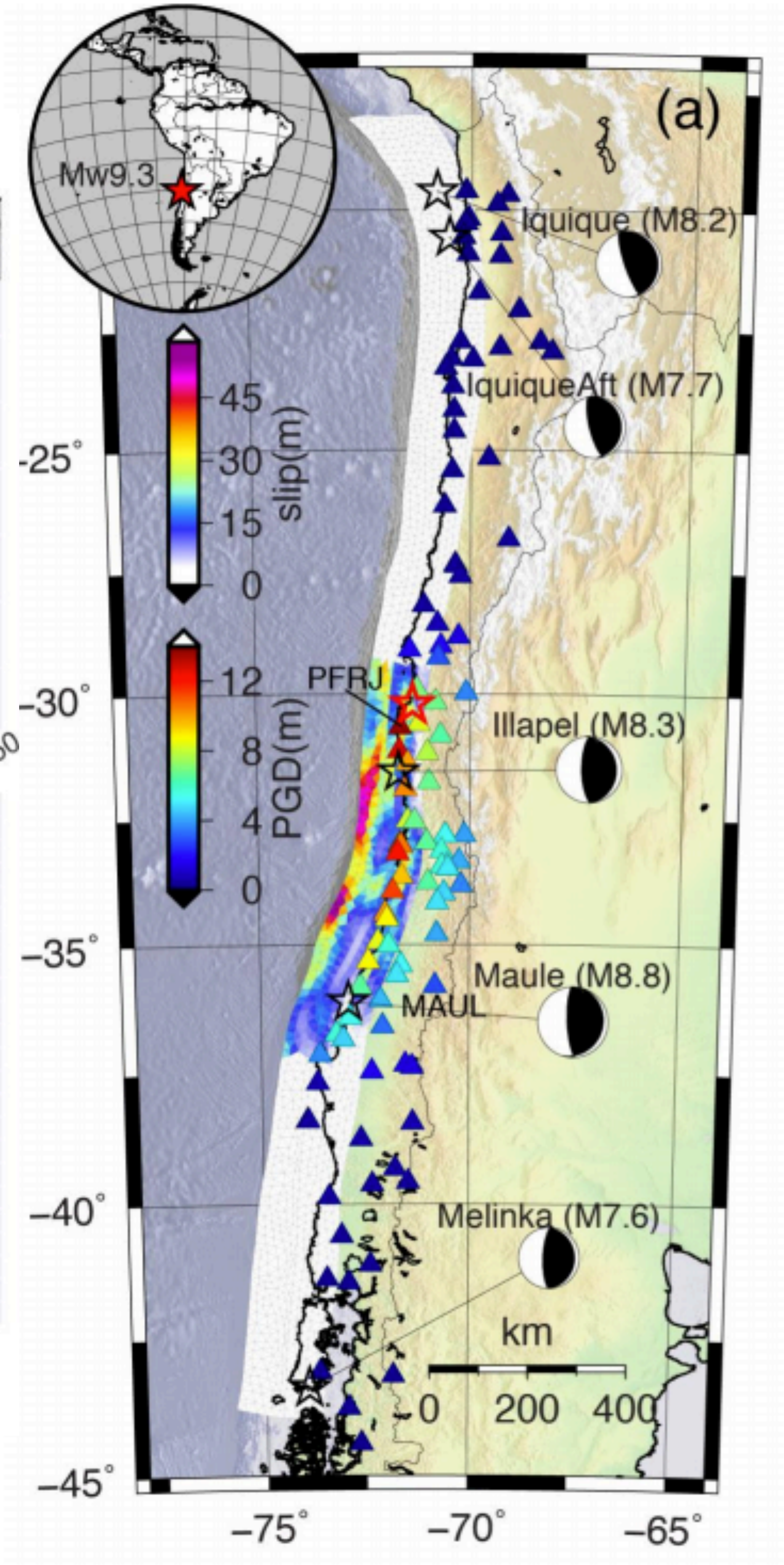
And finally characterize the event and forecast hazards

- We have built an RNN algorithm (**M-LARGE**, Lin et al, 2021, 2023) to characterize EQs and shaking hazards
- Pick rupture from available **simulations**
- Add realistic GNSS noise
- Train algorithm that updates every 5s
- Randomly remove stations to simulate real-world conditions
- Train with 80% validate with 20%
- Labels are the final **source parameters** of the events
- Assess performance on **5 real events**



Validation: Timeliness of results





Lin et al., 2021

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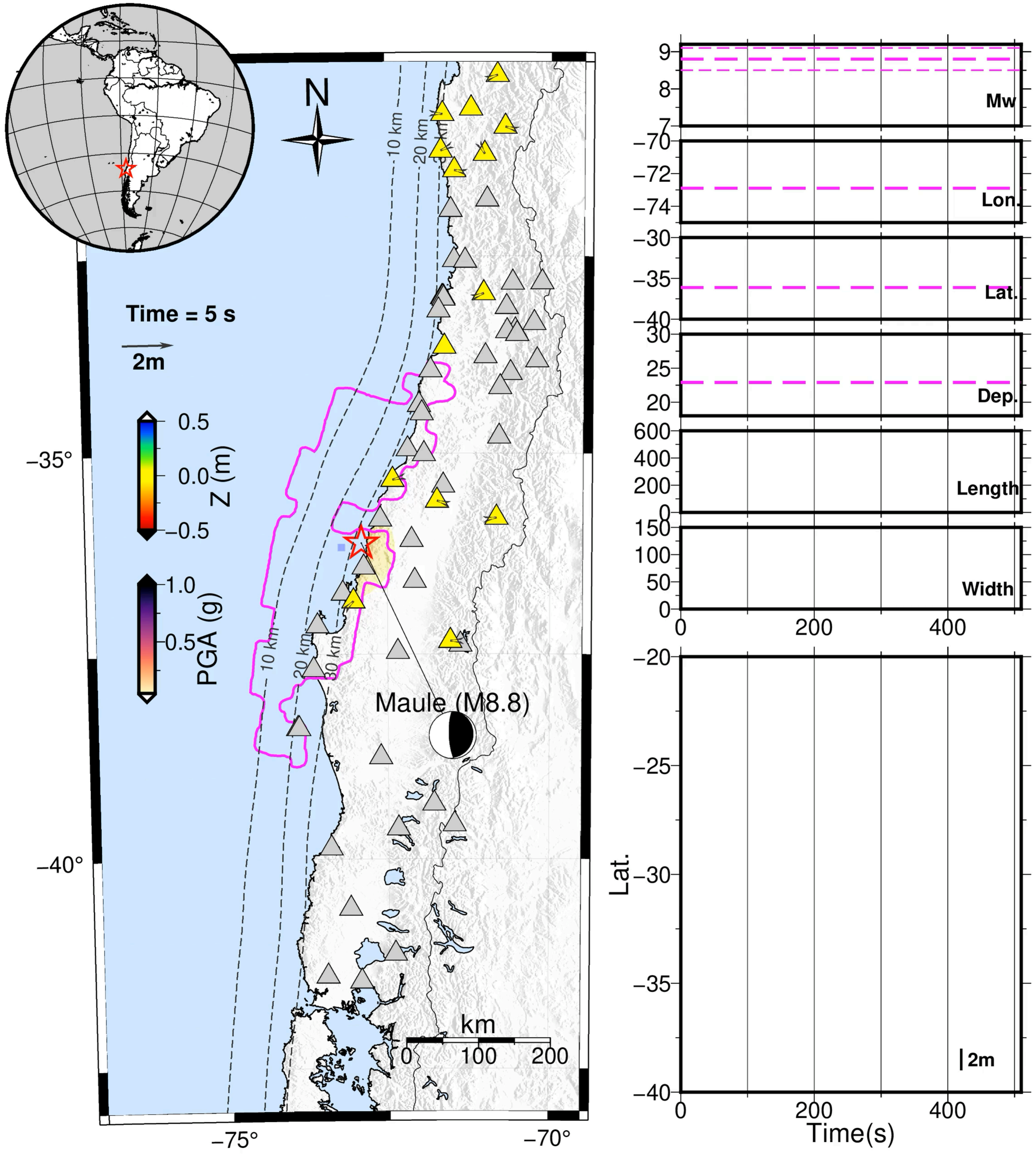
But who cares about the earthquake?

