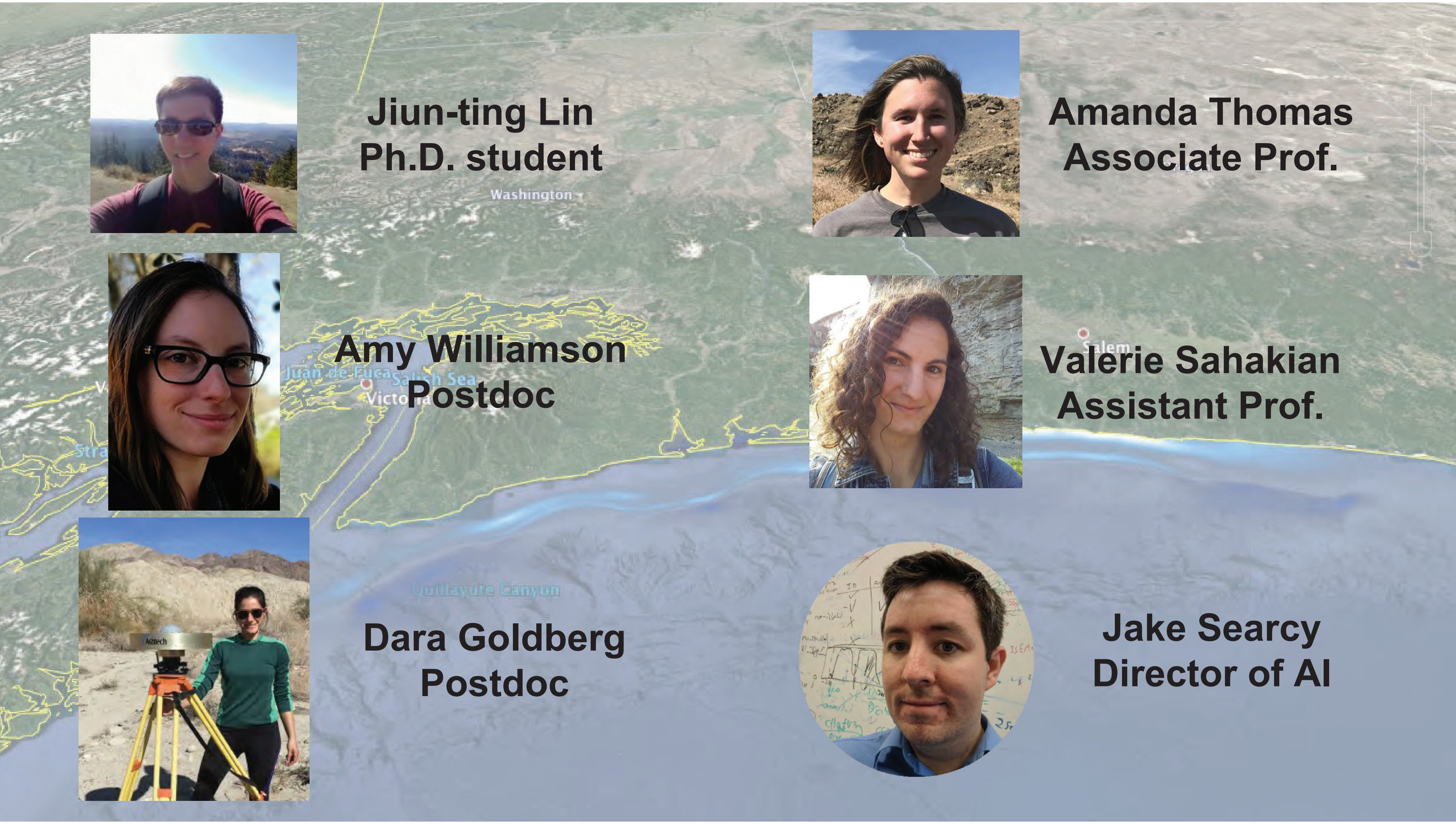
Rapid Forecasts of Earthquake Hazards from Crustal Deformation Patterns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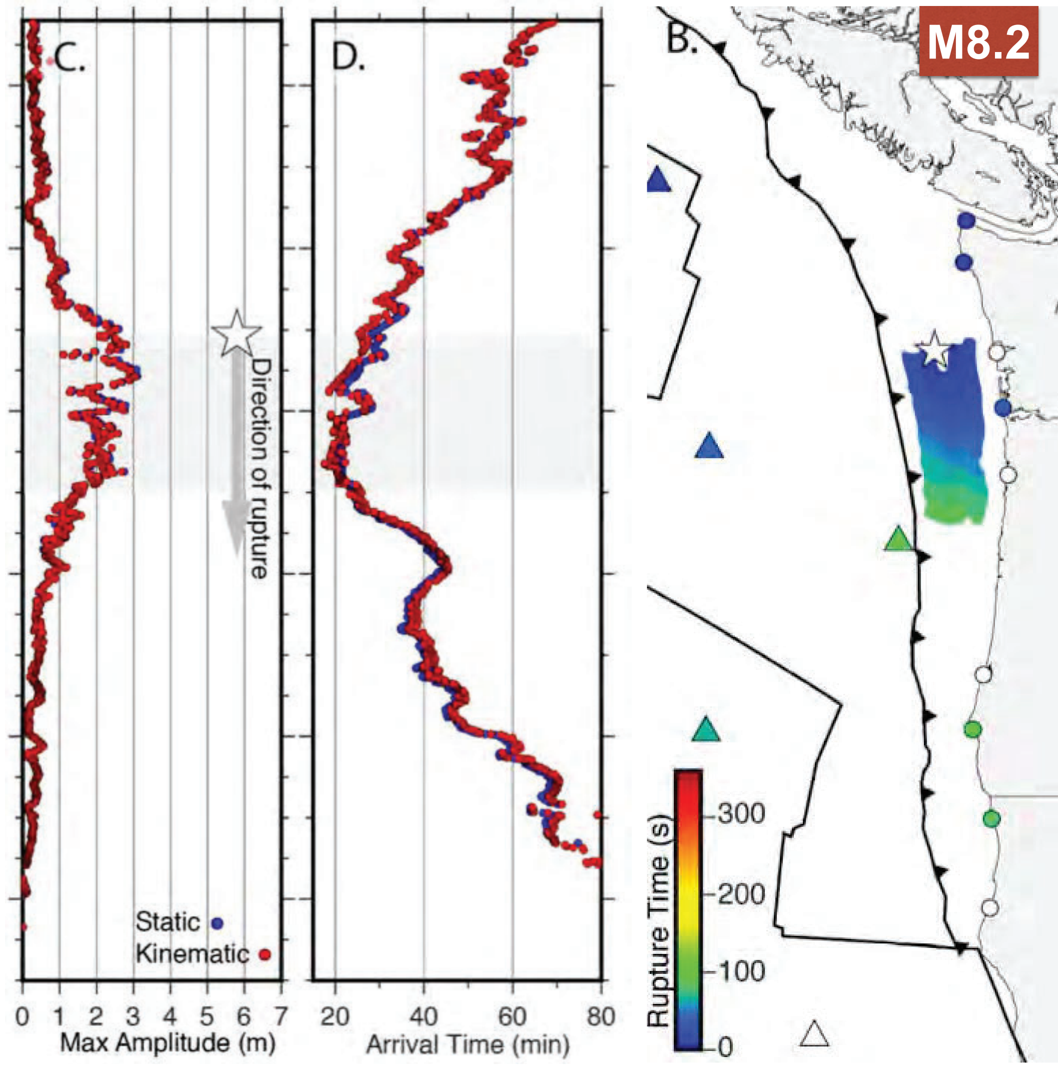
The problem: Local tsunami warning

- Local warning is forecasting tsunami hazards before they impact the coastlines adjacent to a rupture.

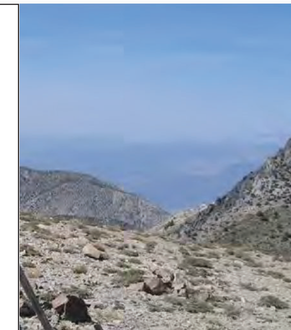
- It requires characterizing the tsunami in minutes

- It remains a challenging problem in all tsunami prone regions



Williamson et al., JGR, 2019

Our solution: Land-based GNSS



Our solution: Land-based GNSS

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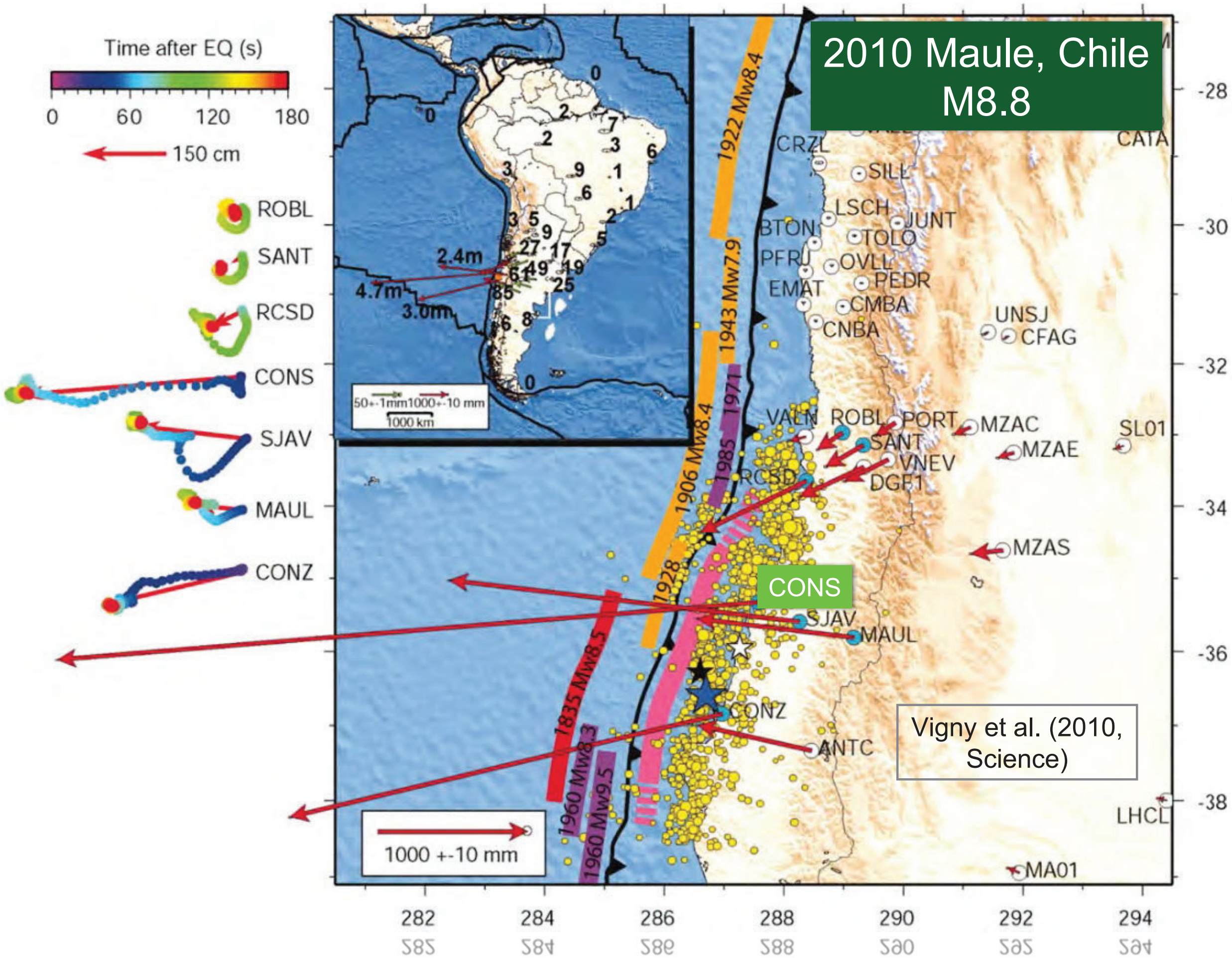
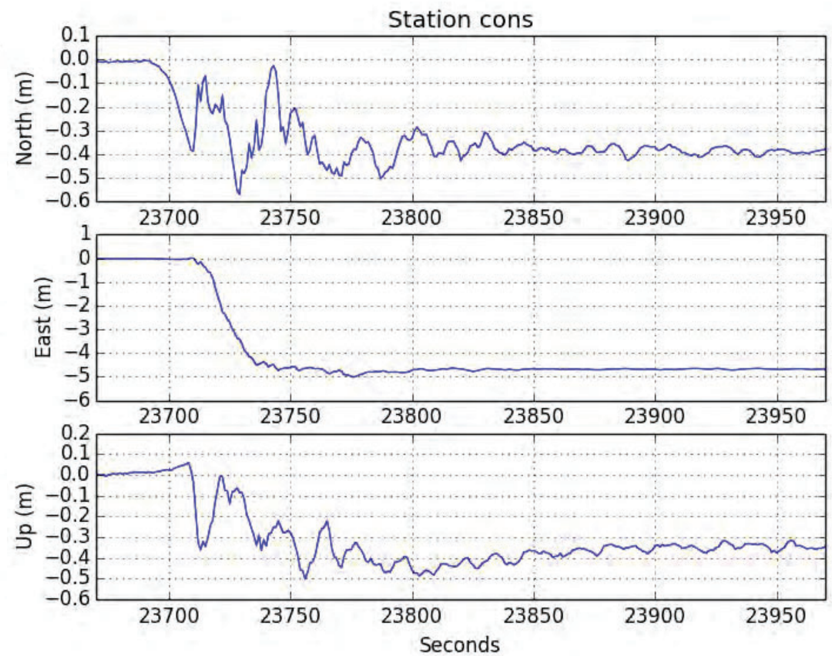
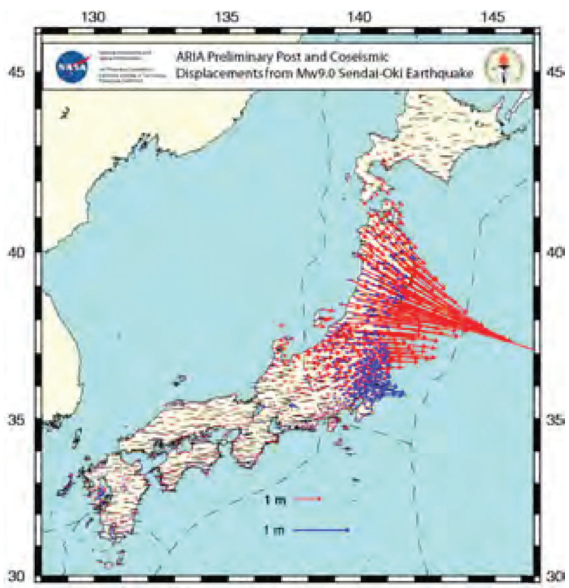
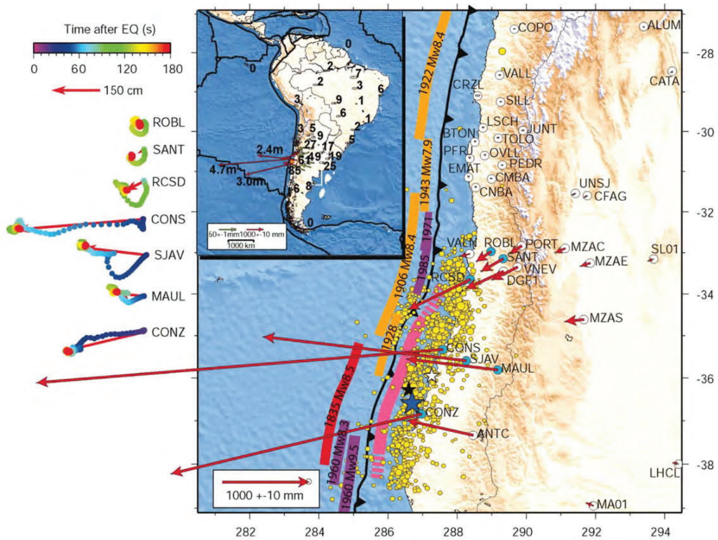




