A hybrid ML-physical modelling approach for efficient approximation of tsunami at the coast and onshore

Naveen Ragu Ramalingam
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GEM GLOBAL EARTHQUAKE MODEL working together to assess risk

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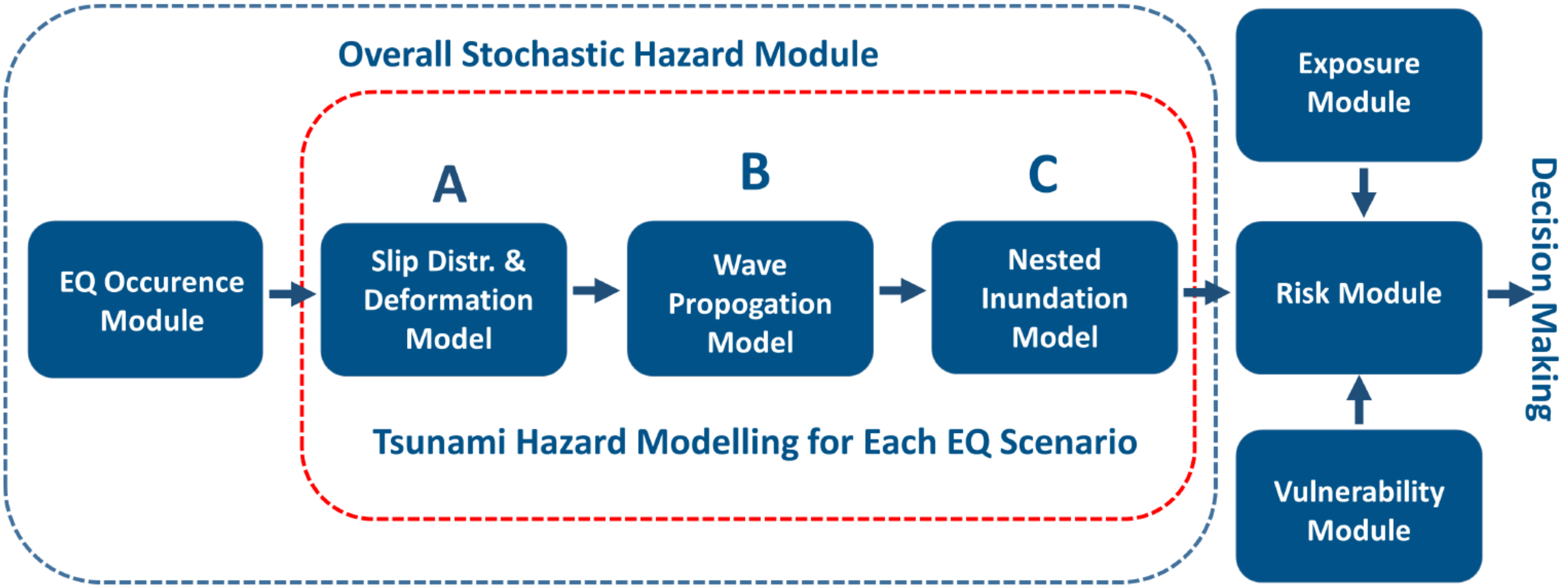
Workflow of probabilistic tsunami risk assessment(EQ sources)



What's your connection to tsunami / risk?

State of Art – How to solve this challenge of scales?

1. **Reduce the number of events**: A-Source (SROM), B-Propagation(Unit Sources/Green Function), C-Inundation – Clustering, Importance sampling etc.
2. **Approximations:** Modified Green's Law, Amplification Factors, Attenuation based inundation schemes
3. **Computational or Modelling Approaches:** Computational(GPU&HPC, Solvers – Coupling and using simpler ones, Variable Grids, Decomposition, Nesting), Reduce scope and prioritise resources
4. **Surrogate Models:** Statistical - RS,GP,PC and Neural Network – ANN,CNN and Deep Learning

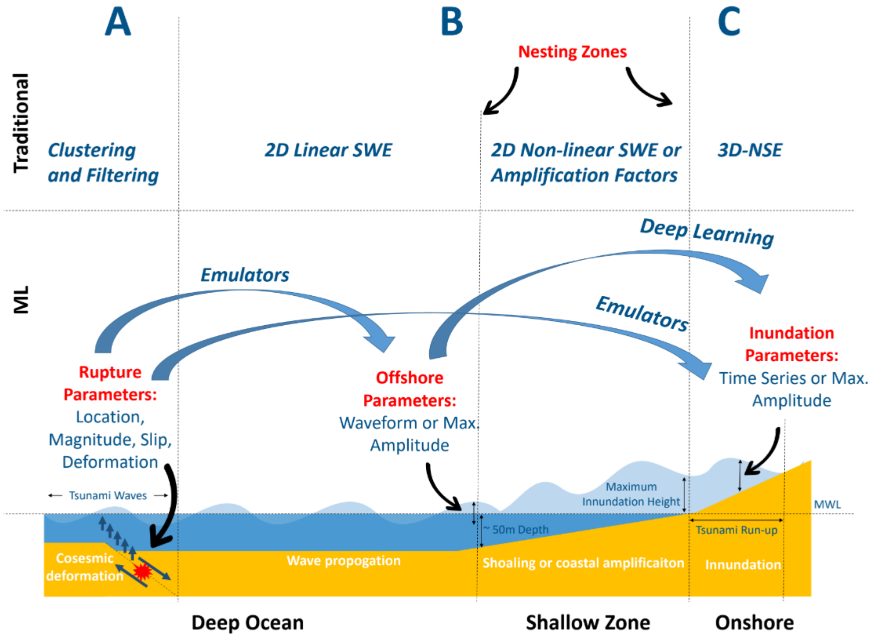
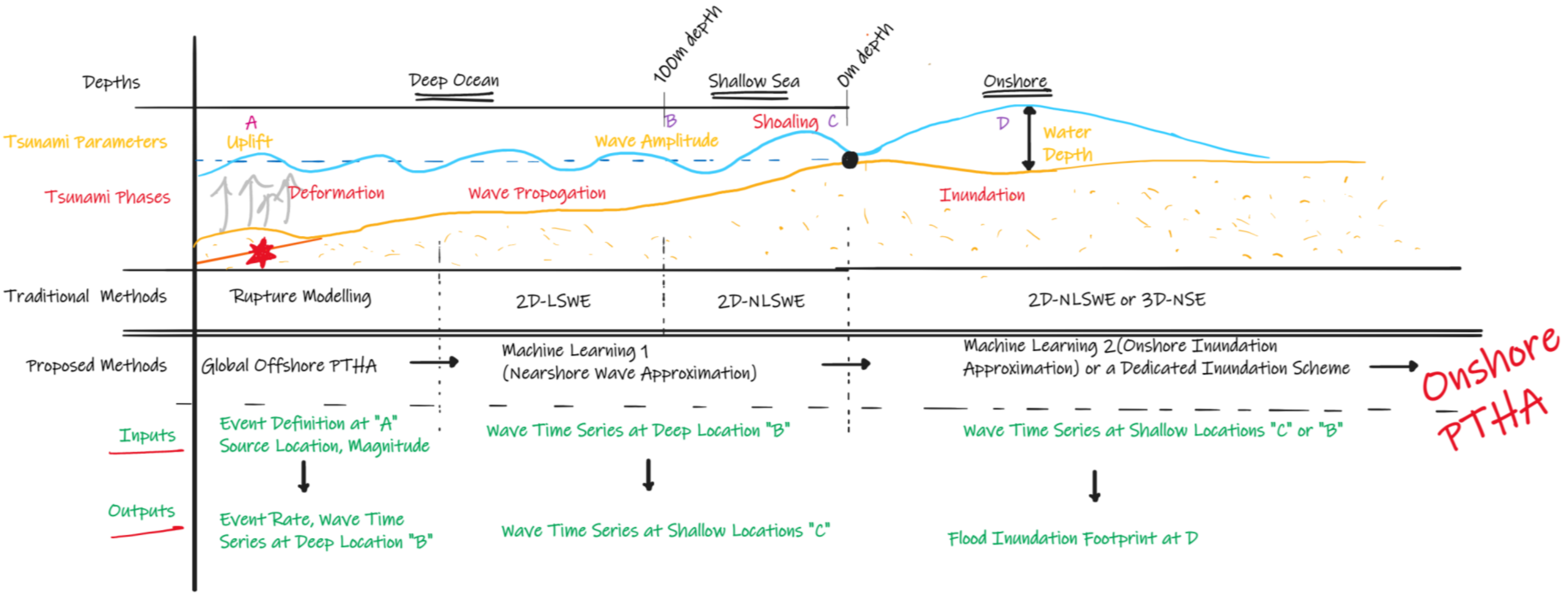