- Predict the **extent of faulting** (the rupture polygon)
- This is the most important thing for **forecasting shaking** in real-time
- Use ground motion to determine shaking everywhere

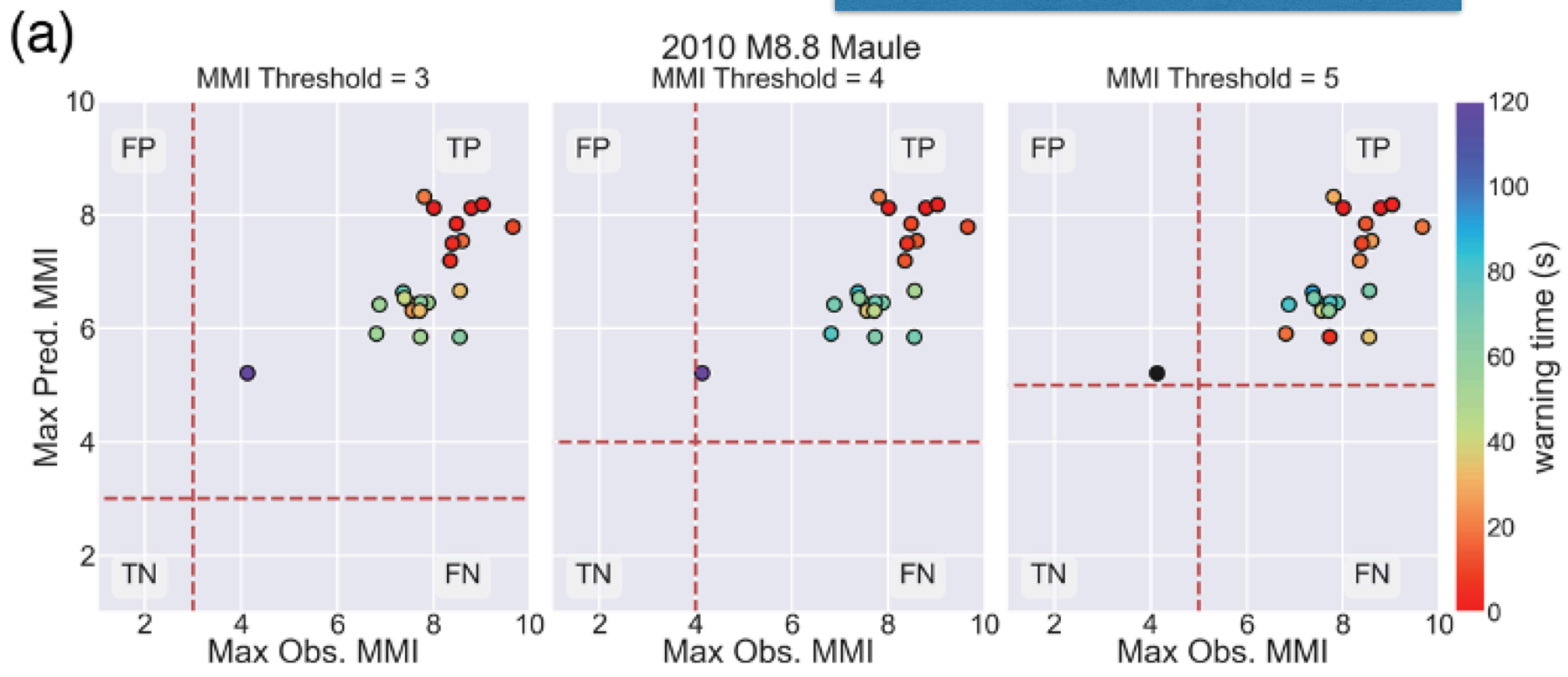
Lin et al., 2023



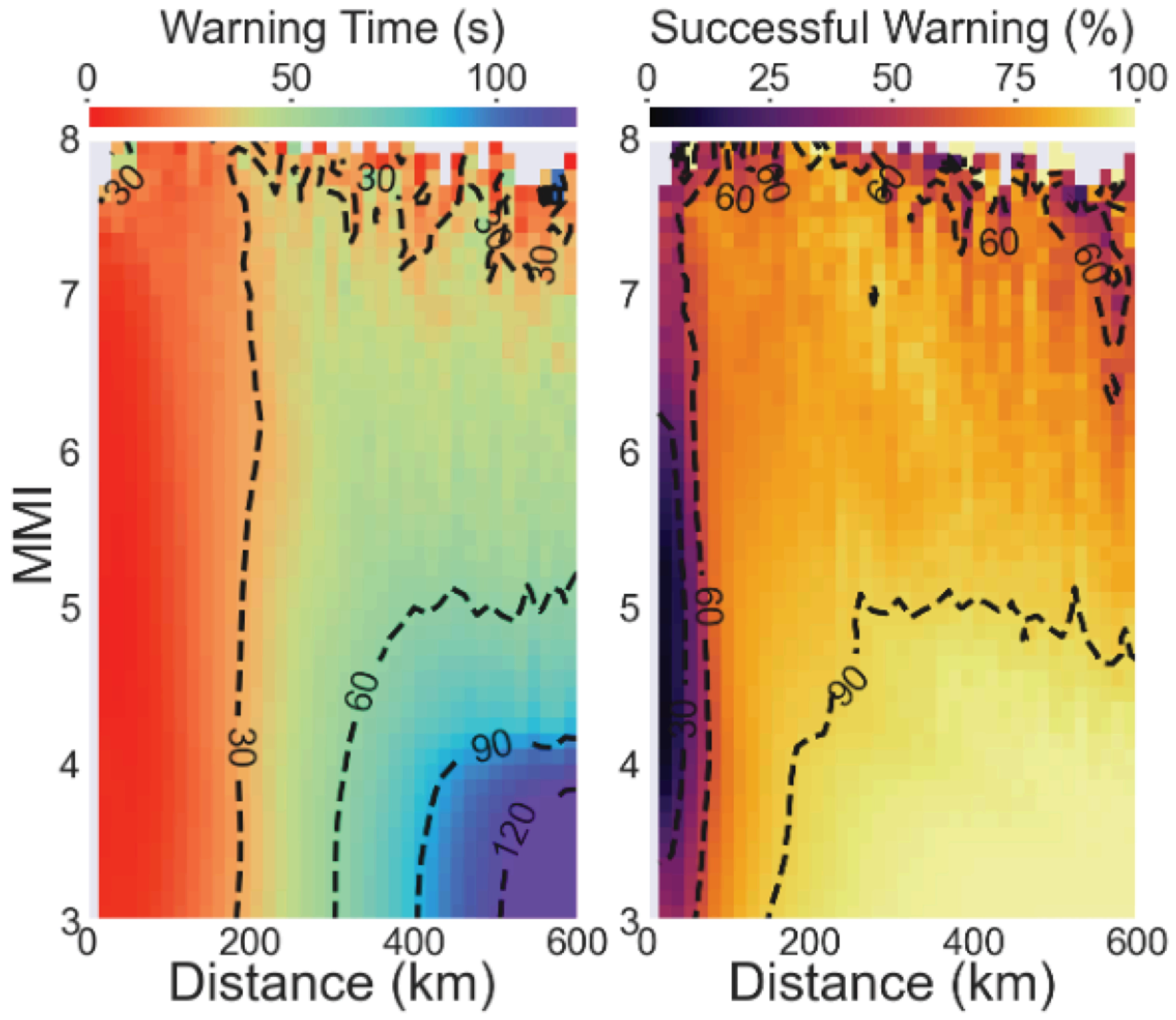
But who cares about the earthquake?

- Can accurately issue alerts with **meaningful warning times**
- Though accounting for **uncertainties** remains challenging