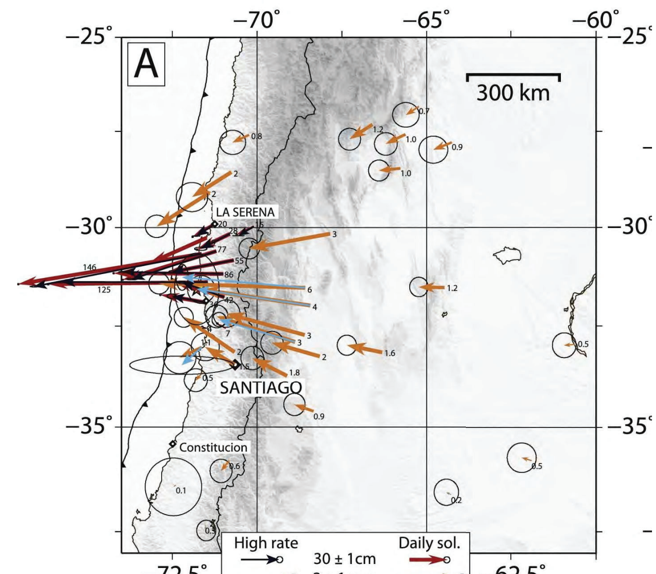
GNSS correlates to tsunami impacts



NASA/JPL



Vigny et al. (2010, Science)



Klein et al. (2017, EPSL)

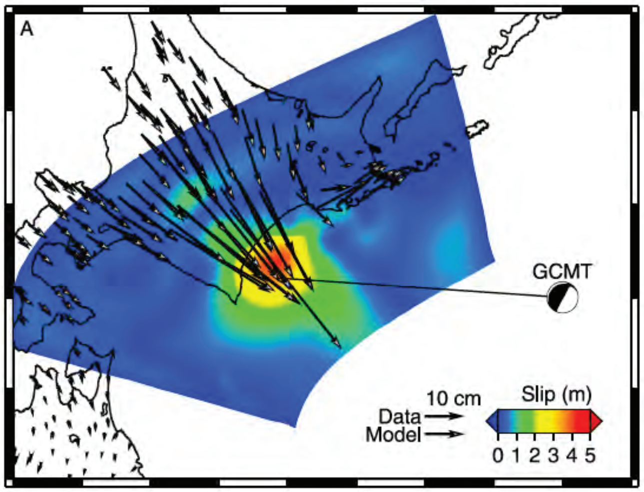
2011 M9.0 Tohoku-oki
5m displacements
30m+ tsunami

2010 8.8 Maule
5m displacements
20m tsunami

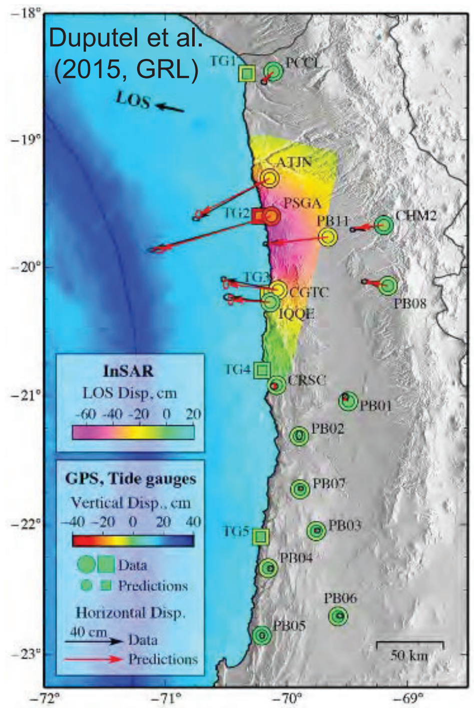
2015 8.3 Illapel
2m displacements
10m tsunami

GNSS correlates to tsunami impacts

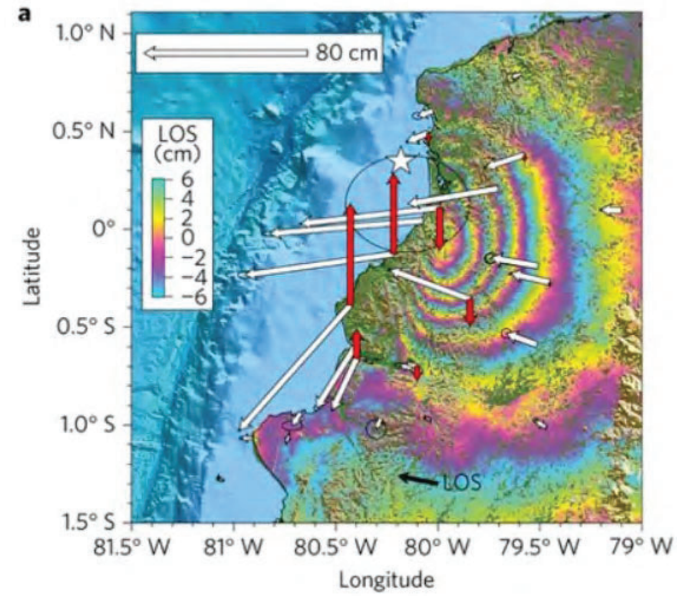
Crowell et al. (2012, GRL)



Duputel et al. (2015, GRL)



Nocquet et al. (2016, Nat. Geo)

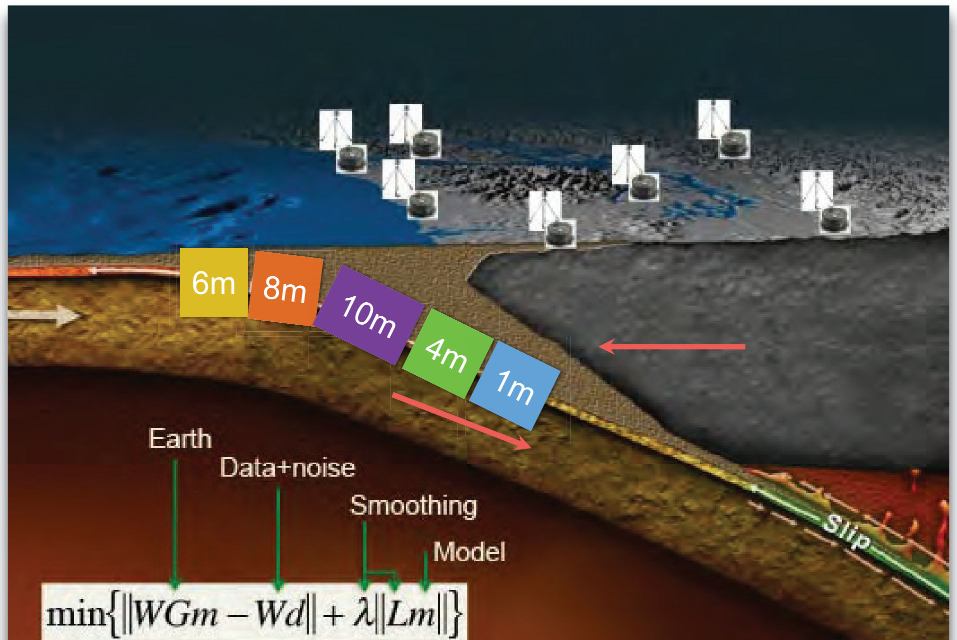


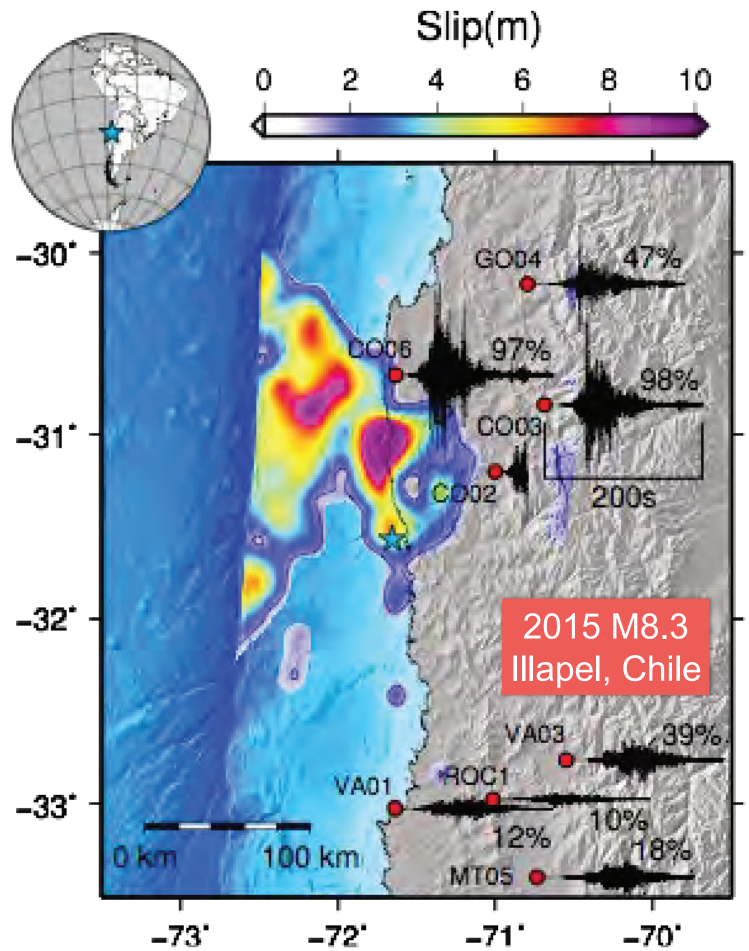
2003 M8.3 Tokachi-oki
0.5m displacements
1m tsunami

2014 M8.1 Iquique
1-2m displacements
2m tsunami

2016 M7.8 Ecuador
1m displacements
1m tsunami

The correlation is complex

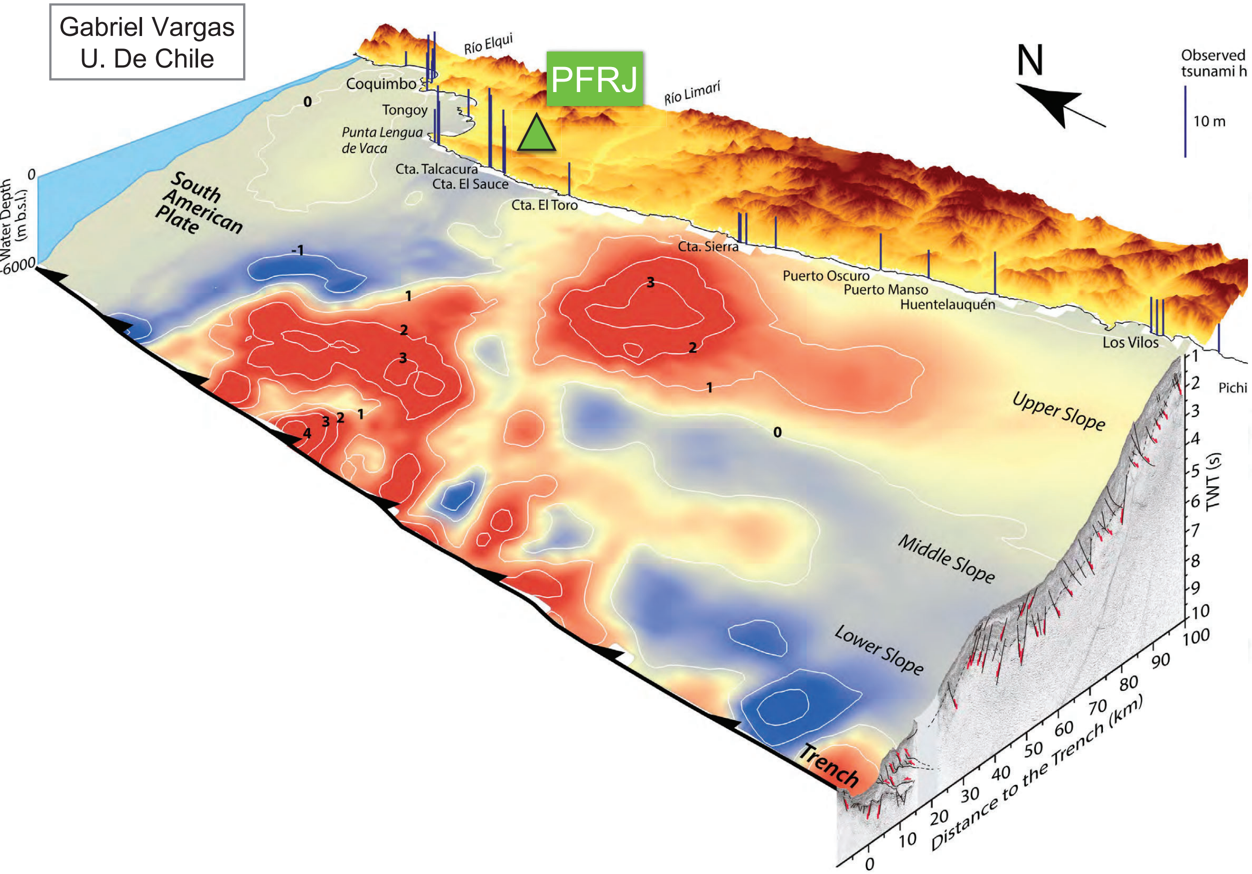


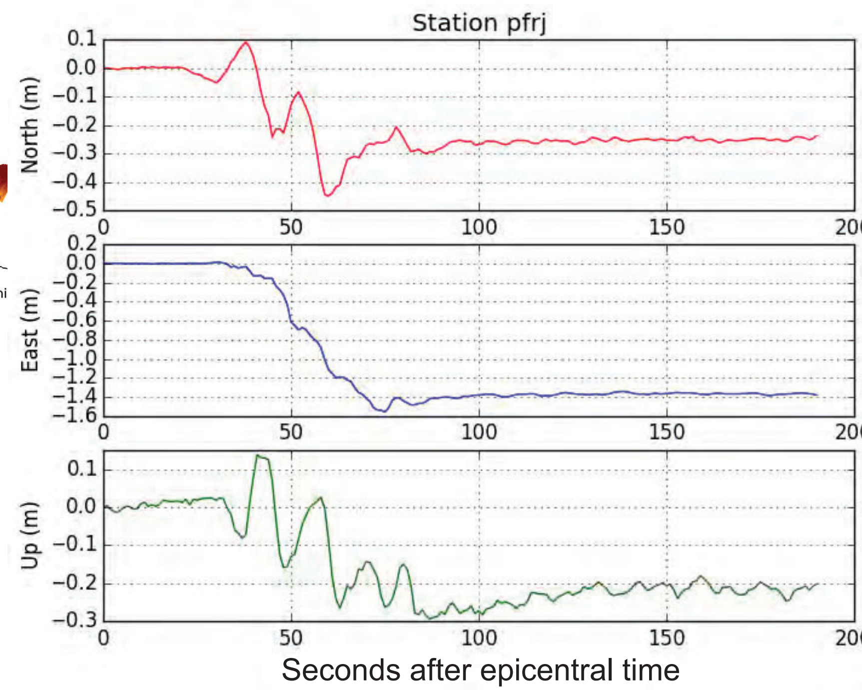


Melgar et al. (2016, GRL)