***Figure 2.** Representation of tsunami from off-to-on-shore and methods*

Note: Similar challenges are handled in other situations like this:

- Warning and forecasting **where time, information and resources** may be a constrain to conduct real-time modelling.
- In other science/geoscience field but particularly other coastal hazards like storm surge which has a similar modelling chain.

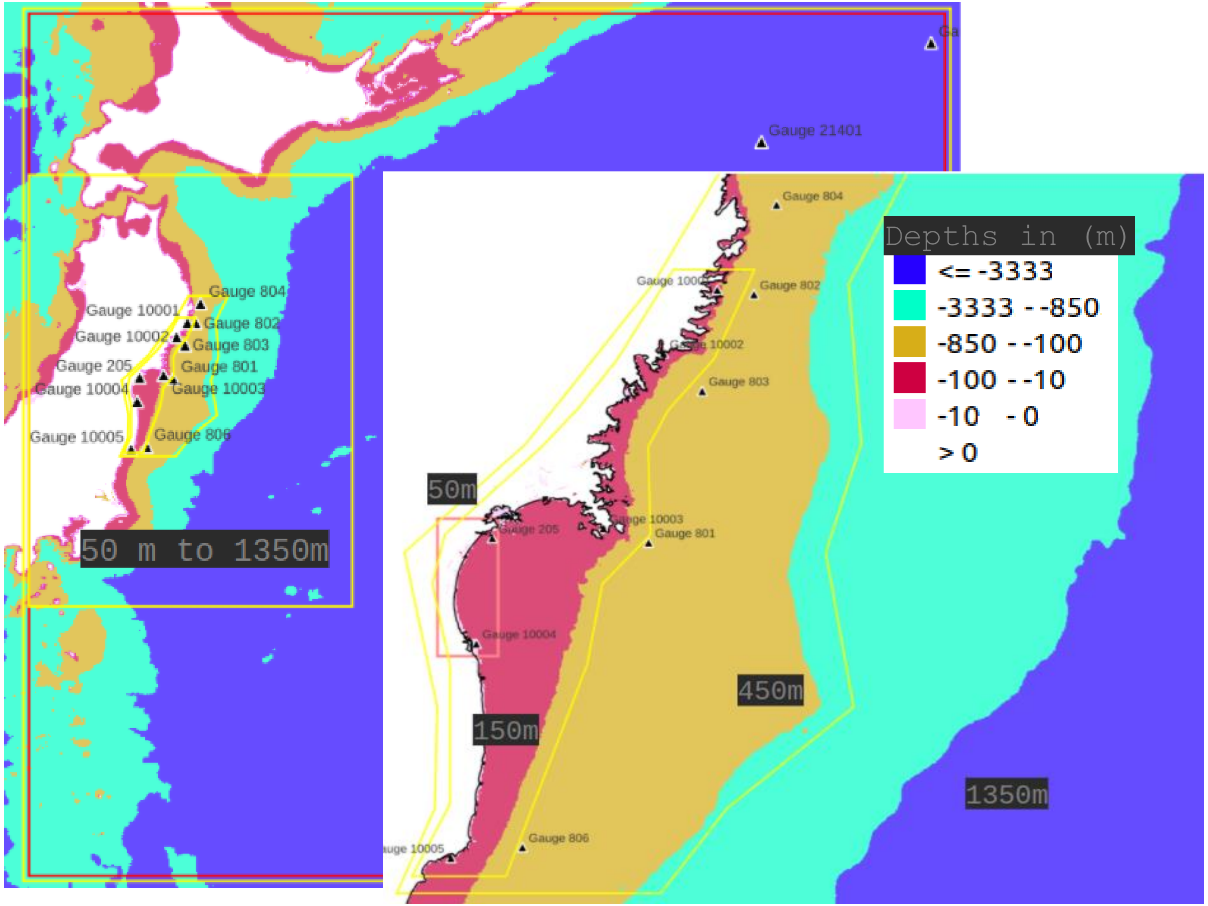
Proposed Workflow



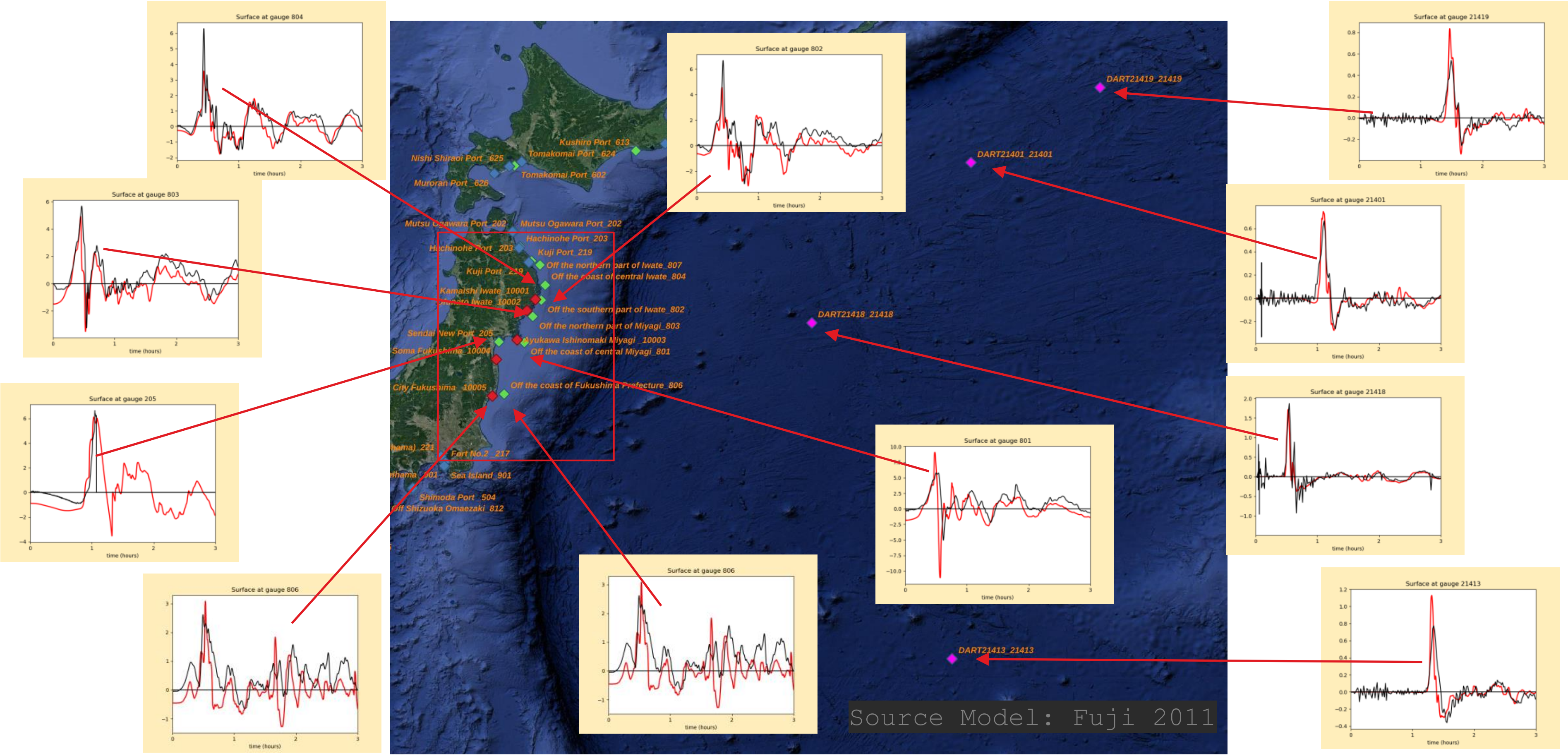
Offshore Tsunami Model + ML Based Approximation = Nearshore and Onshore Tsunami Hazard