Alert timeliness in real event

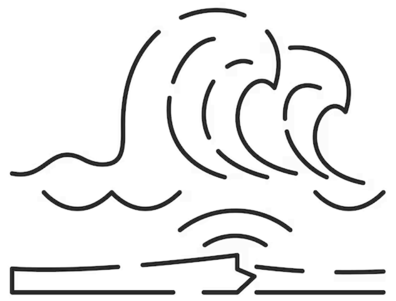


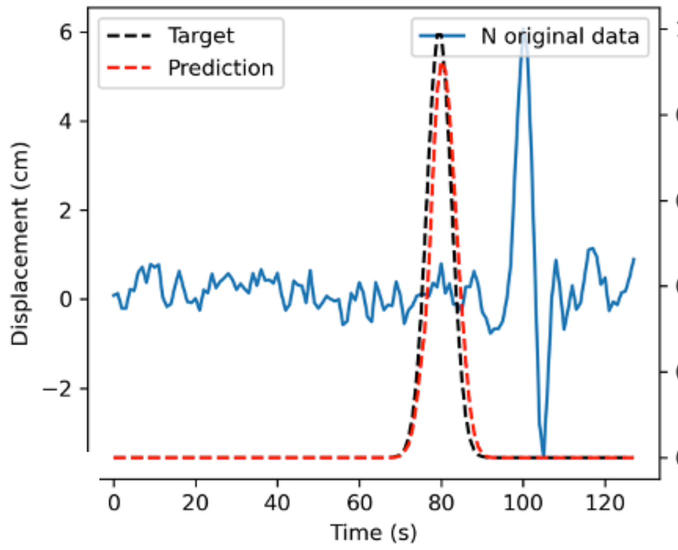
Lin et al., 2023

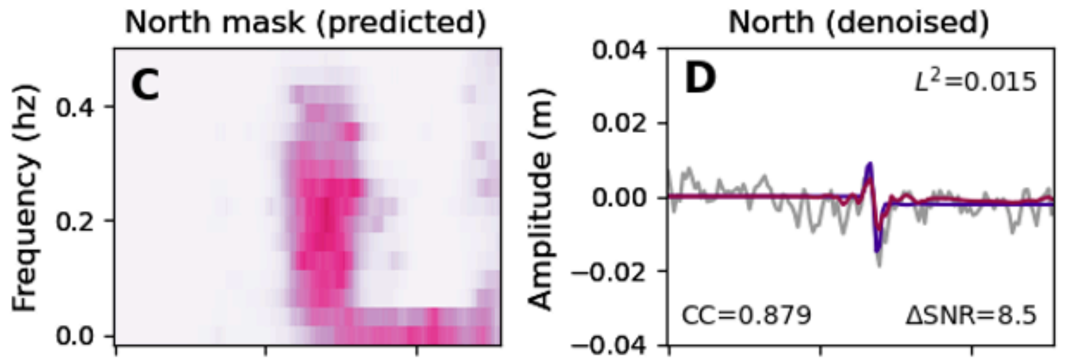


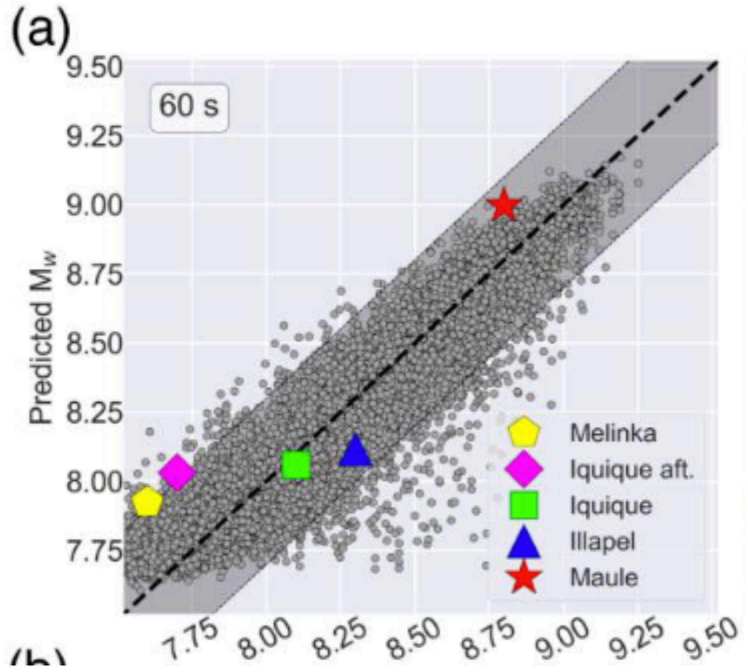
Alert timeliness in simulations

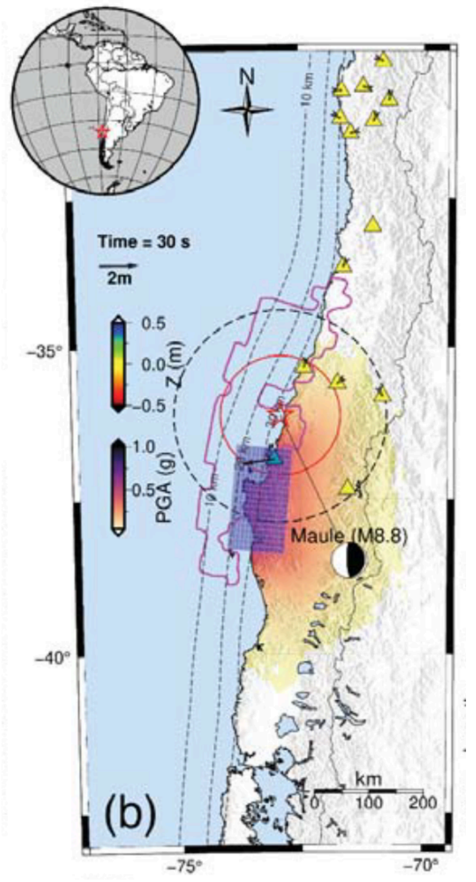
A HR-GNSS workflow: ML can (should) help every step of the way