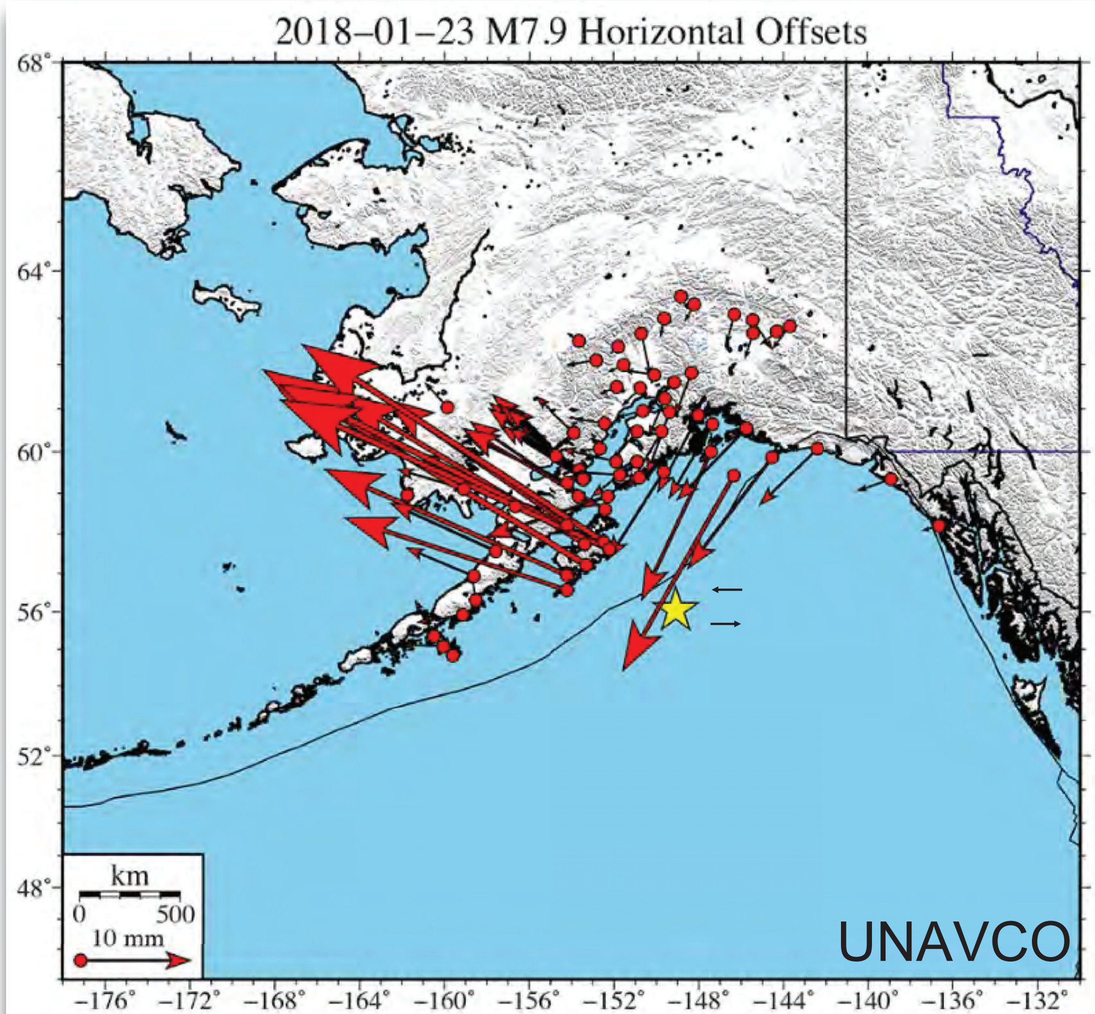
The correlation is complex

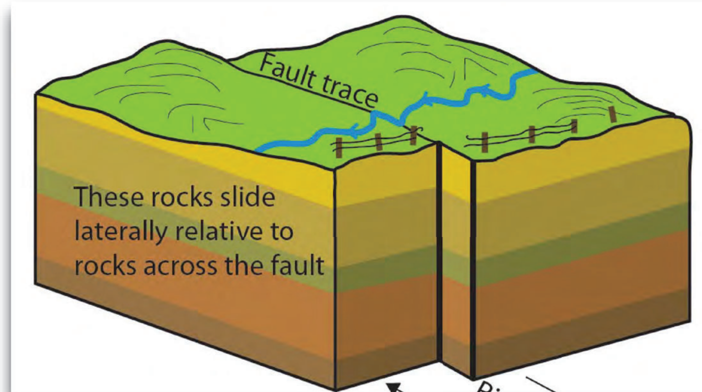
Gabriel Vargas
U. De Chile





GNSS identifies non-events as well





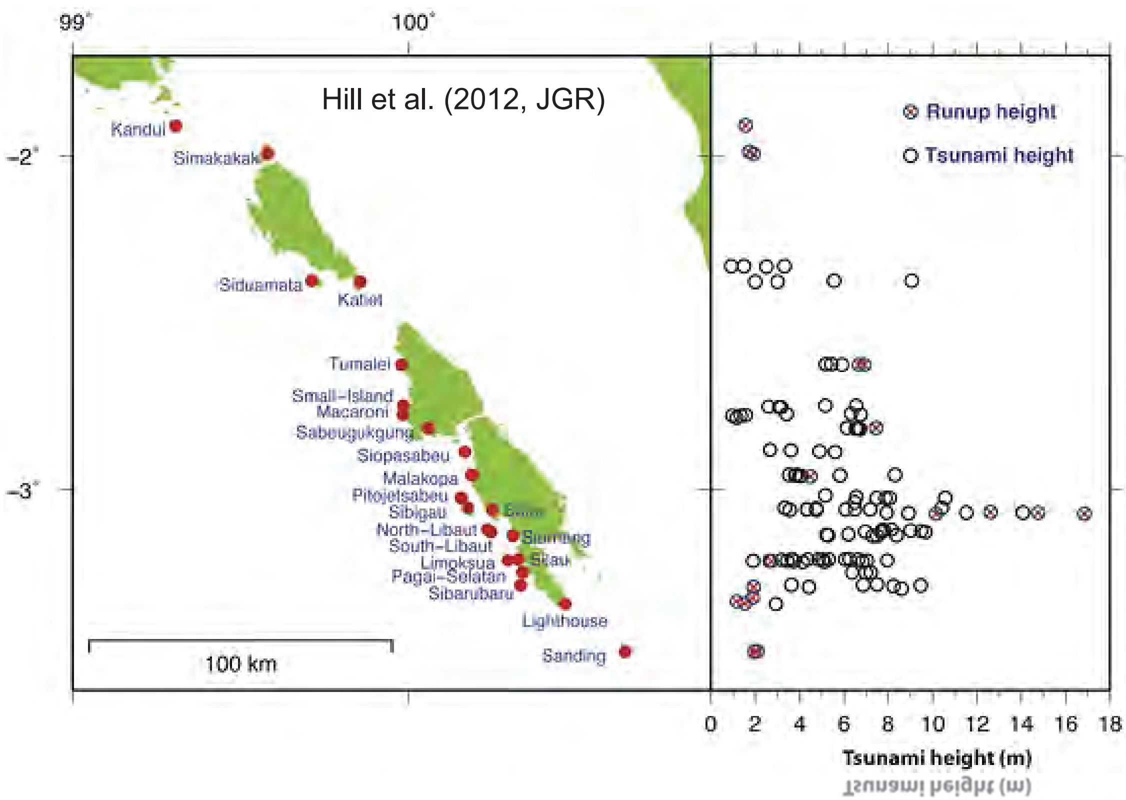
- Large near-trench earthquake
- Strike-slip mechanism
- Tsunami < 20cm
- PTWC issued warning for Alaska & U.S. West Coast

GNSS identifies tsunami earthquakes too

A *tsunami earthquake* produces a tsunami **much larger** than what would be **expected for its magnitude**

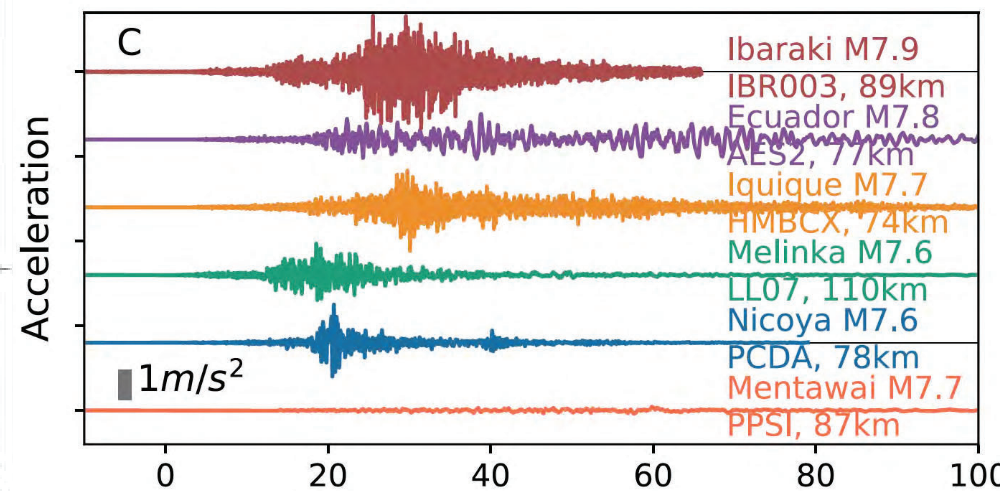
- 2010 M7.8 Mentawai, Indonesia
- ~15m tsunami

GNSS identifies tsunami earthquakes too



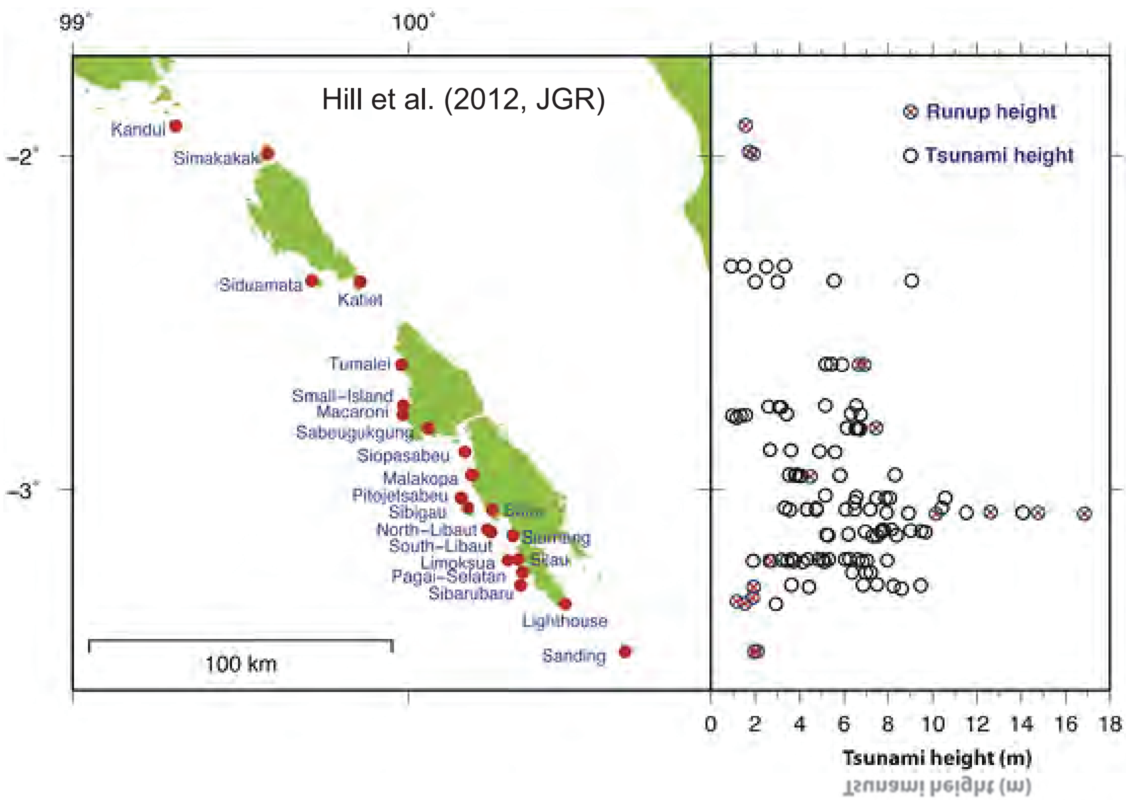
2010 M7.8
Mentawai, Indonesia

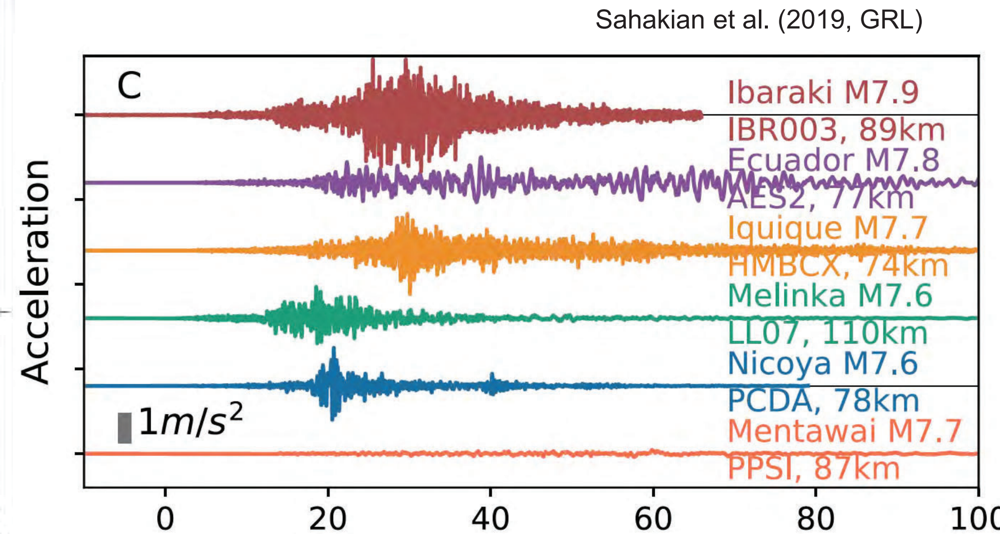
Sahakian et al. (2019, GRL)



GNSS identifies tsunami earthquakes too

These events **shake like a magnitude 6** but make a **tsunami like a magnitude 9**