A Hydrodynamic Model (to capture the nearshore and onshore dynamics)

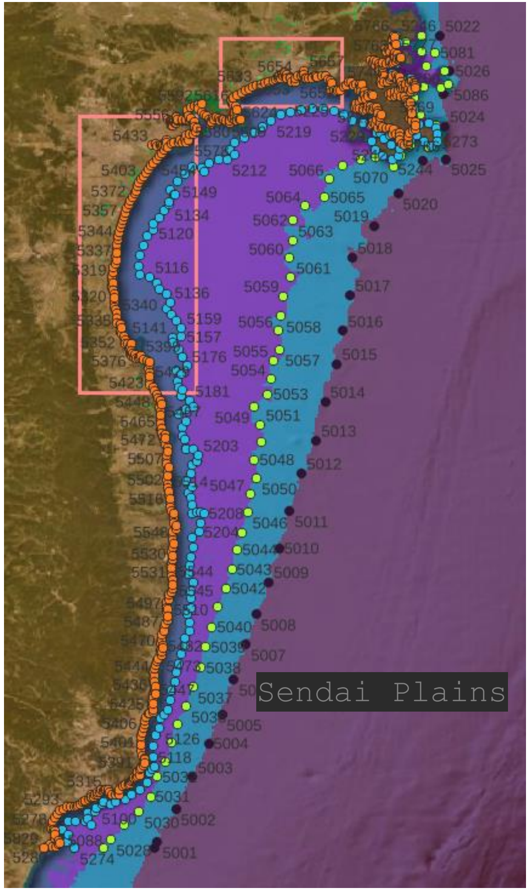
- Tsunami model for Tohoku region of Japan with GeoClaw
- Uses topo-bathy-defense data from global and local sources - (JP Cabinet project data + GEBCO 2021 + Copernicus DEM)
- Calibrated with offshore and onshore observation data for Tohoku 2011 event and different source models
- For validation of wave approximation ML model, we simulated other historical/ synthetic events

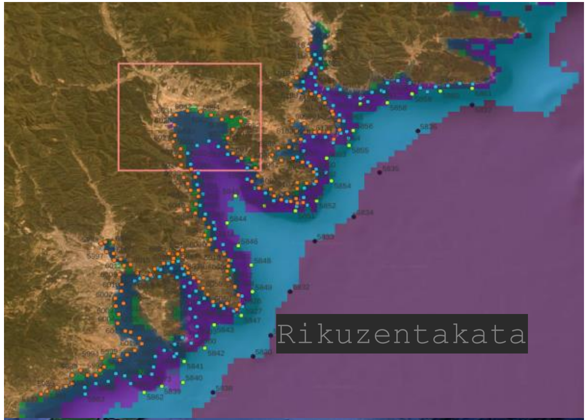


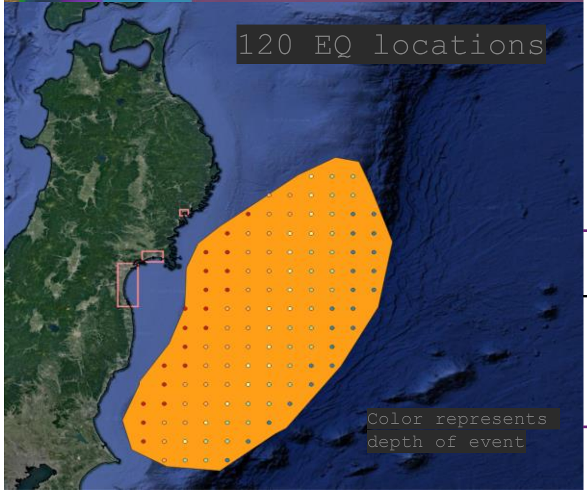
Typical validation for Tohoku event – offshore and nearshore



Propagation/Inundation database for ML







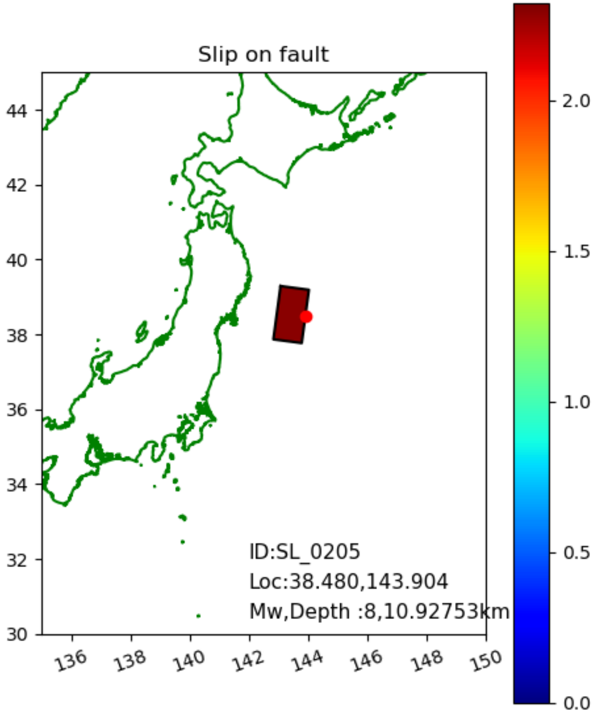
- 1133 locations for observing waveform at different depths (5,25,50 and 100m)
- 3 selected AOI selected to record the max flood depths highlighted by pink rectangles.
- 120 EQ Locations, 383 events with varying location and magnitude are used of 6 hour simulation
- Homogenous slip events for rectangular fault whose dimensions are scaled based on Mw(7.5, 8, 8.5, 9)
- Fault parameters(angles) defined using SLAB.2 data and deformation modelled using Okada solution