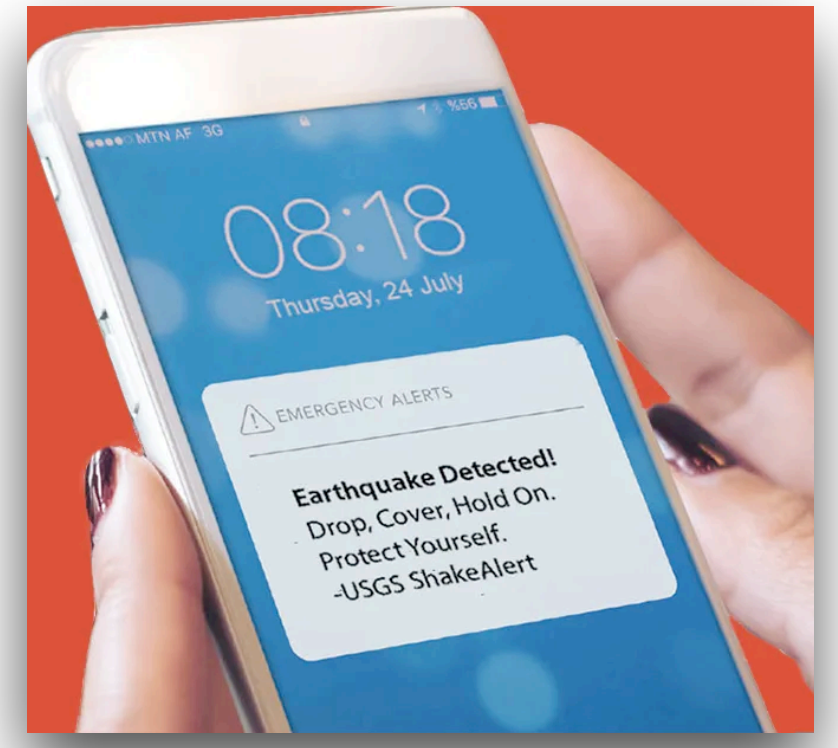












Detection/ picking

Denoising/ QC

Event characterization

Hazard forecast

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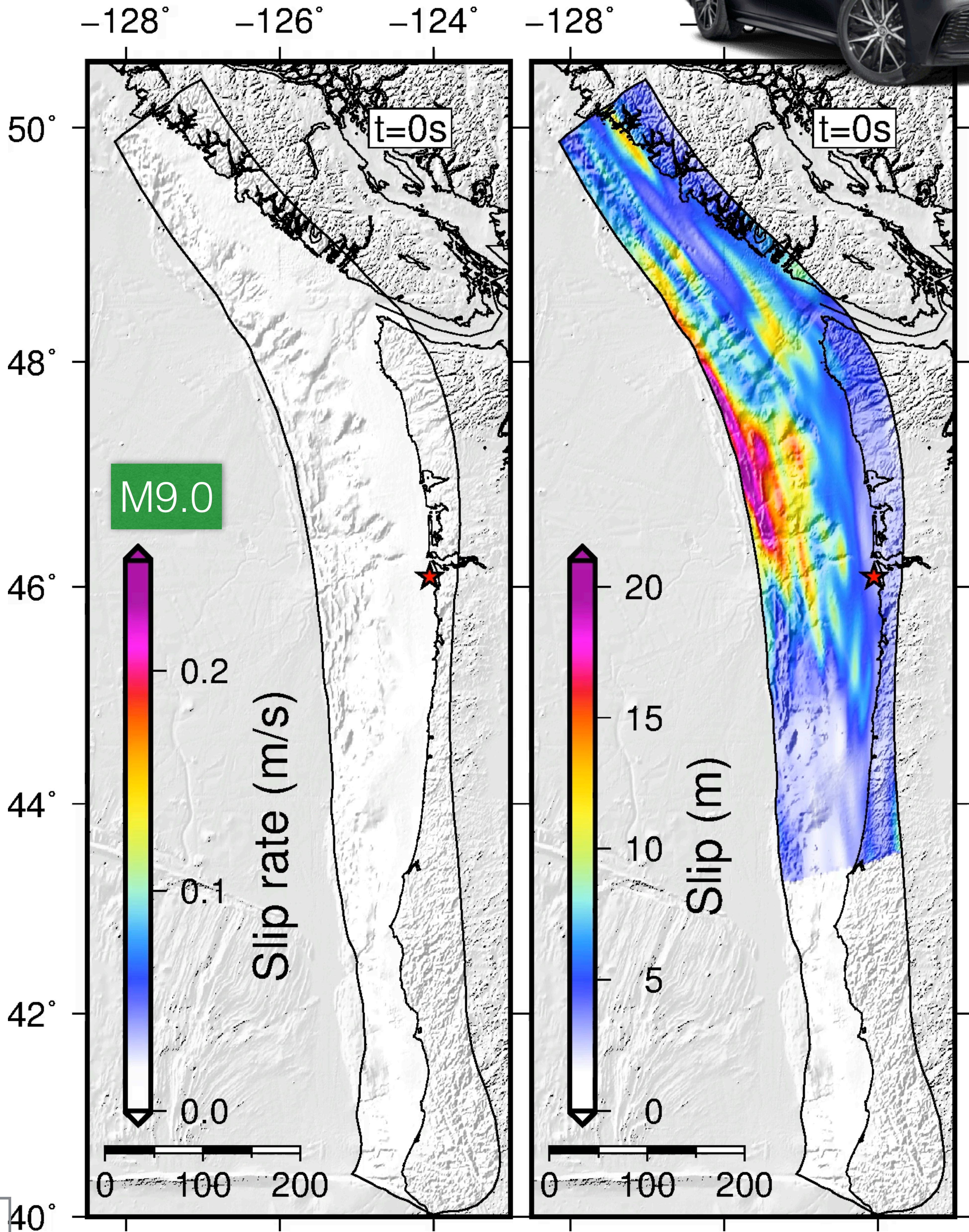
But the approaches we've implemented are still rudimentary – There is ample opportunity for growth!

Semi-stochastic kinematic ruptures

- We really heavily on simulated waveforms. **Are they any good?**
- "**Reduced physics**" but *reasonable* approximations