GNSS identifies tsunami earthquakes too

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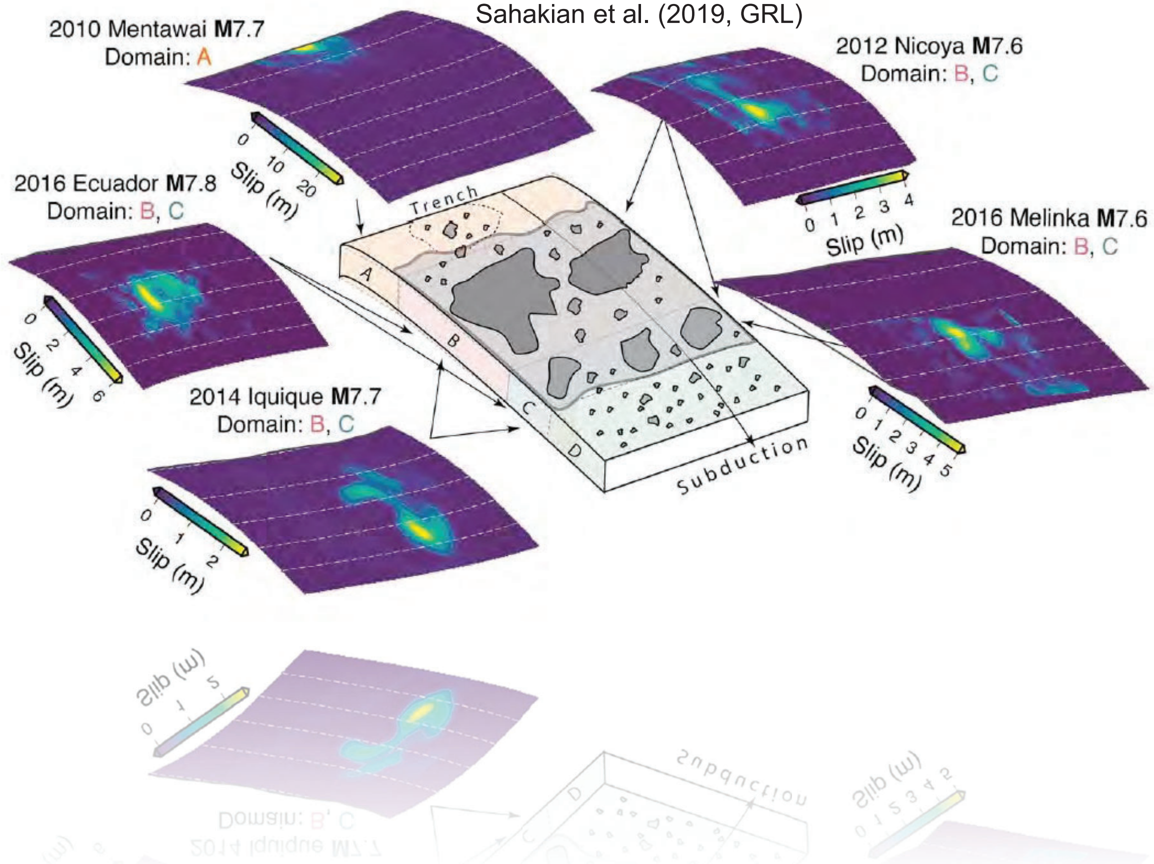
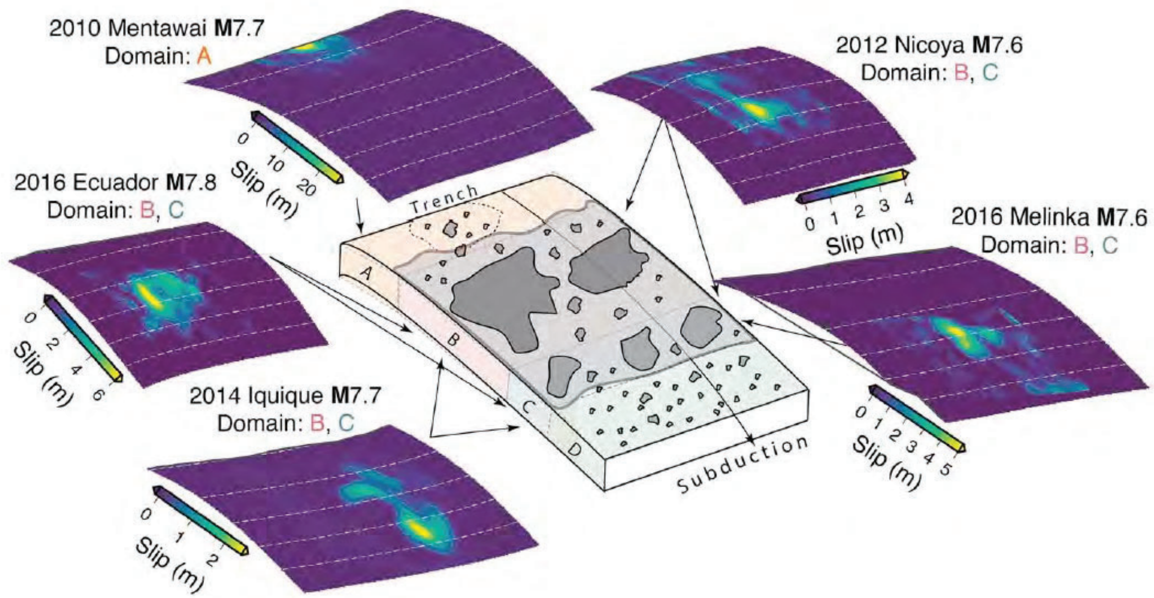


GNSS identifies tsunami earthquakes too



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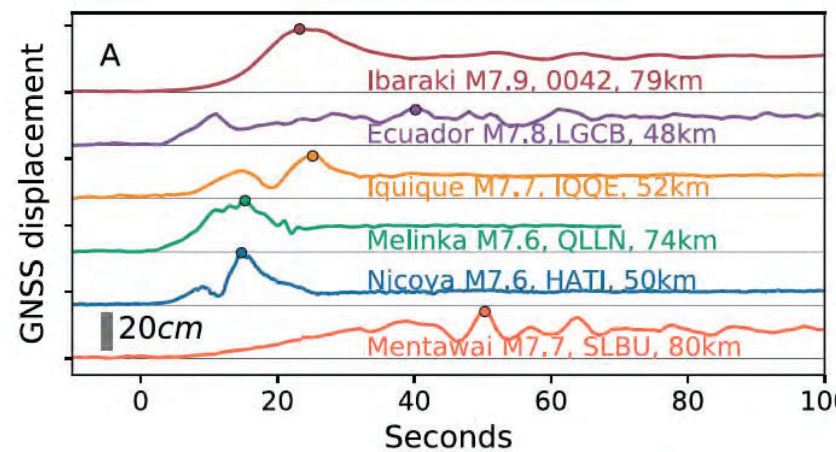


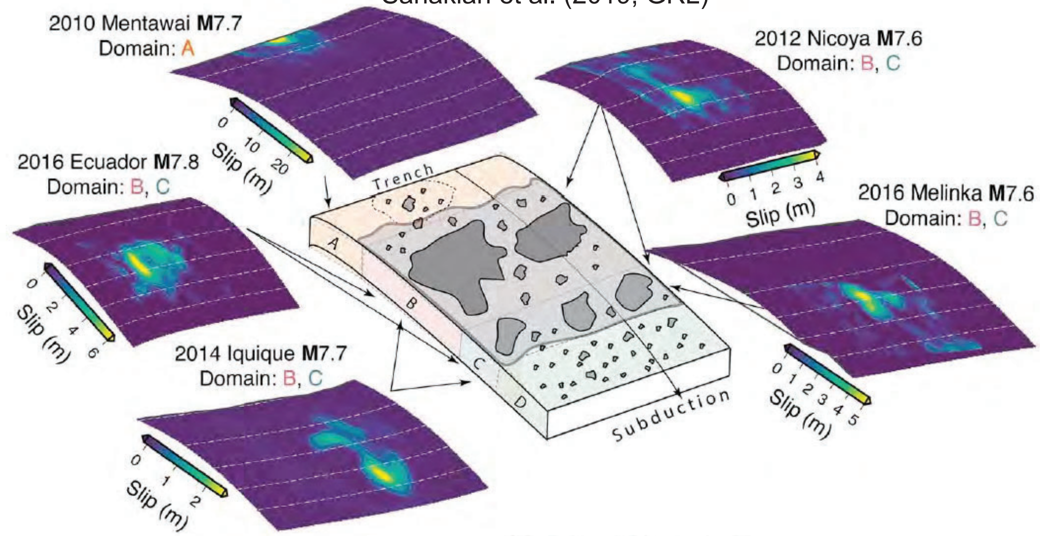
We need a flexible algorithm

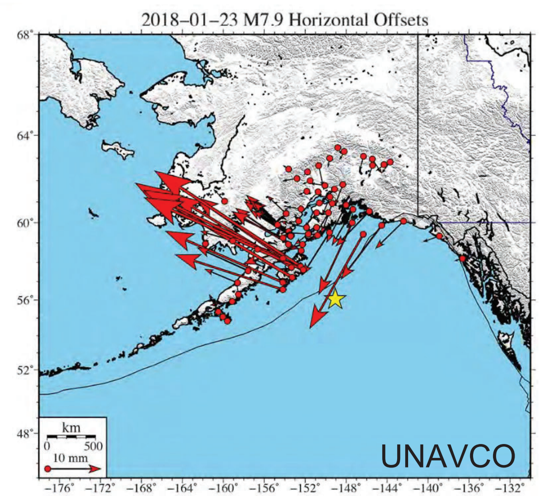
- Our working hypothesis is that **time-dependent** GNSS can be used to **forecast** tsunami impacts

- GNSS contains information that **correlates** strongly to the deformation of the **seafloor**

- But the relationship is not simple and **traditional** seismological algorithms do not perform well for all potential situations

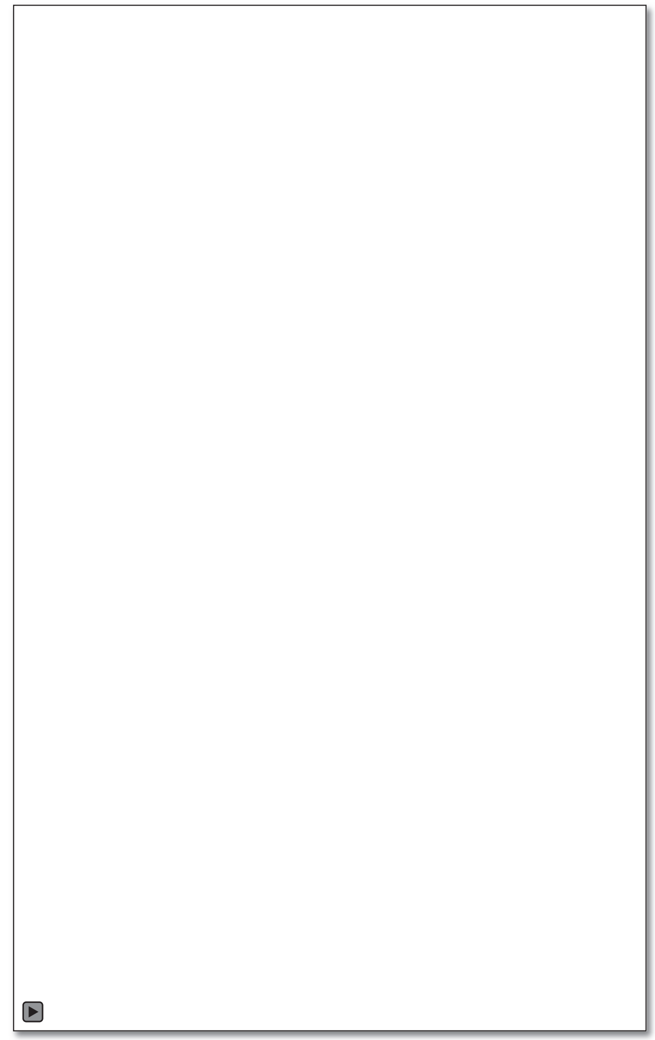
Sahakian et al. (2019, GRL)





We need a flexible algorithm

- Our solution is to use machine learning
- The challenge is to develop a large enough dataset for training
- We solve this through simulation



Fakequakes and Geoclaw: Simulating large events

- Can we simulate O(100k - 1M) **realistic** earthquakes, GNSS waveforms, and tunsamis?

- Can we train a **time-dependent** ML algorithm to evaluate the earthquake and forecast hazards?

Fakequakes and Geoclaw: Simulating large events

Fakequakes:

- **Stochastic** slip models based on findings by Mai & Beroza (2002)
- **Kinematic** parameters modified from Graves & Pitarka (2010)
- Parameter space is defined by what has been observed in **real events**
  - Correlation lengths & Hurst exponent
  - Rupture speeds
  - Rise times
  - Stress drops
  - Etc.

Cascadia M9

Melgar et al. (2016, JGR)

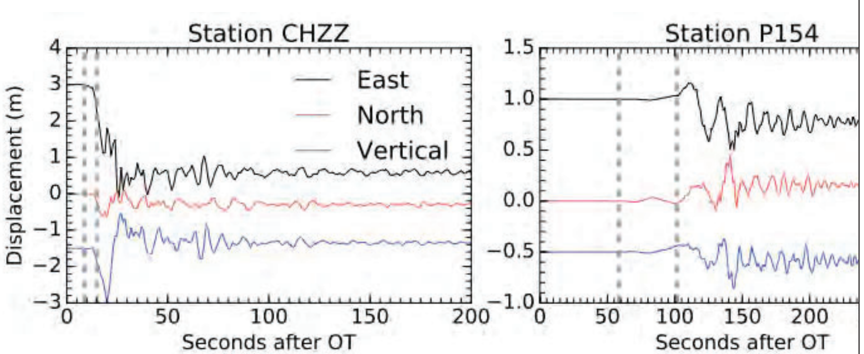
Fakequakes and Geoclaw: Simulating large events

Cascadia M8.6

Fakequakes:

- **Parallelized** and efficiently g
  GNSS across a large networ

- Assumes some reference Ea
  includes **deterministic** propa



Fakequakes and Geoclaw: Simulating large events

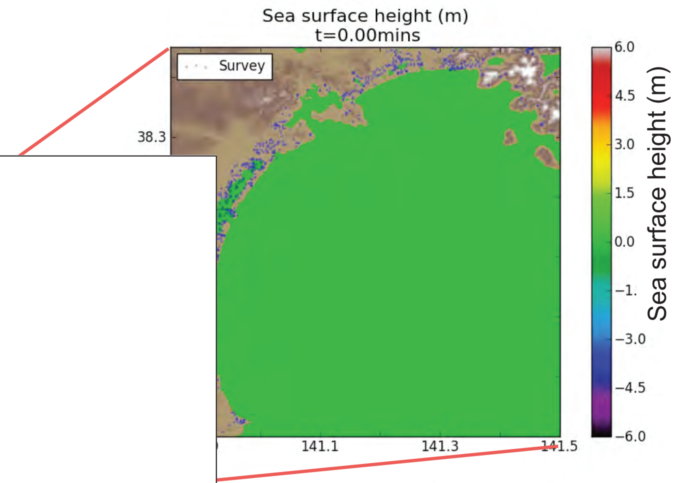
GeoClaw:

- GPU/CPU code that solves the shallow water equations (Qin & Leveque, 2019)

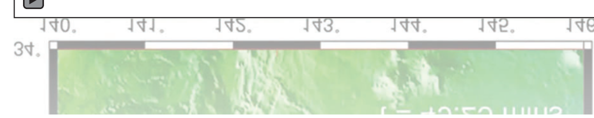
- Uses adjoint methods for efficiently guiding the mesh refinement (Davis et al., 2016)

- Includes inundation effects

Tohoku-oki M9.0



, 2015, JGR

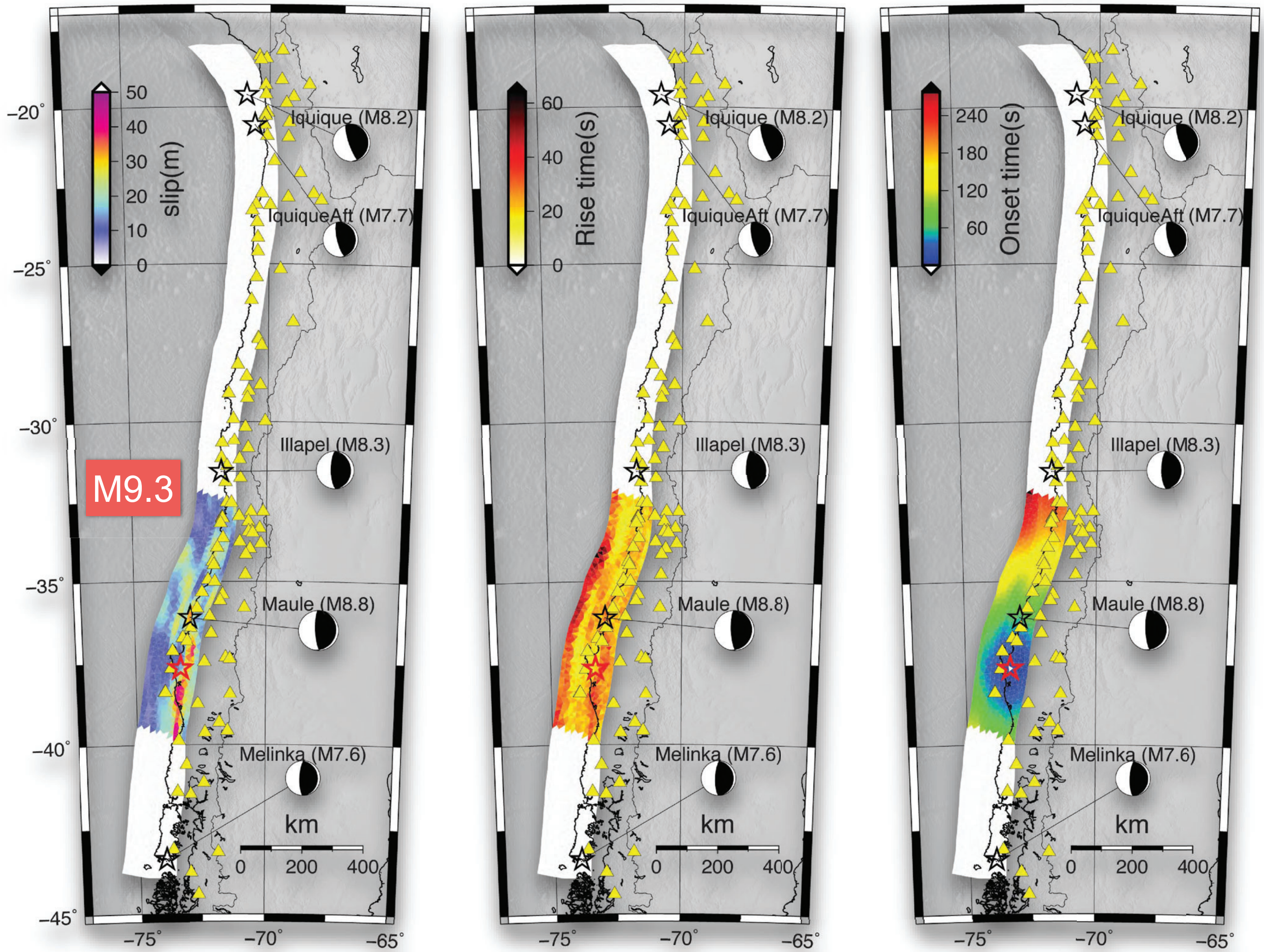


Fakequakes and Geoclaw: Simulating large events

- Can we simulate O(100k - 1M) earthquakes, GNSS waveforms, and tunsamis?
- Can we train a time-dependent ML algorithm to evaluate the earthquake and forecast hazards?
- We use **Chile** as the **testing ground** because it has had 5 large events recorded by GNSS