EQ Source Parameters

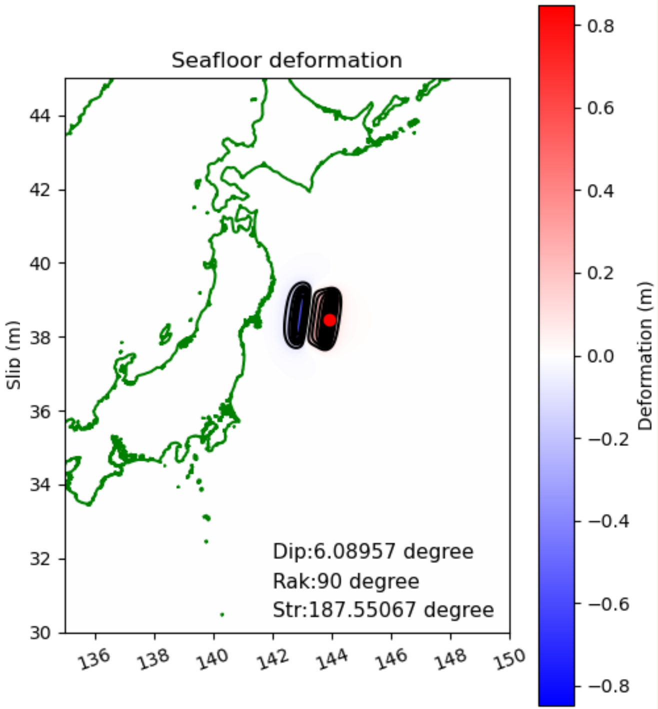
Range	Mw	Lat	Lon	Dep	Rak	Str	Dip
min	7.5	35.73	141.15	10.2	90	187.20	5.54
max	9.0	39.48	143.90	45.7	90	225.78	17.0