- Computationally **very fast**, **10^4-10^5 models** feasible with modest computational resources (**~10-100 cores**)
- They can be used as **initial conditions** for tsunami, deformation, ground motion modeling, crustal deformation



Ruhl et al, 2017

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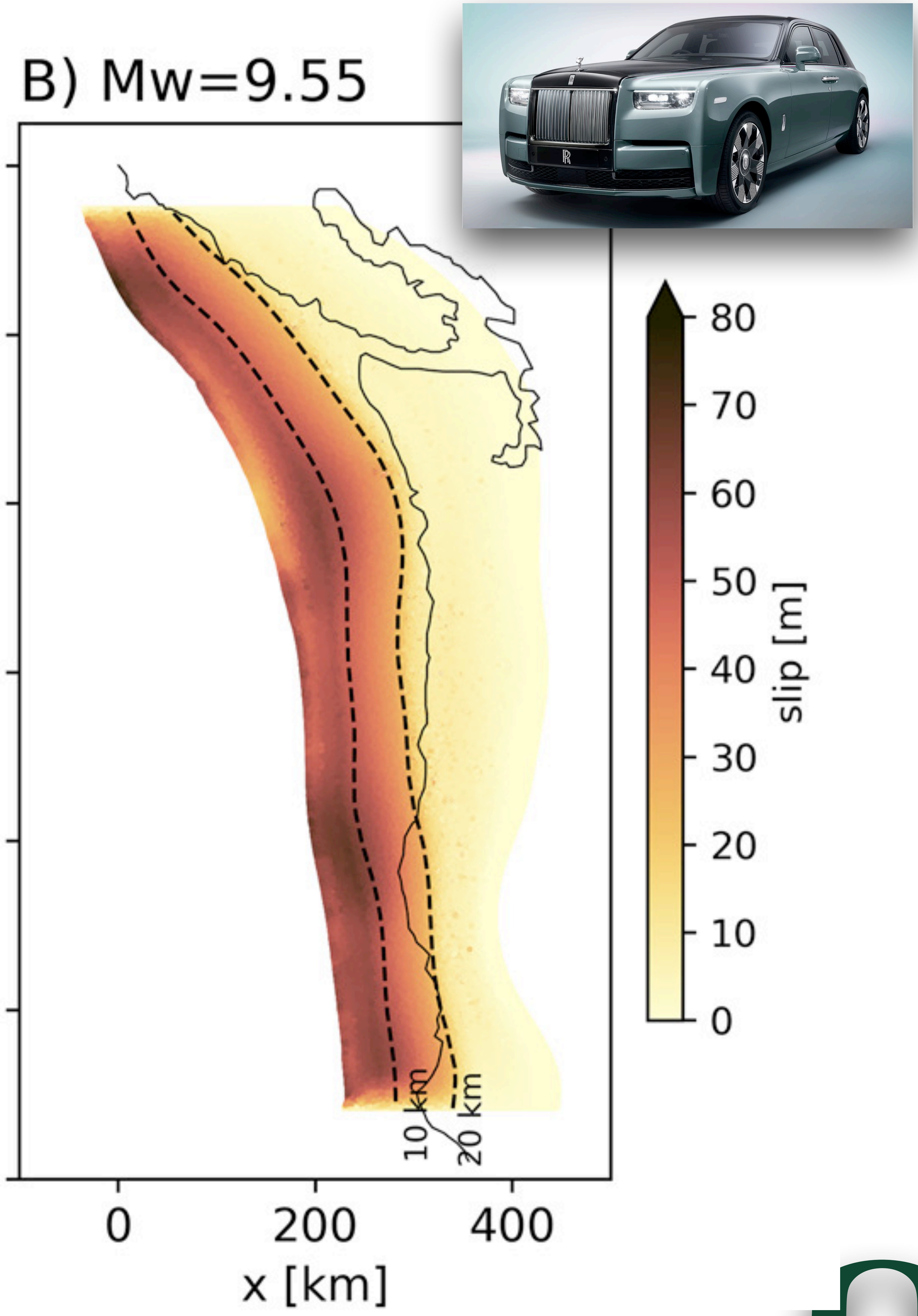
Dynamic rupture models

- Captures “**full physics**” (or at least more physics)

- Needs knowledge of **constitutive properties**

- Can be used as **initial condition** to study deformation, ground motion, tsunami etc.