Simulations in Chile

- Subduction geometry from **Slab 2** (Hayes et al., 2019)
- **50,000** simulated earthquakes (M7.5-M9.5) range
- GNSS data at 121 locations from the **operational network**
- 5 **real events** that can be used as validation



Lin et al. in prep

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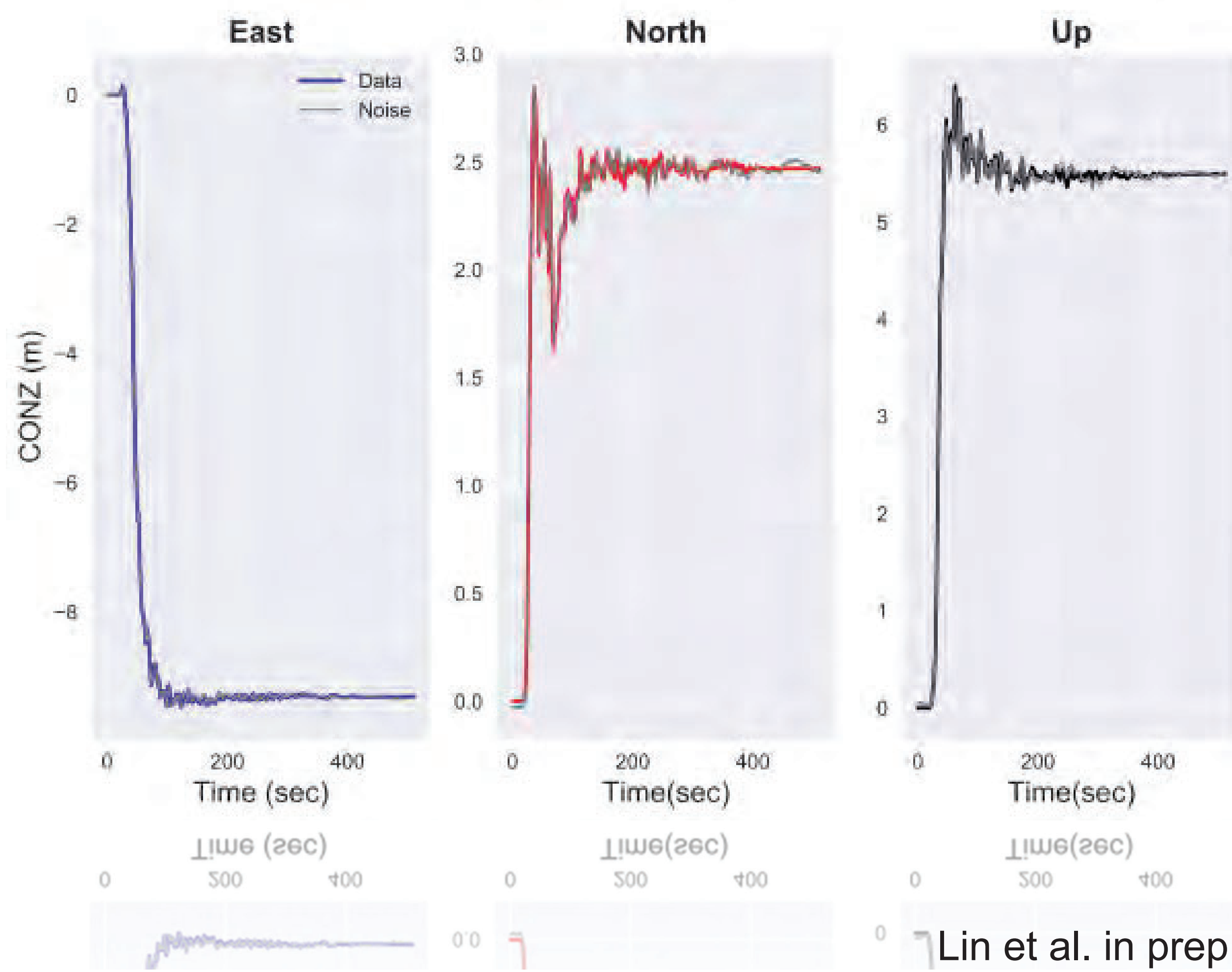

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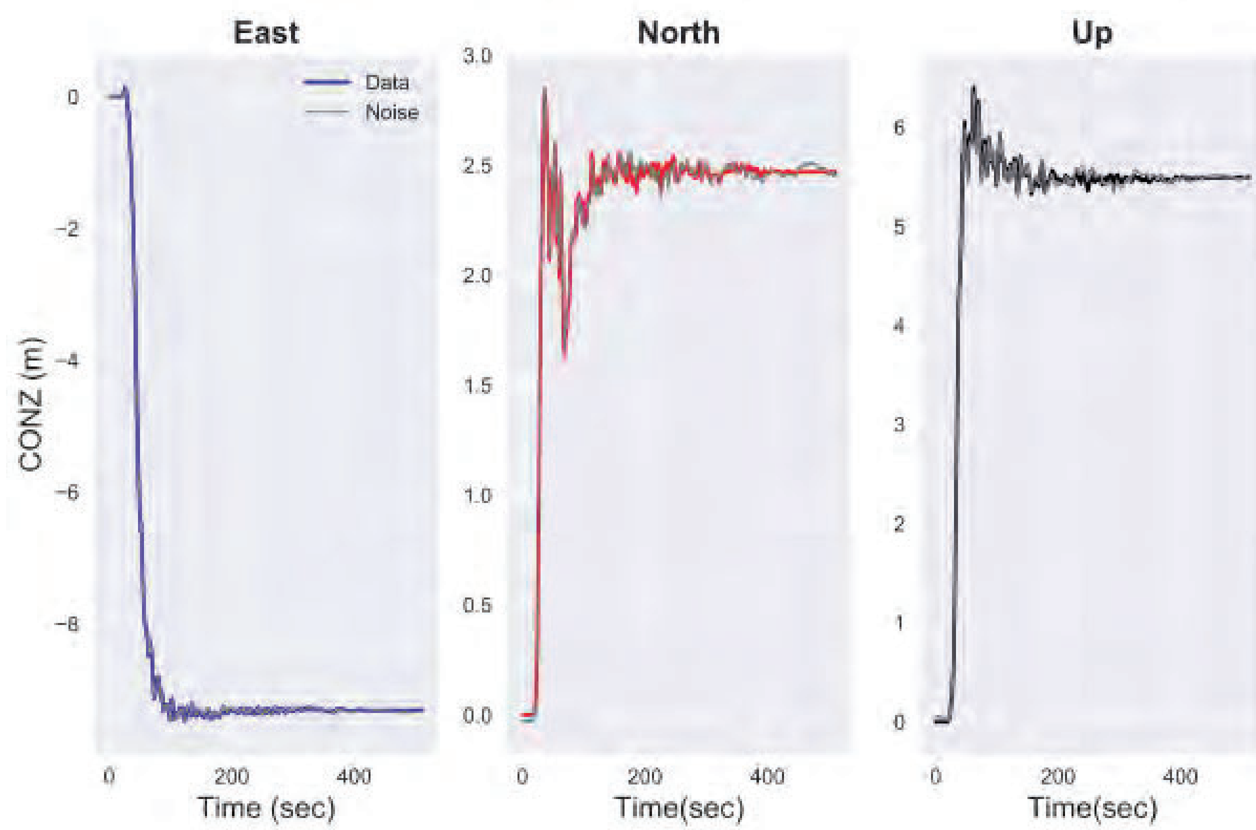
Building an RNN

- We need a **temporally dynamic** algorithm.
- It's not just about what is happening now.
- The short-term **history** of the event has value
- We use a standard **recurrent** neural network architecture



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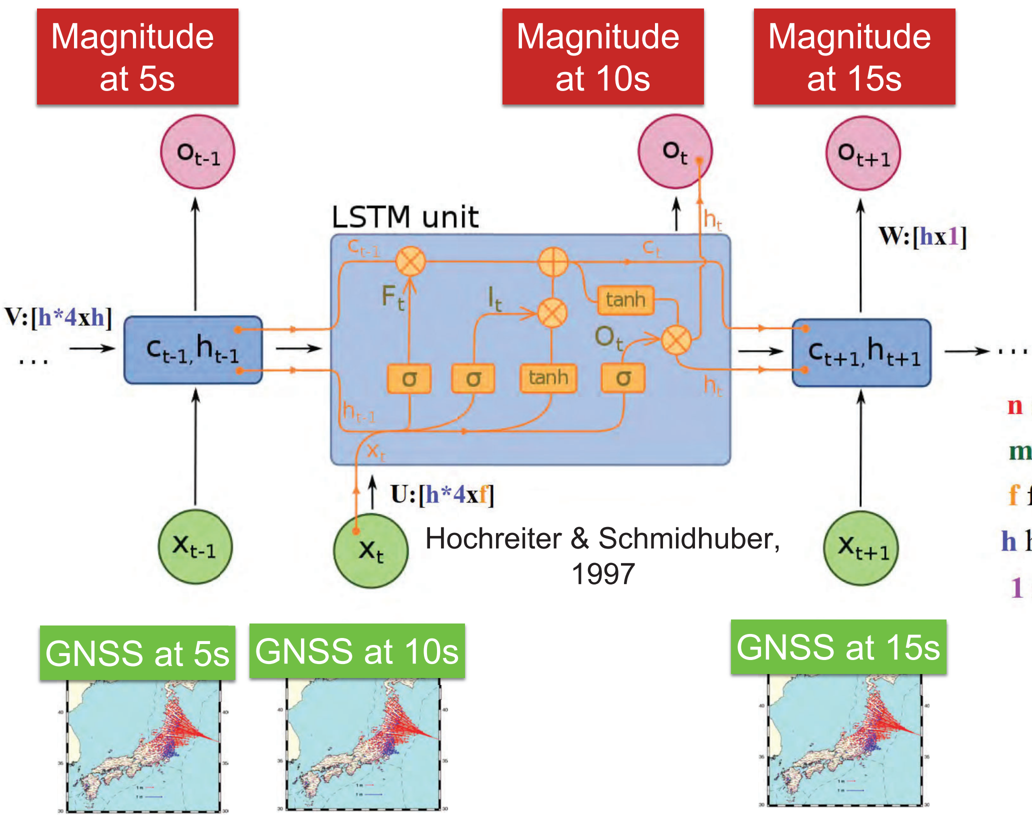
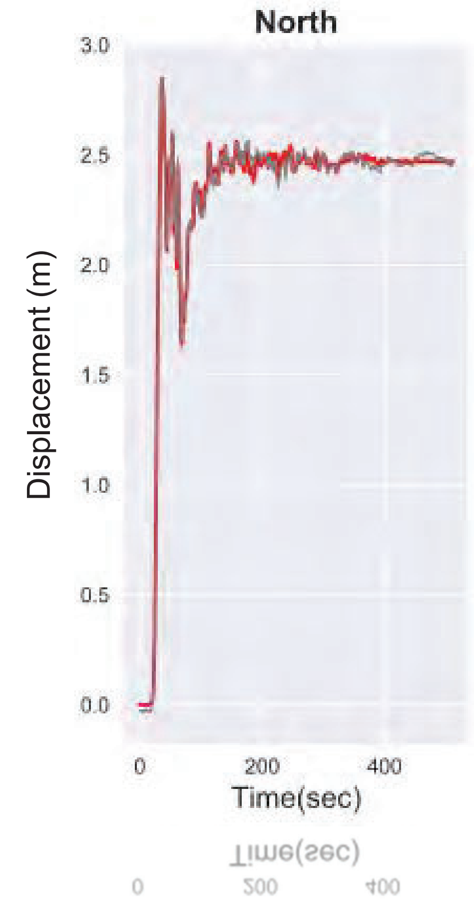
Building an RNN

- First we simply predict magnitude
- Data is provided at 5s increments



X:[nxmxf]
O:[nxm]
U:[h*4xf]
V:[h*4xh]
W:[hx1]

n rupture scenarios
m time sample points (updates ever 5s)
f features (number stations + station on/off)
h hidden units
1 final output (i.e. M_w) for each time



Lin et al. in prep

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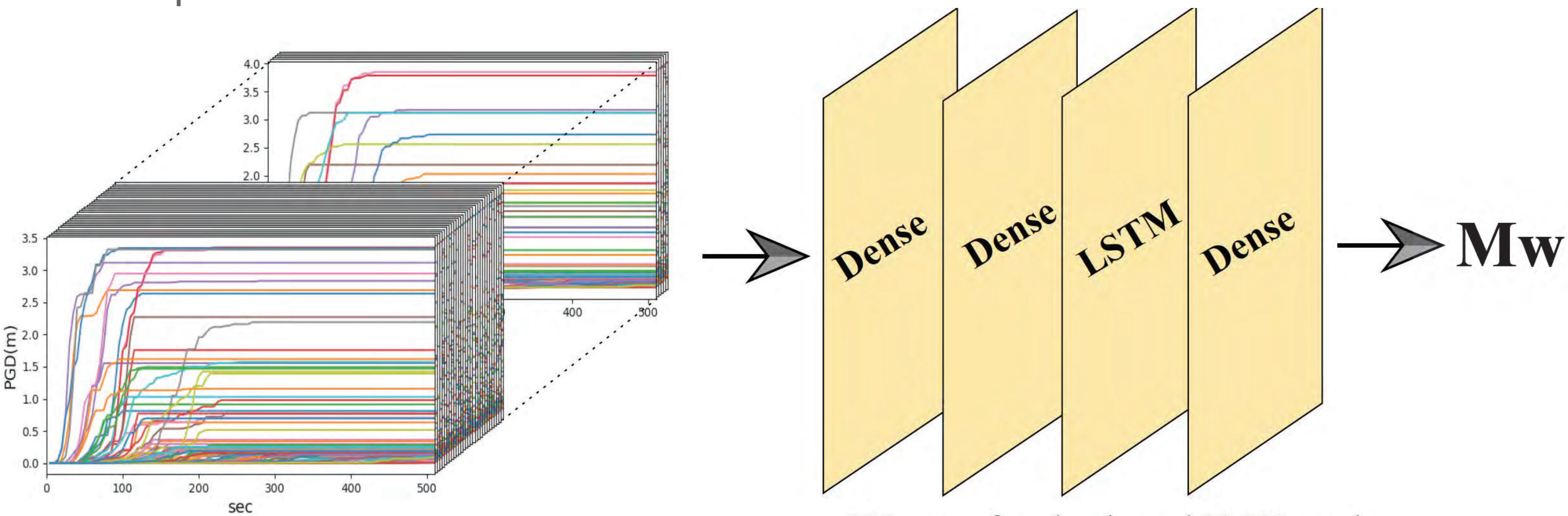

256 events for a batch, total 10,000 epochs.
2,560,000 events, 121 stations, 512 seconds.