Model and preprocessing events – Feature design for ML

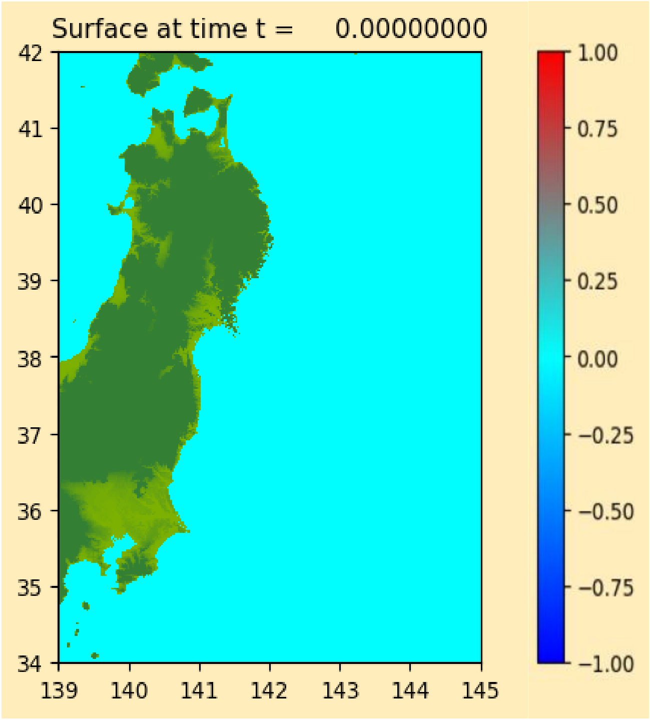
Event 205



Step 1

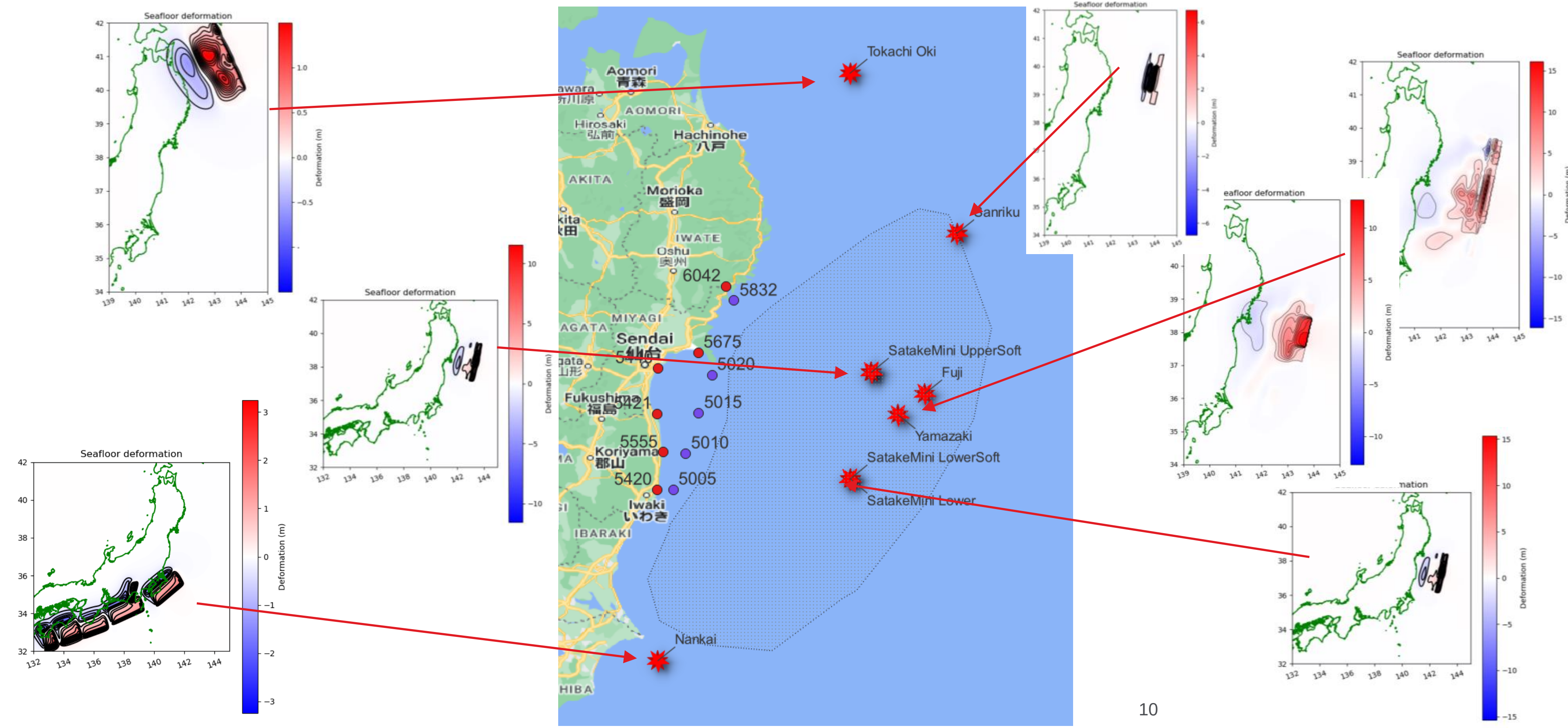


Step 2

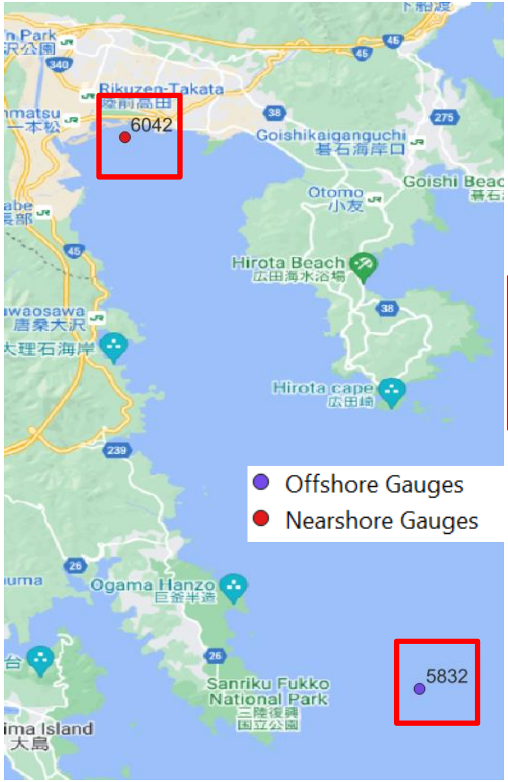


Step 3

Some non-homogenous distributed slip historic events



Possible ML and training configuration



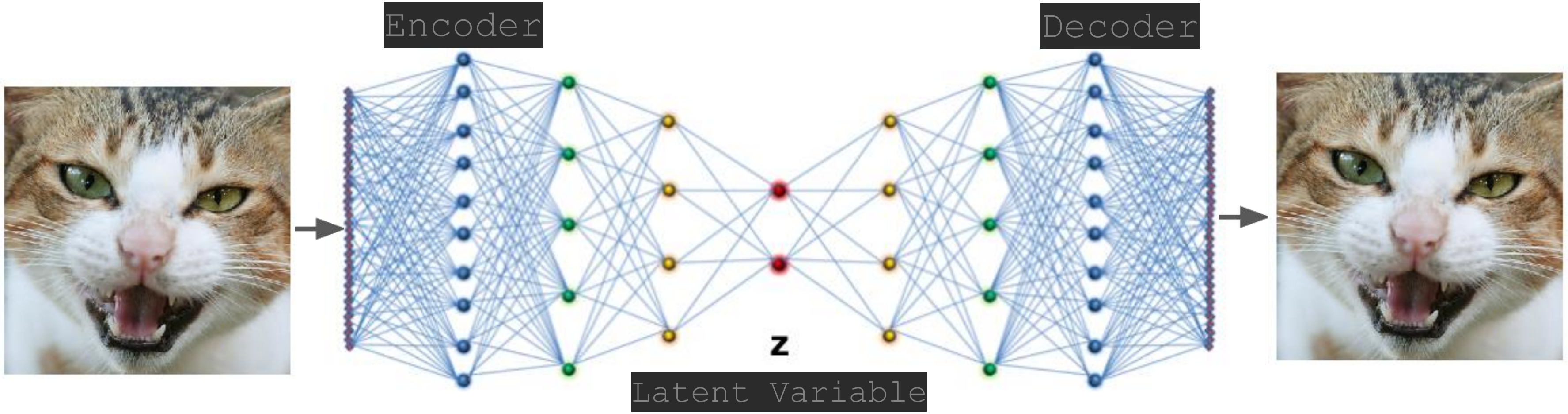
Offshore Parameter → ML Methods → Nearshore Parameter

Option 1:
Tsunami wave time series → Support Vector Machines → Max tsunami amplitude

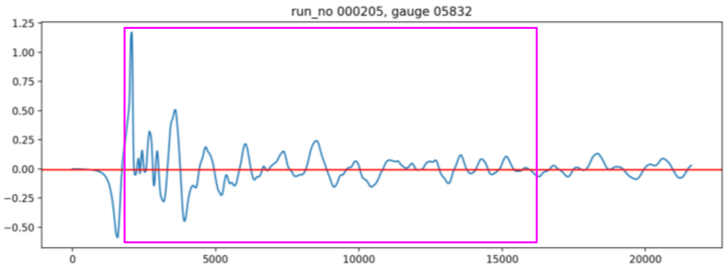
Option 2:
Tsunami wave time series → Variational Autoencoder → Tsunami wave time series

Option 3:
Tsunami wave time series → Variational Autoencoder → Max tsunami Inundation

Time to feed the ML model - VAE(variational autoencoder)