- Dynamic rupture can be **computationally expensive** (hours-days per model on biggish computers)



Ramos et al., JGR, 2021

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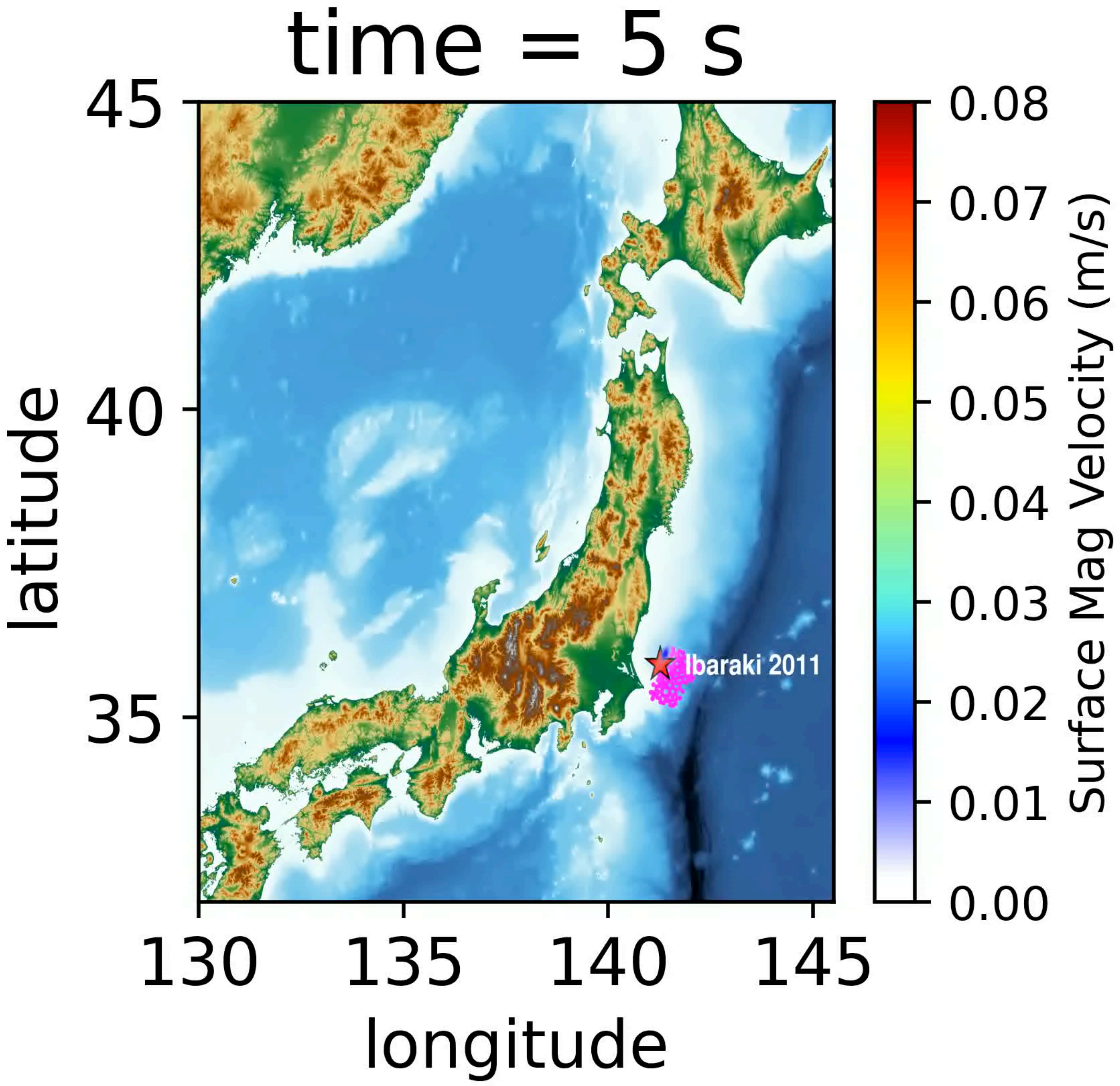
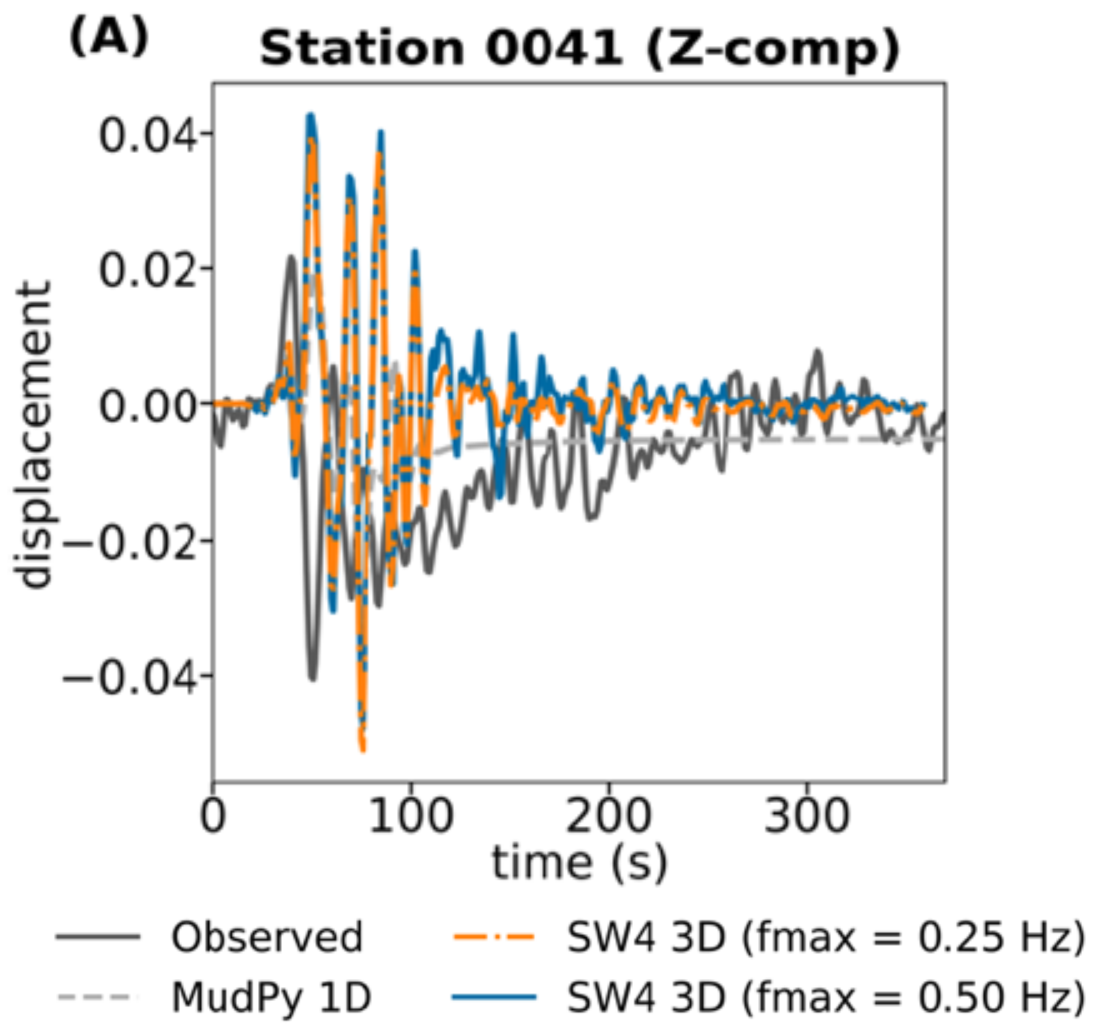
We need physics informed approaches for generating the ruptures and/or the waveforms