Lin et al. in prep

RNN training steps

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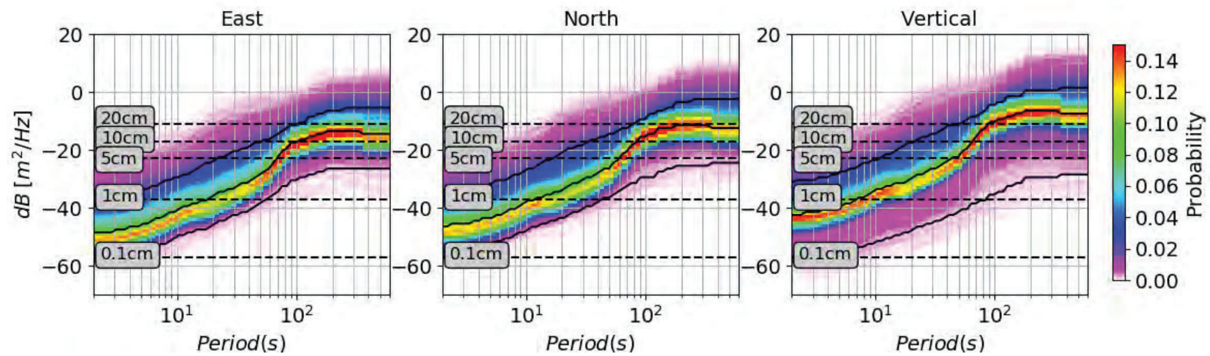
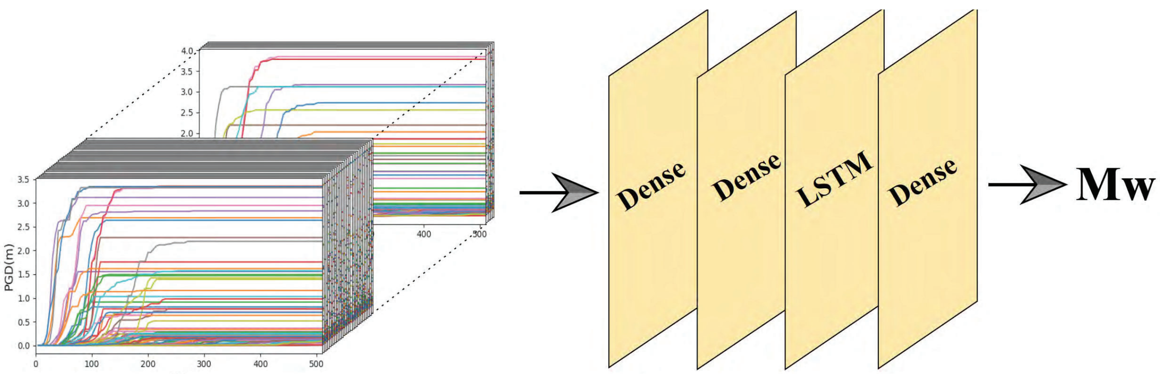
- 1) Pick rupture from available **simulations**
- 2) Add realistic GNSS **noise**
- 3) Randomly **remove stations** (set existence code)
- 4) **Repeat** steps 1-3 for 256 times to generate a minibatch
- 5) **Train** with 10,000 mini batches
  - Train with 80% validate with 20%
- 6) Labels are the **final** magnitudes of the events

Melgar et al. in review





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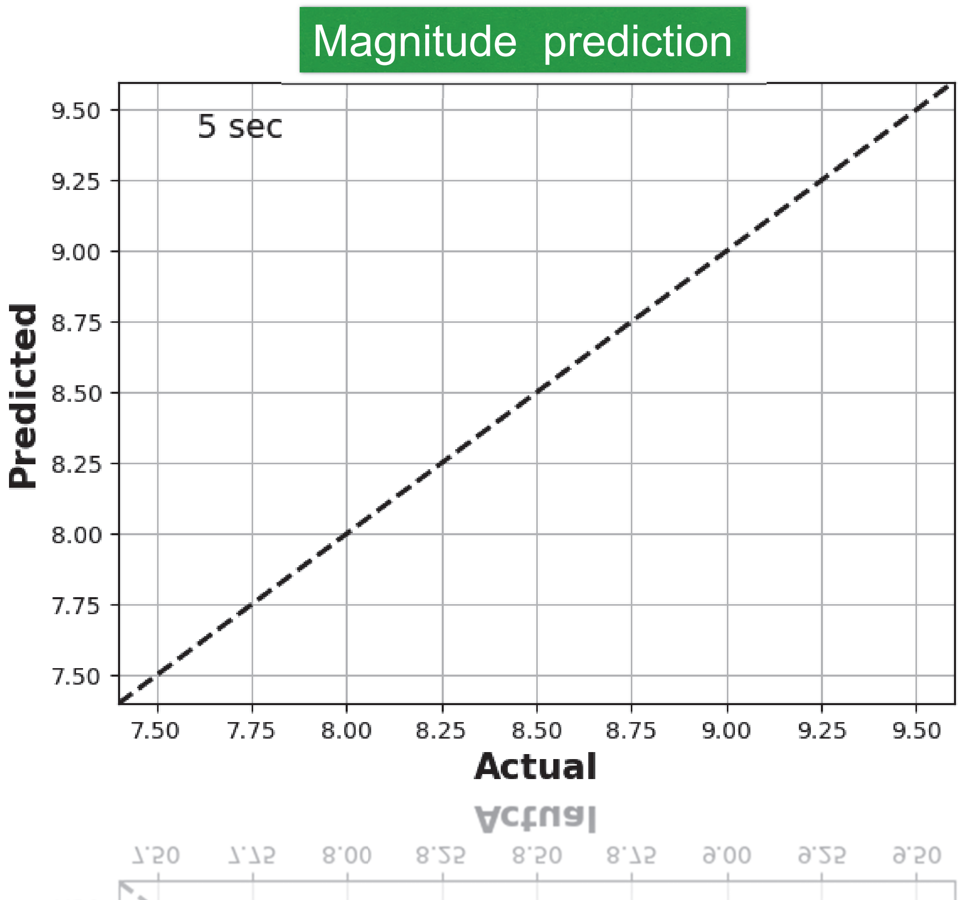
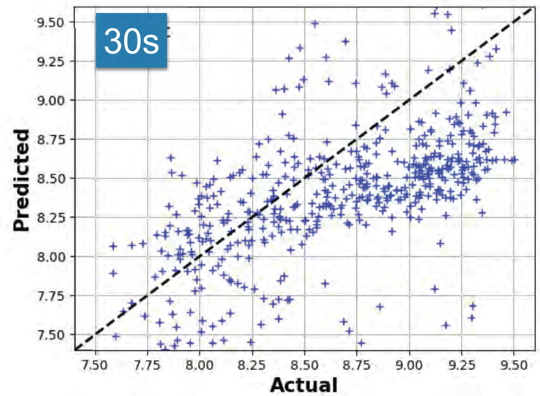
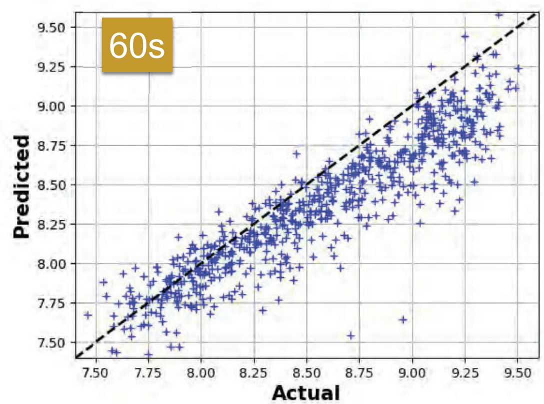
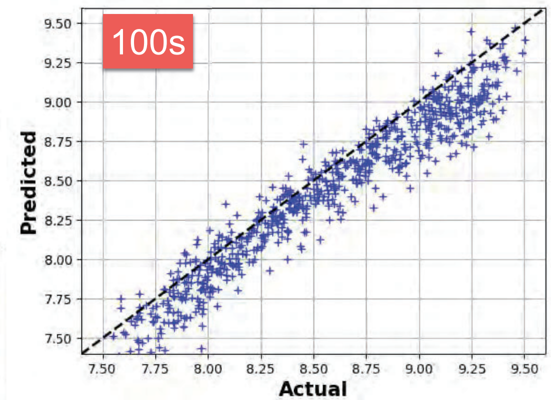
Lin et al. in prep

RNN Performance on Validation Data









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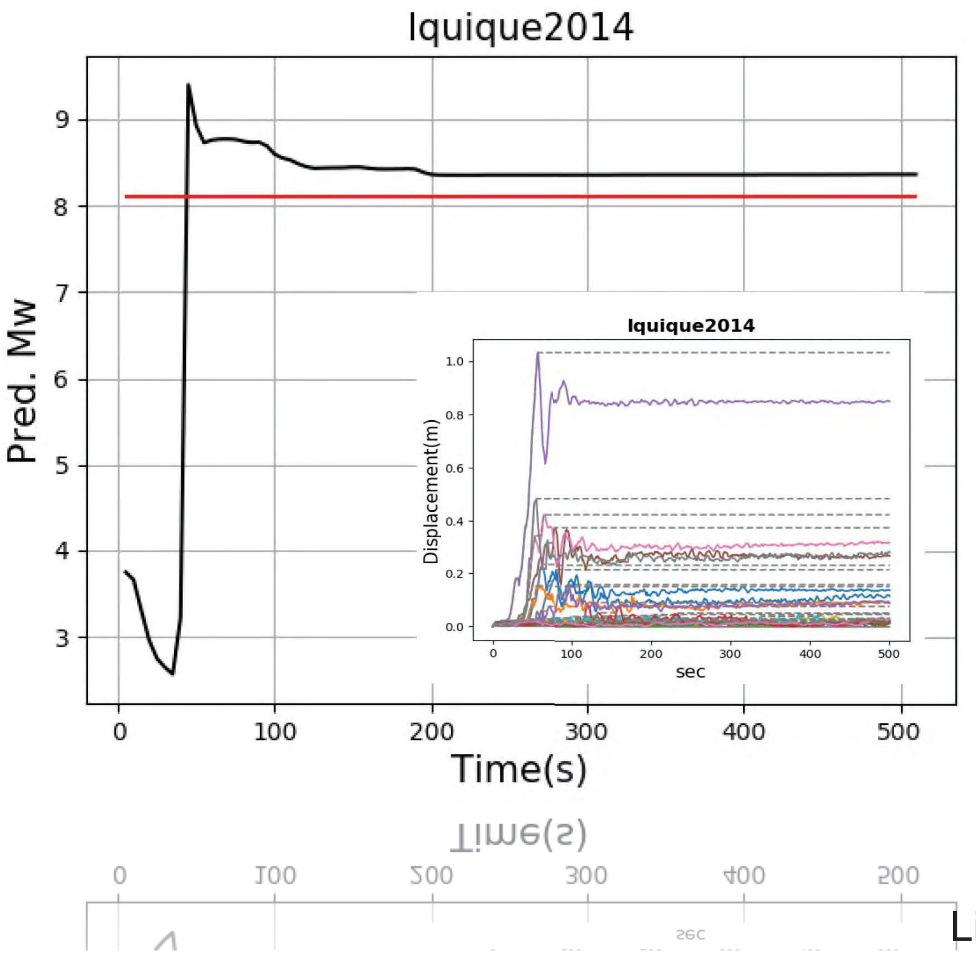
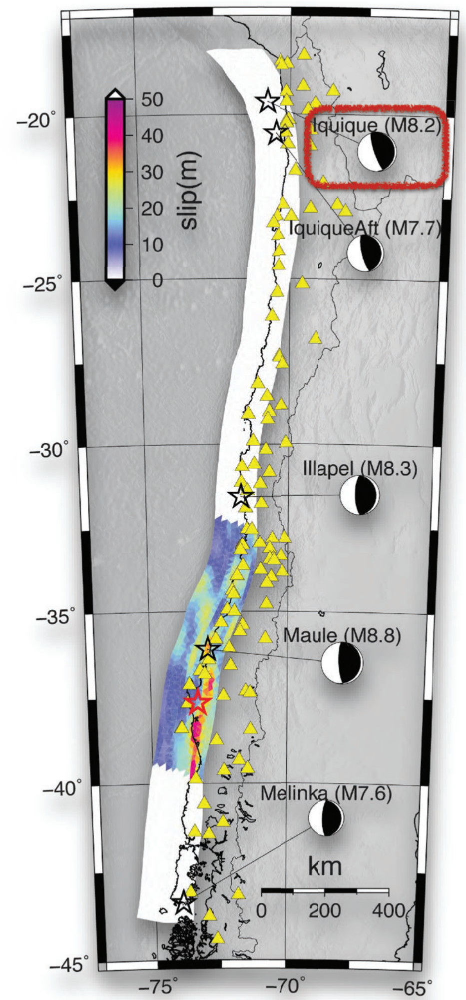
RNN Performance on real events





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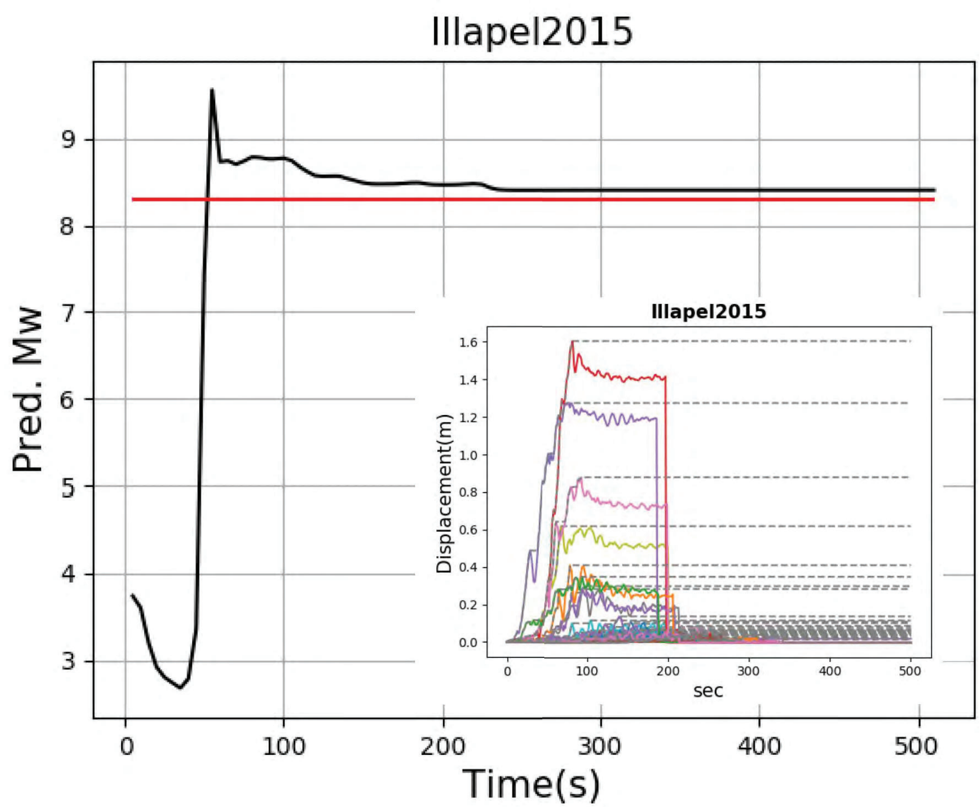