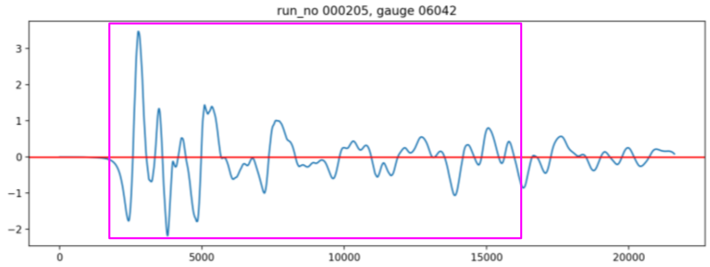


Offshore Gauge



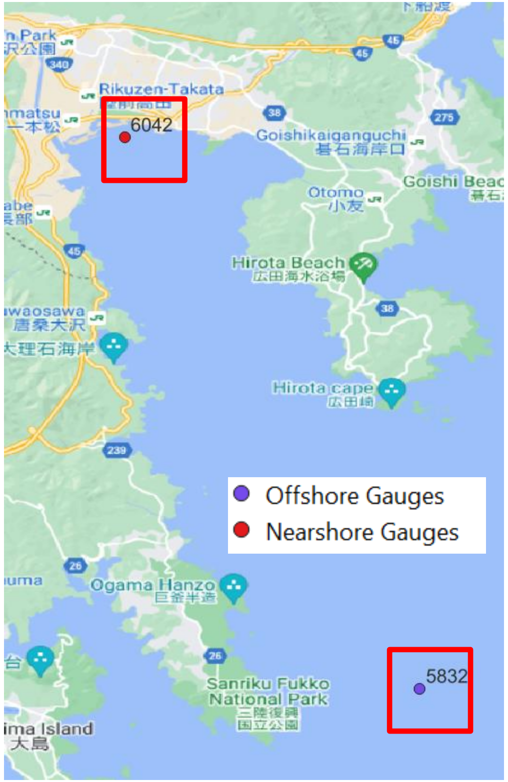
VAE Transformer

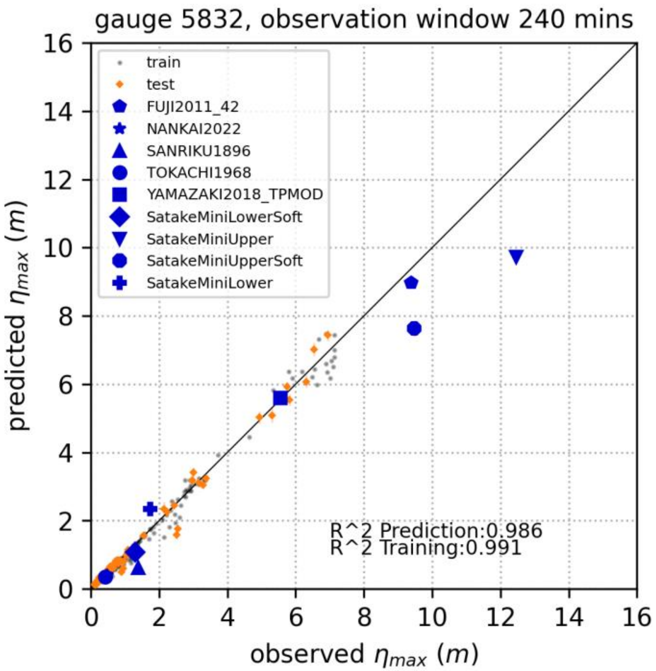
Nearshore Gauge



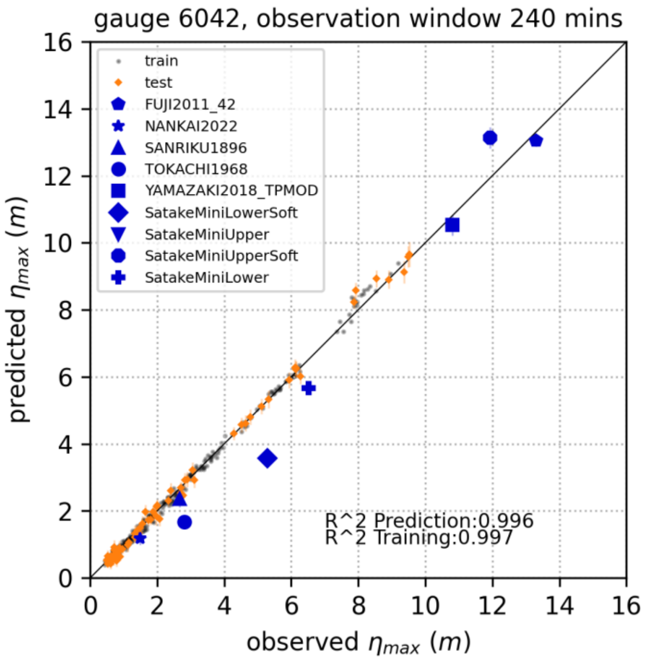
Liu et al 2021

But does it work? Simple 1D channel like region at Rikuzentakata





Offshore Gauge

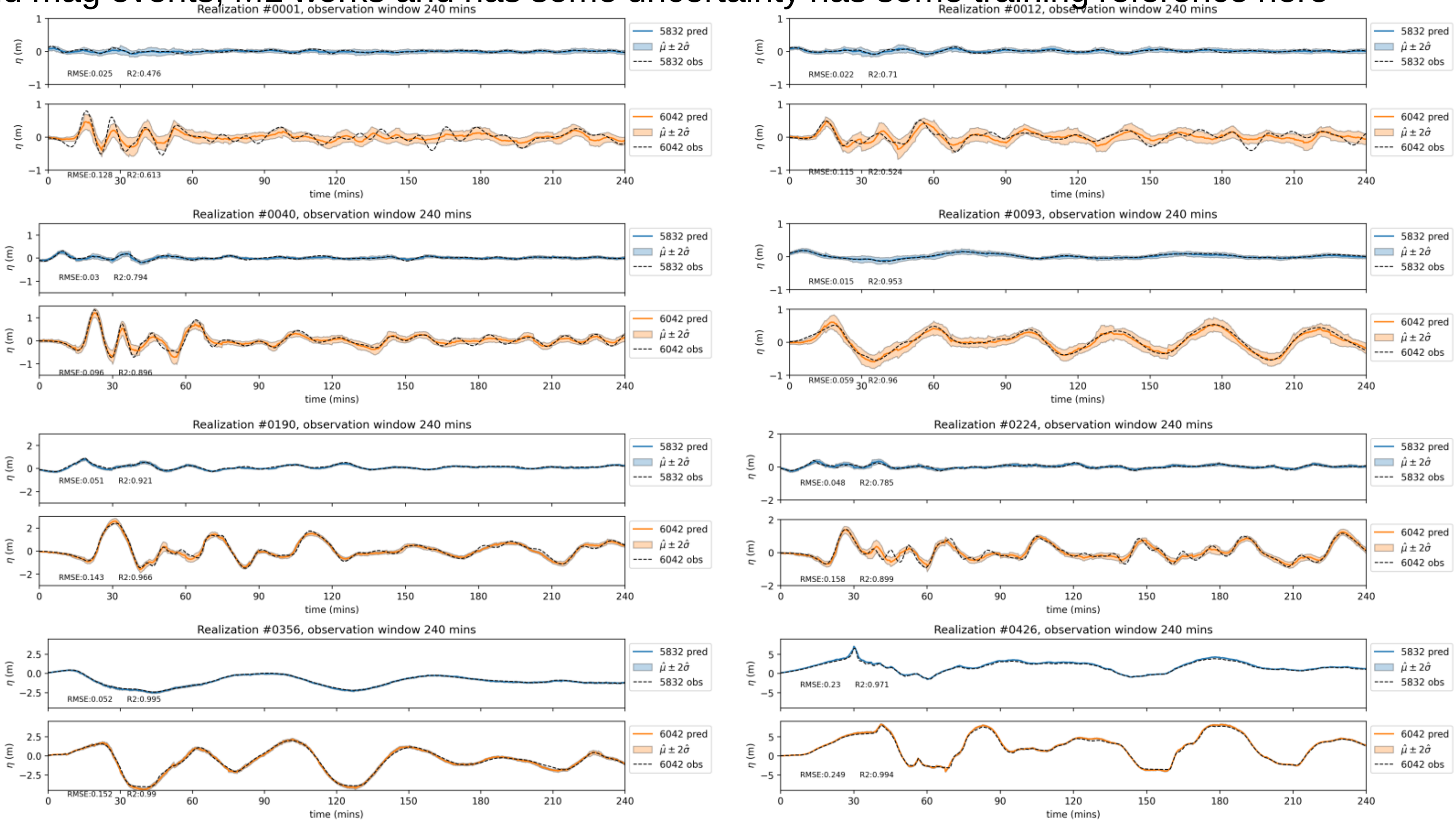


Nearshore Gauge

Sample size: Events passing threshold – 314, Training set – 251 , Test set – 63 , Historical Set - 9

Predicting the test events – are similar to training events but new

Small/mid mag events, ML works and has some uncertainty has some training reference here

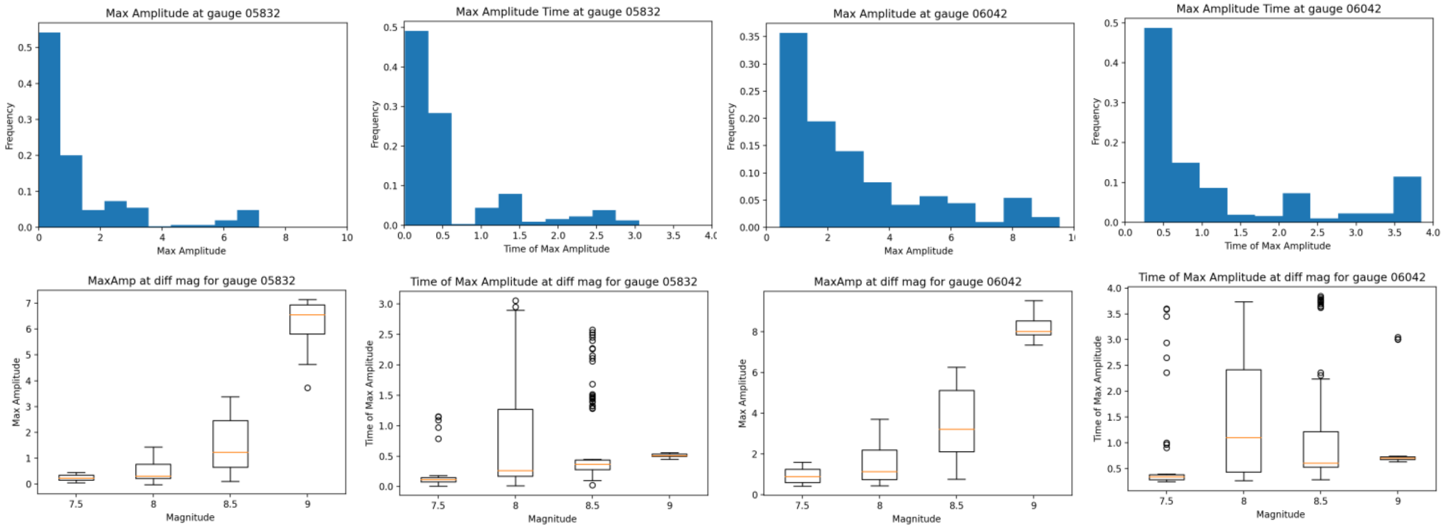


Large mag events, ML works very well and gives exact match – few training reference for the type