And we are still limited because we frequently neglect real 3D structure and complex Earth properties

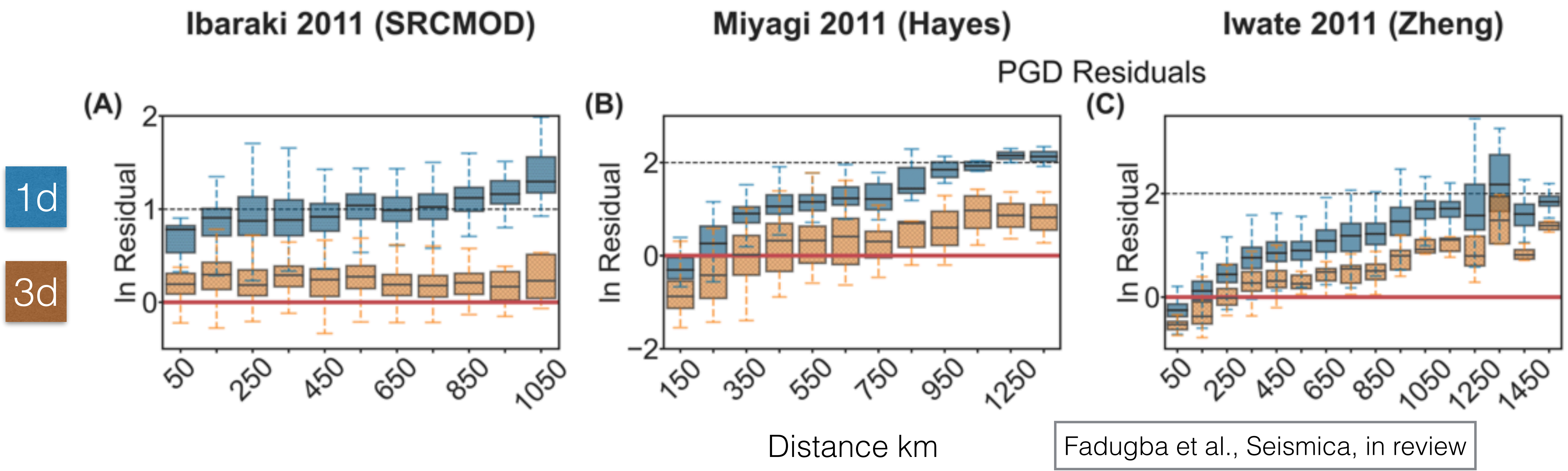
The “real” Earth

- While GNSS is “long period” it is still deeply **affected by heterogeneity**
- **Simplifying assumptions have downstream impacts** on the usefulness of ML algorithms for hazards/warning
- 3D models not available everywhere or in **unified** formats





Peak ground displacement residuals
= 0 is perfect match between data and simulation