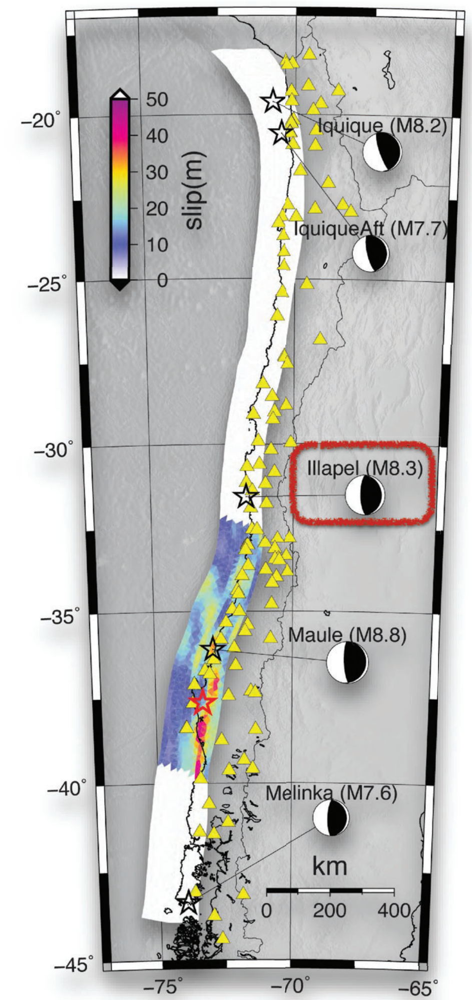

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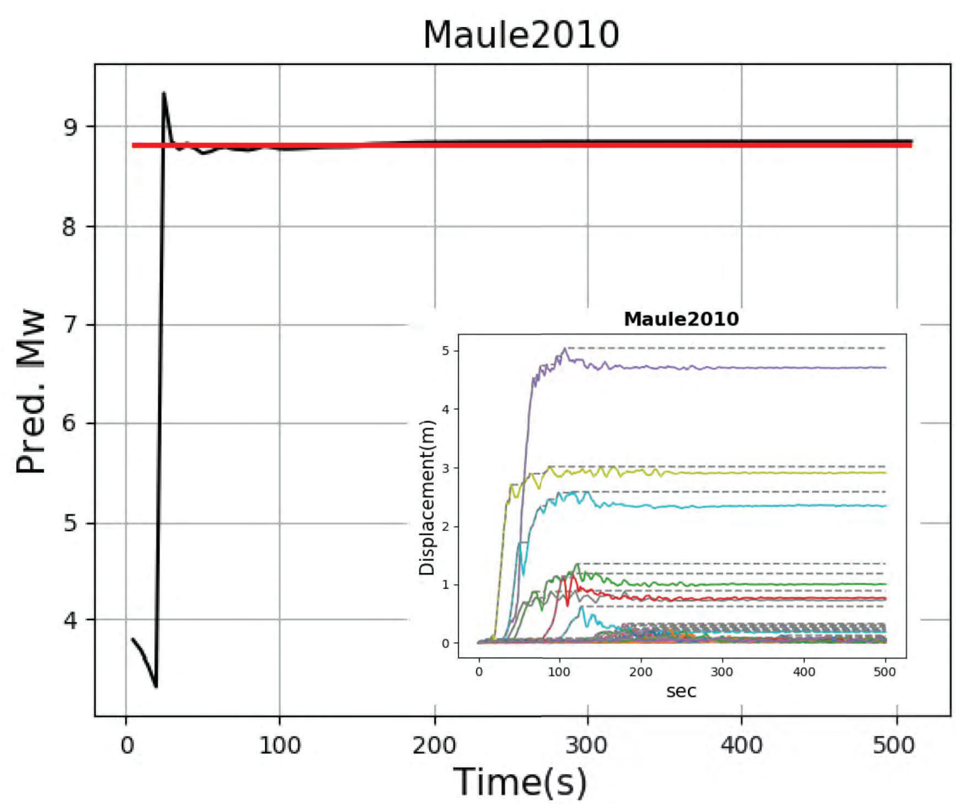
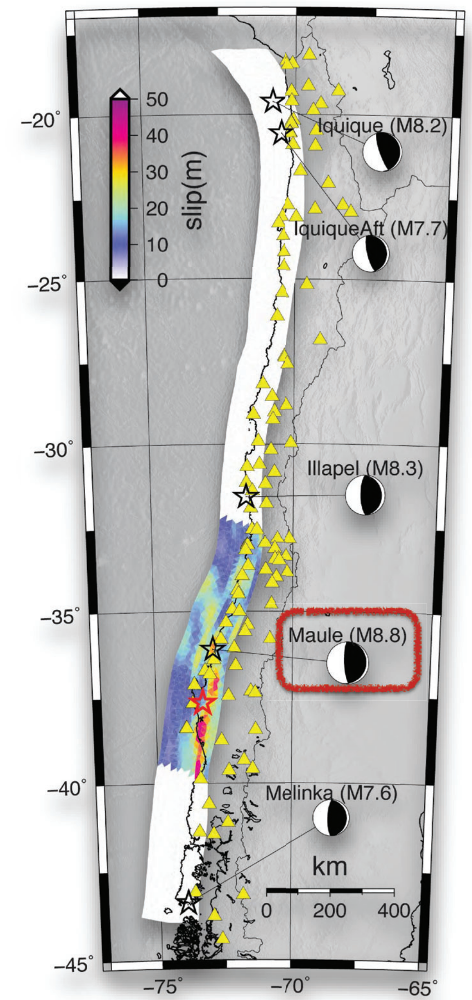
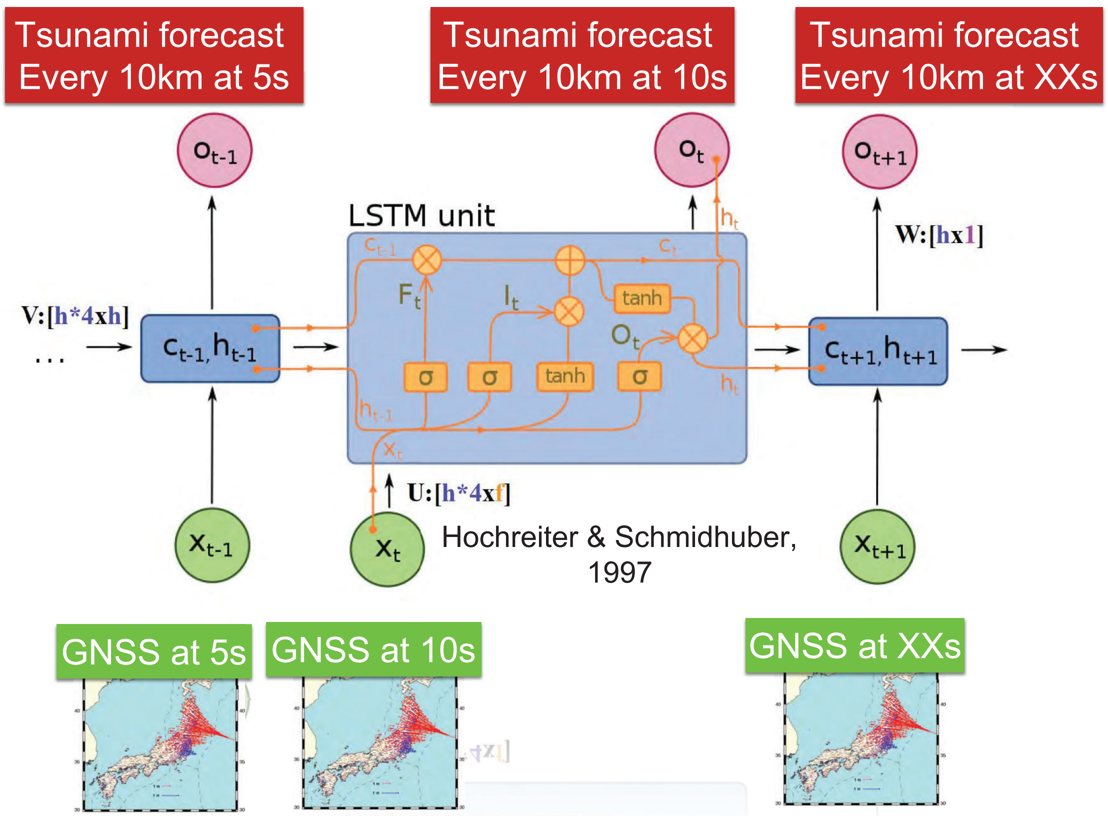


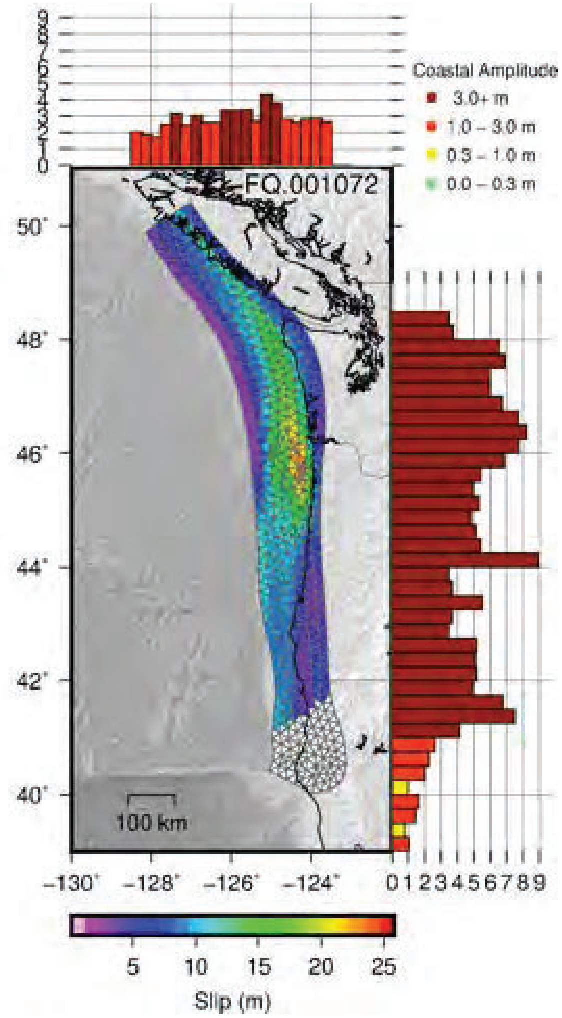


Lin et al. in prep

But who cares about the earthquake?

Train the RNN to **forecast the hazard**. In this context properties of the earthquake source are **unimportant**

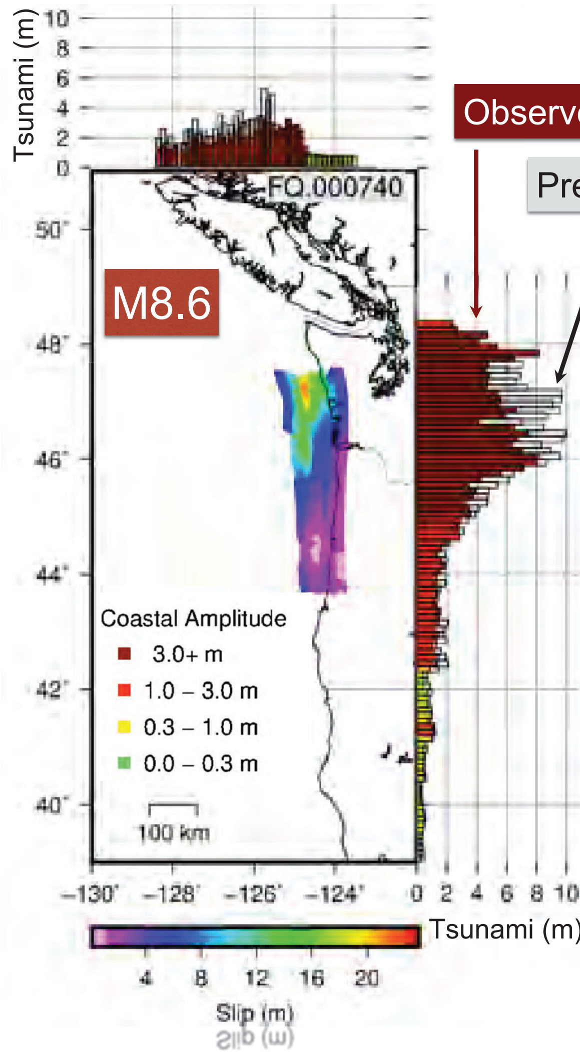


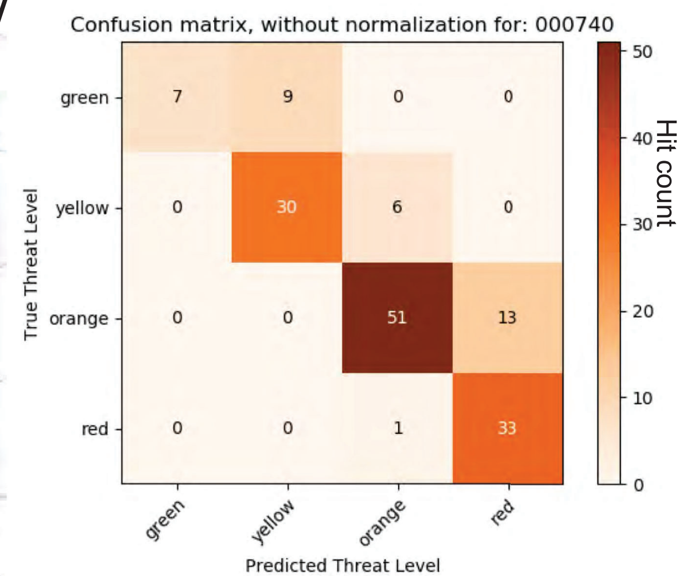


Lin et al. in prep

Can we forecast the tsunami? First results

- **Predict** the tsunami amplitude at the coastline
- Take the peak value over **10km** bins
- Use **threat levels** defined by NOAA (different for JMA)
- Only **tested on Cascadia** simulations, now expanding to Chile data set
- **Validation** is challenging but we have surveys/tide gauges

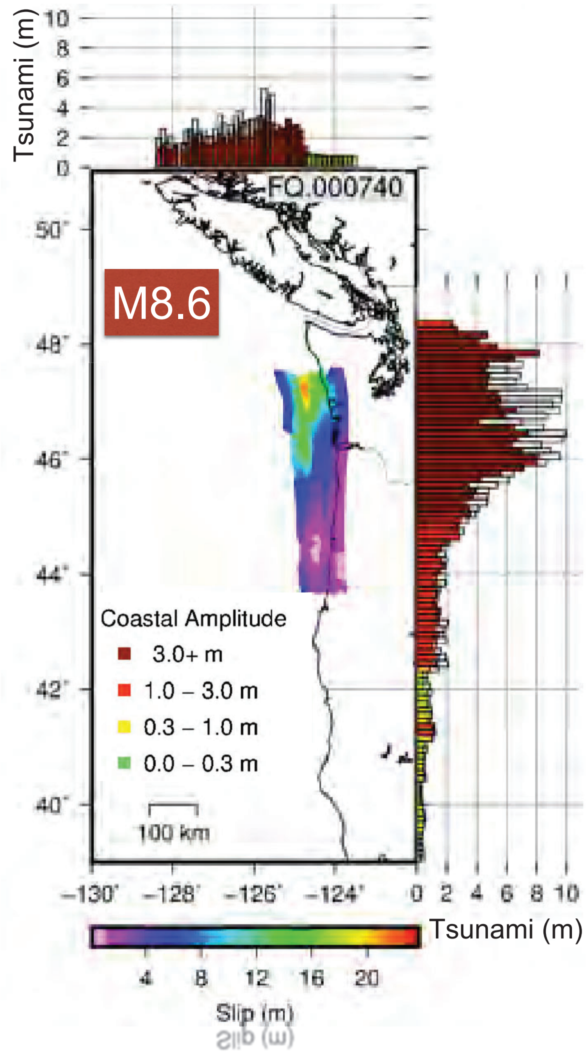




Williamson et al. in prep

The holy grail: Inundation modeling

- The ultimate goal is to forecast **inundation** and eventually damage
- This is exceedingly difficult in a rapid response setting
- It is very sensitive to **fine scale** structure of the tsunami
- Requires more complex computations



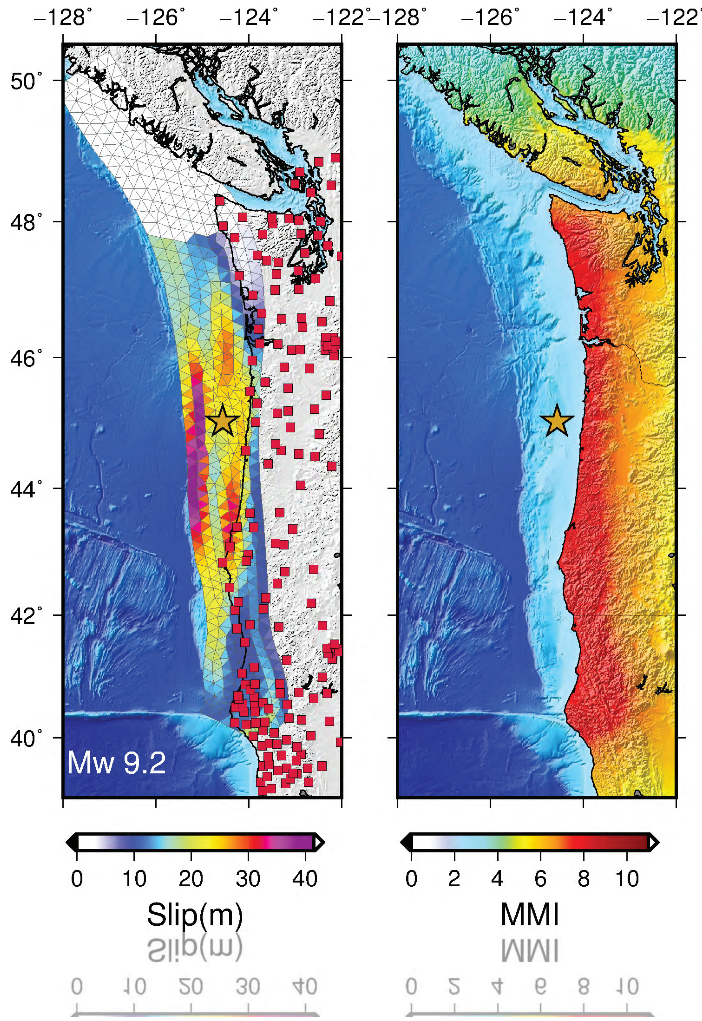
Why does this (tentatively) work?