Some statistics to describe the database(Rikuzentakata)

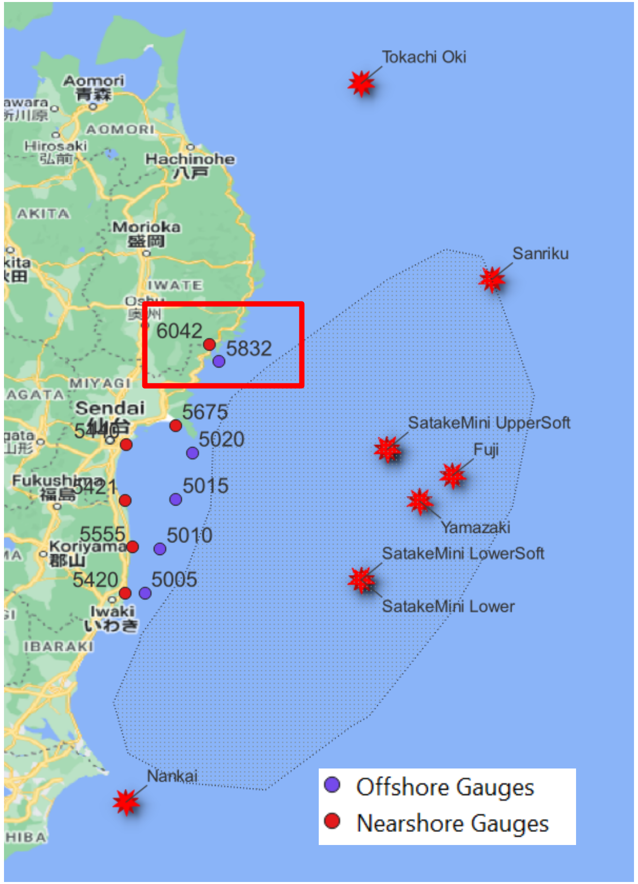
Offshore Gauge

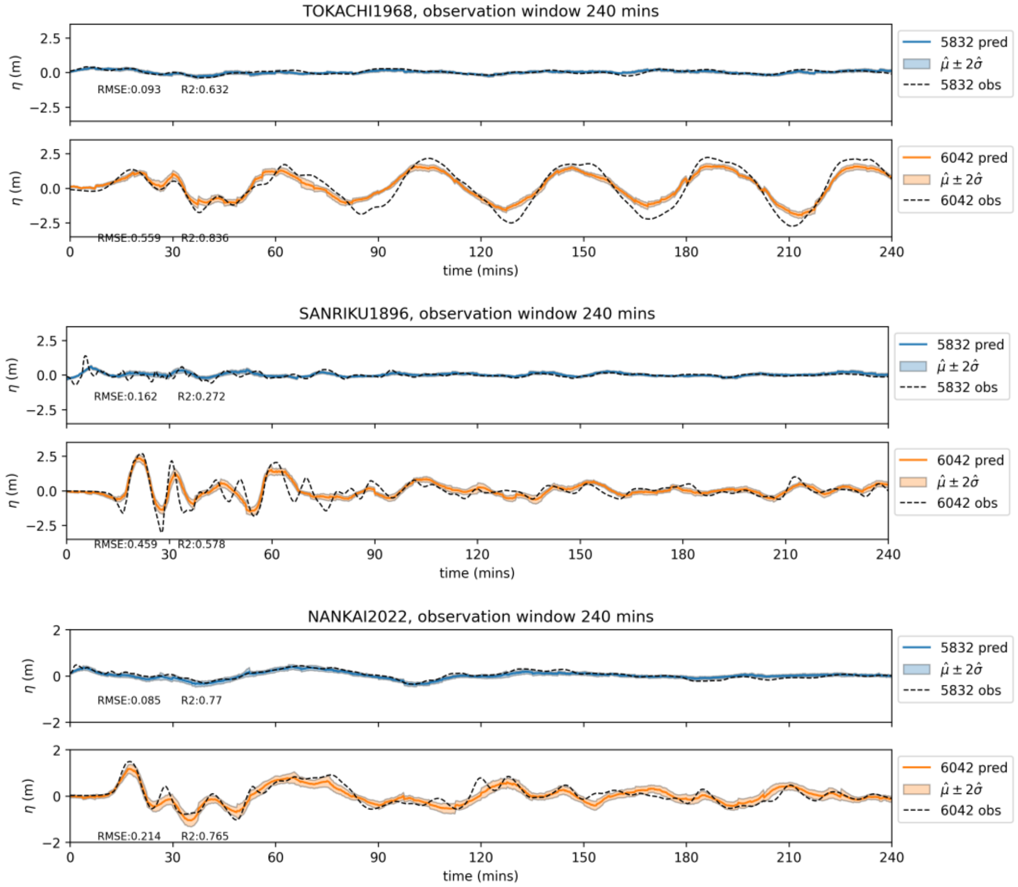
Nearshore Gauge



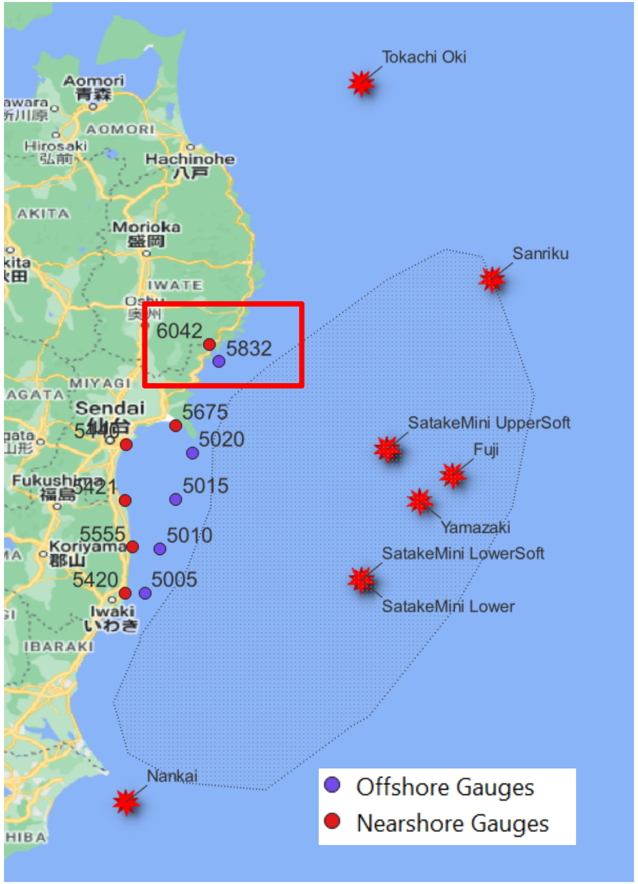