Fadugba et al., Seismica, in review

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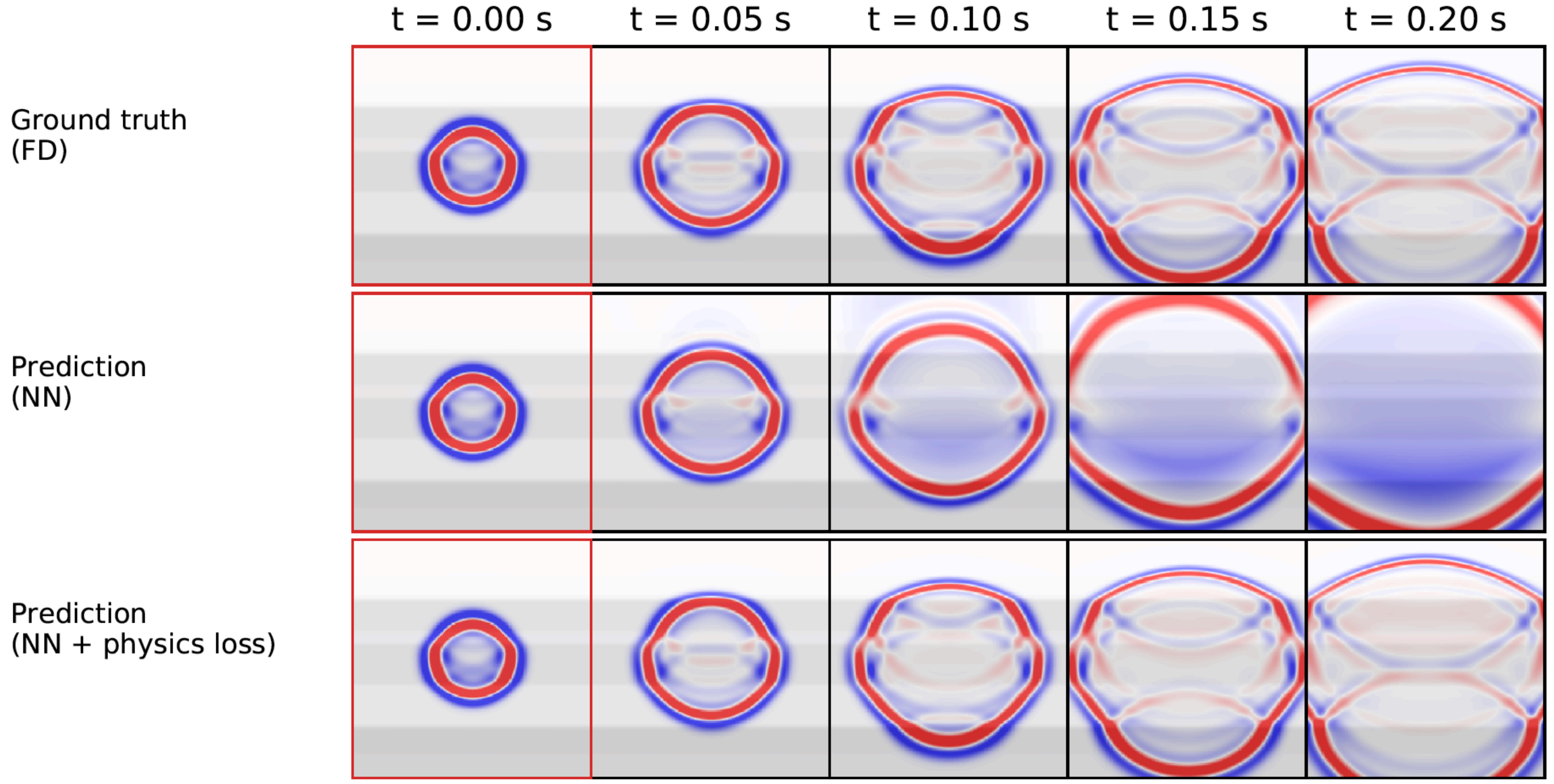
The way forward

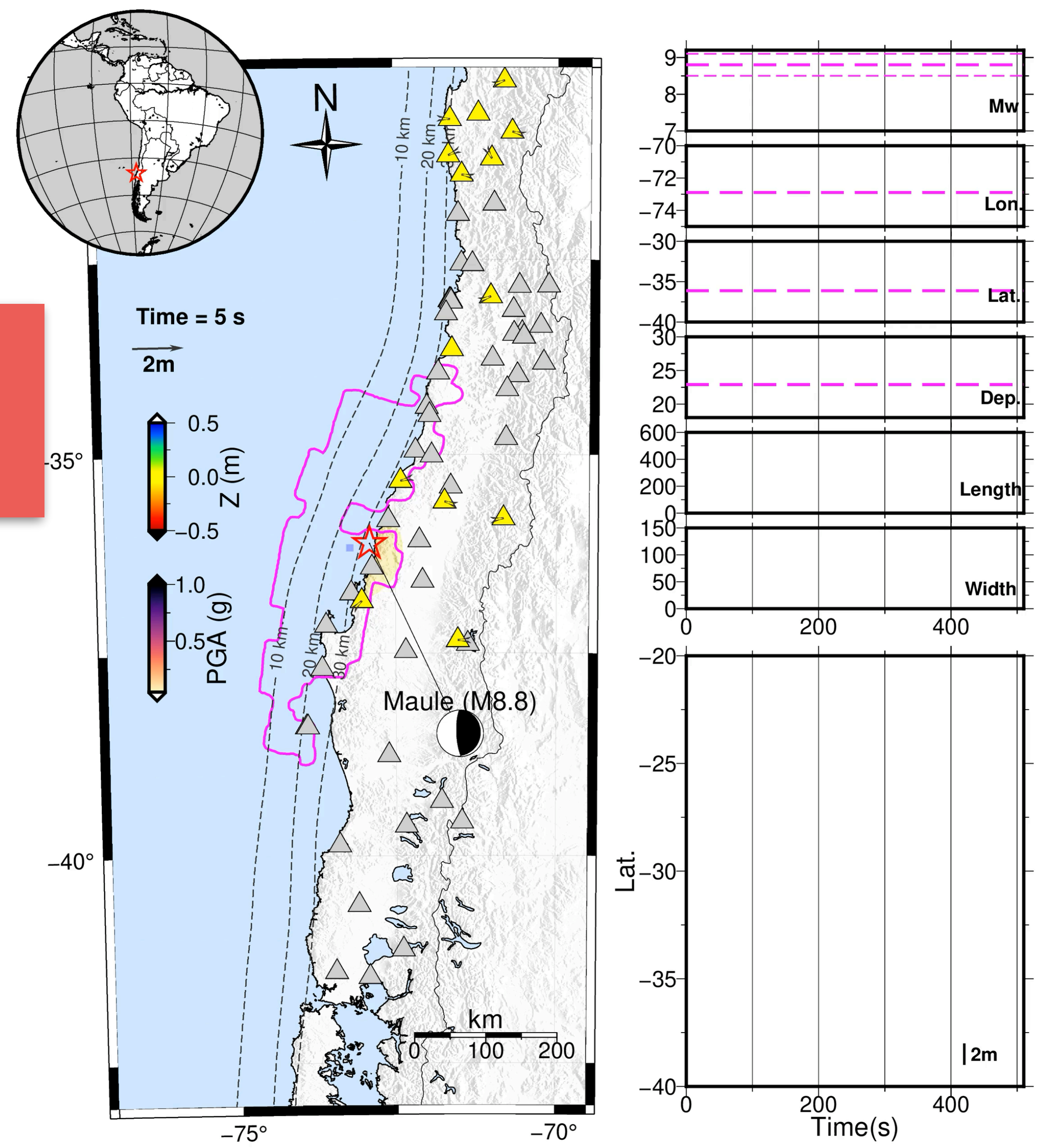
- Large earthquakes and their associated hazards are **complex** phenomena
- We will not observe **sufficient large earthquakes** in our lifetimes to use as training data
- If we want **precise forecasting** we need better approaches
  - Physics informed NN?
  - Generative adversarial networks?
- We also need big improvements in **uncertainty awareness** because in many regions networks are still sparse and imperfect
- **All geophysical data should contribute**

Physics informed ML simulation of a 2D seismic wavefield



Moseley et al., 2020

Only 6 sites in this forecast!



Thank you!

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github.com/UO-Geophysics/