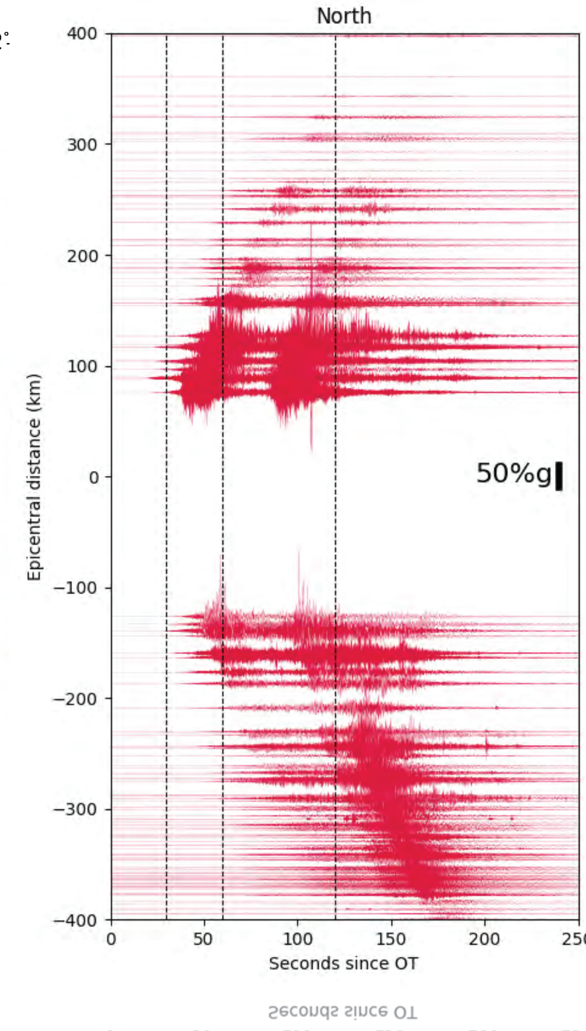
- Because the physics is (fairly) well understood
- The different modeling steps are robust and validated. They map well to reality
- And we can efficiently run many simulations and adequately sample the range of possible behaviors

Other hazards: Towards shaking forecasts

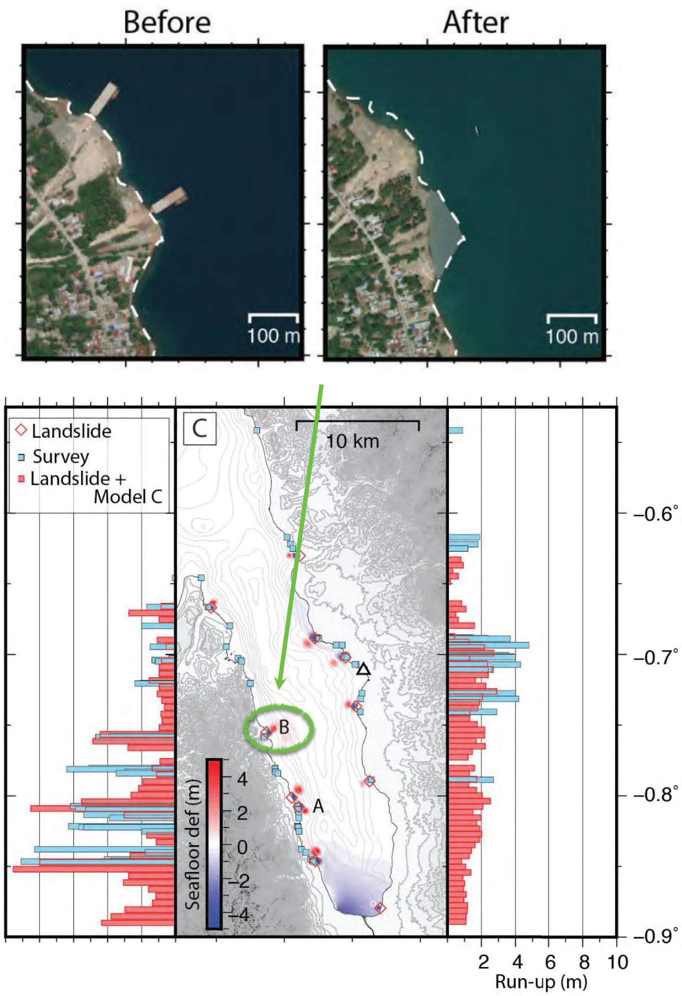
- Combine GNSS with **seismic** data
- We can generate broadband seismograms
- It's **slower** but possible
- Details of the source and path are much more important
- Relies on **approximate** (semi-stochastic) methods
- Do we know enough about the process for this to be **meaningful**?

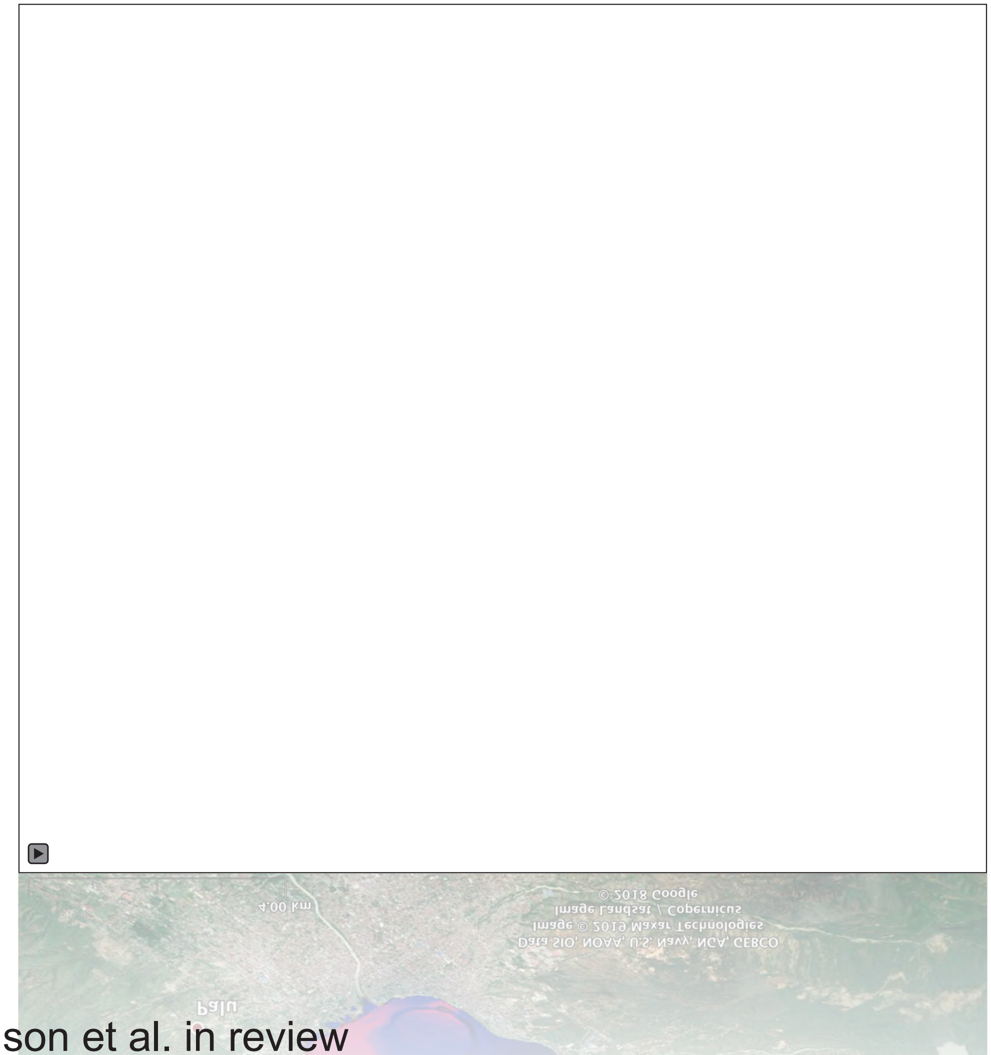
Goldberg et al., in prep





Without a physical understanding there is no forecast





Williamson et al. in review

Summary

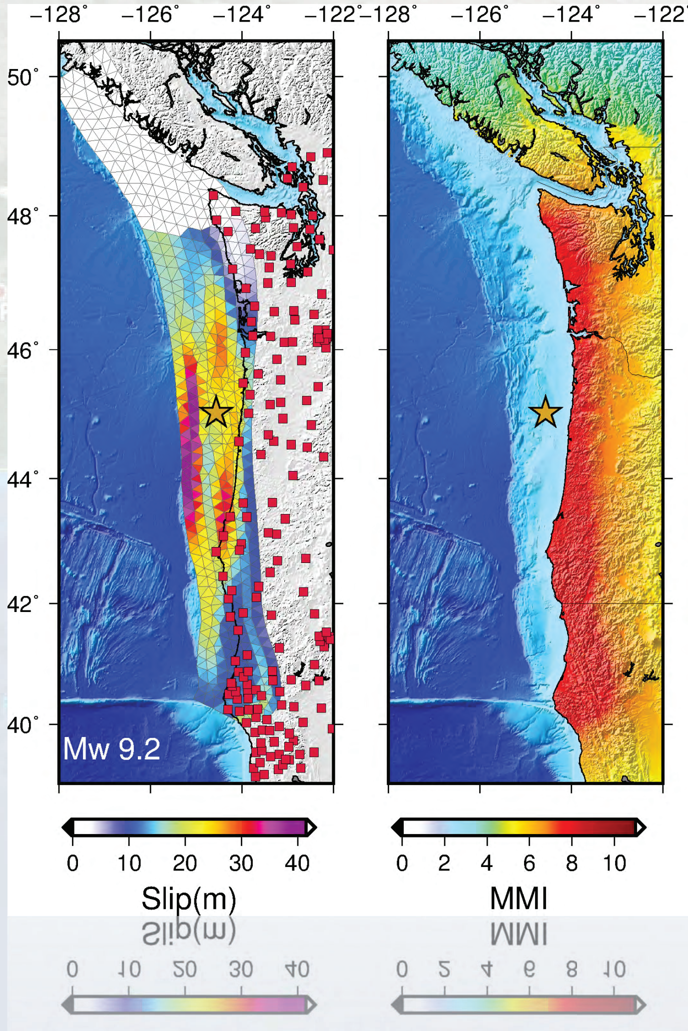
- Machine learning provides a great way to establish **complex correlations** between GNSS **observations** and earthquake **hazards**

- For tsunamis this works well because the underlying physics is well understood

- And so we can efficiently run **many simulations** and adequately sample the range of possible behaviors

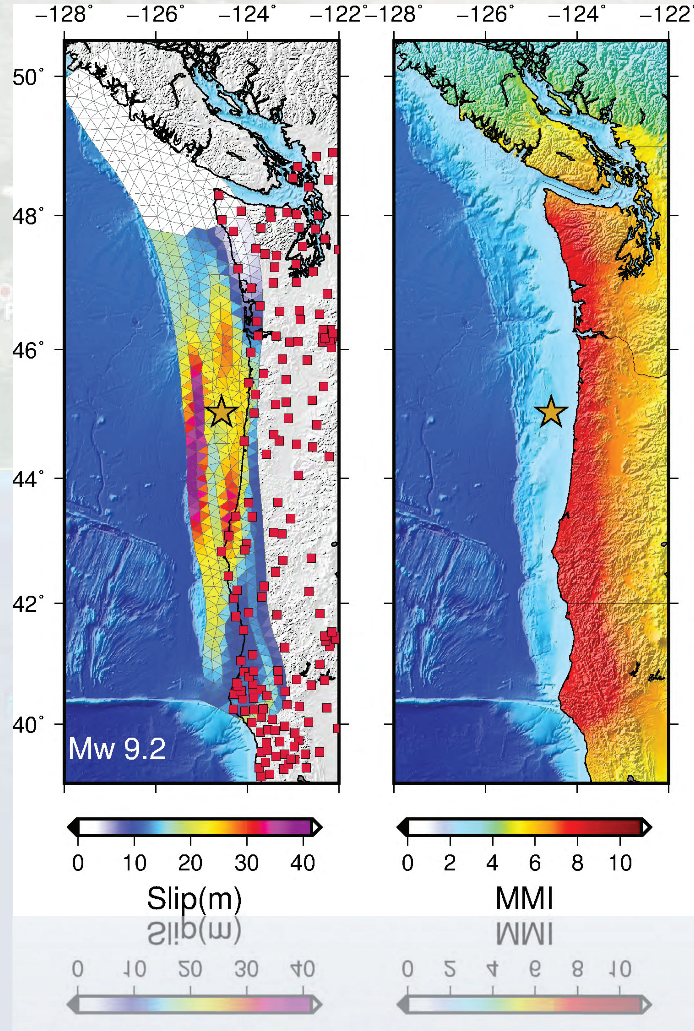
Summary

- The **physical connections** between earthquakes and other hazards are less well understood
- But as our knowledge of these improves these methods will become important
- GNSS is comparatively simple but in the future a **diversity** of geophysical data feeding algorithms will be the norm.



Challenges

- For earthquake hazards in particular:
  - How does the wedge deform?
  - Where is strong shaking generated?
  - How does shaking trigger subaerial/submarine land sliding?
- **Multiphysics** simulations that capture all the relevant phenomena
- Large events are comparatively **rare**. The simulation -> ML path requires very efficient codes.($1x10^5$ simulations)
- **Capacity building**. There are still barriers to entry for massive parallels computing and machine learning methods



Thanks!


Washington
Oregon
Portland
Salem
Vancouver
Strait of Juan de Fuca
Salish Sea
Victoria
Strait of Georgia
Quillayute Canyon
Thanks!
Creager Ridge