314 / 383 available events

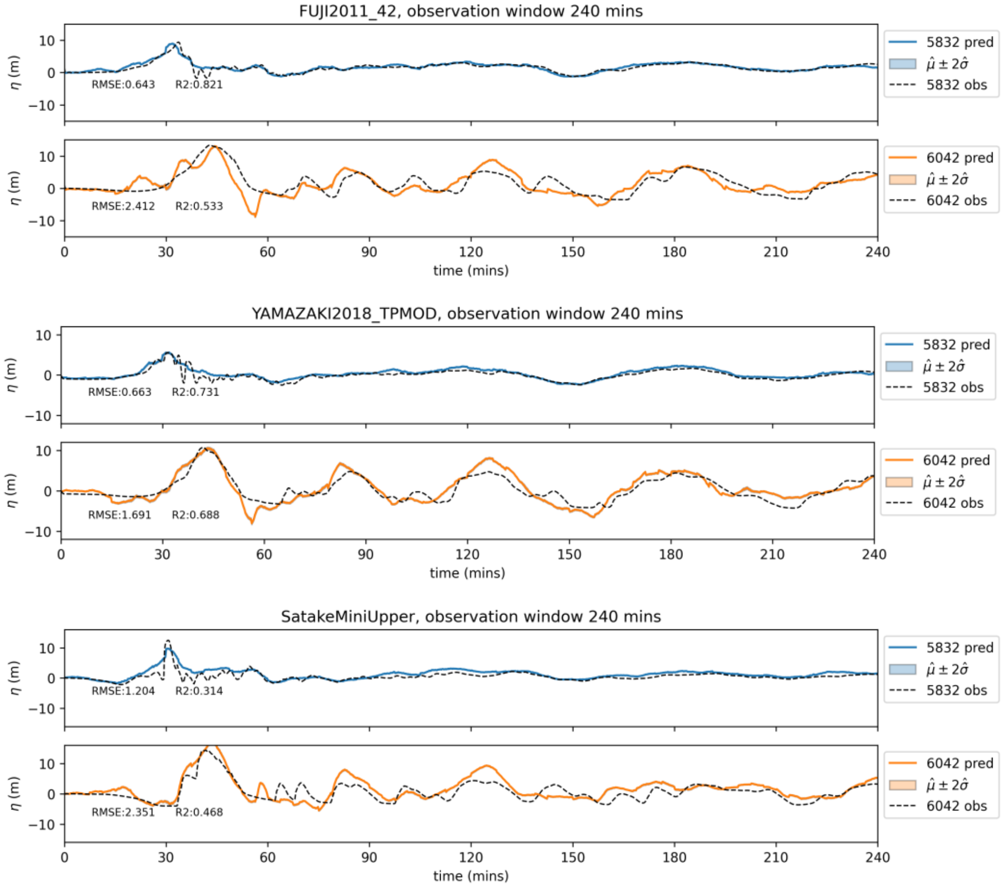
Some historical events – unseen events



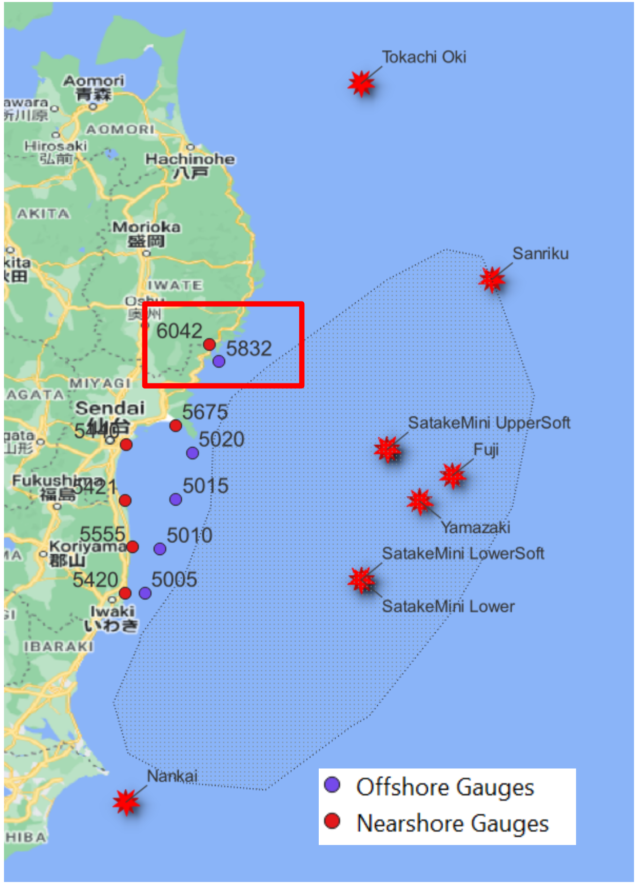


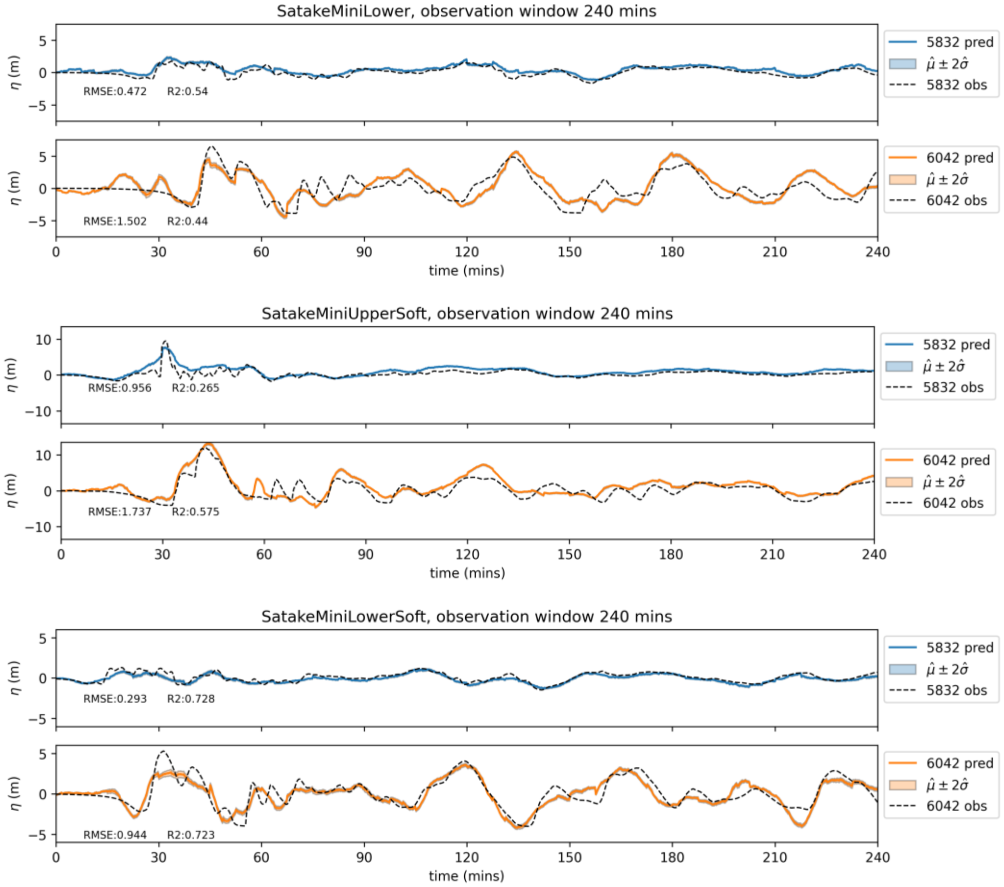
Some historical events – Tohoku Variations



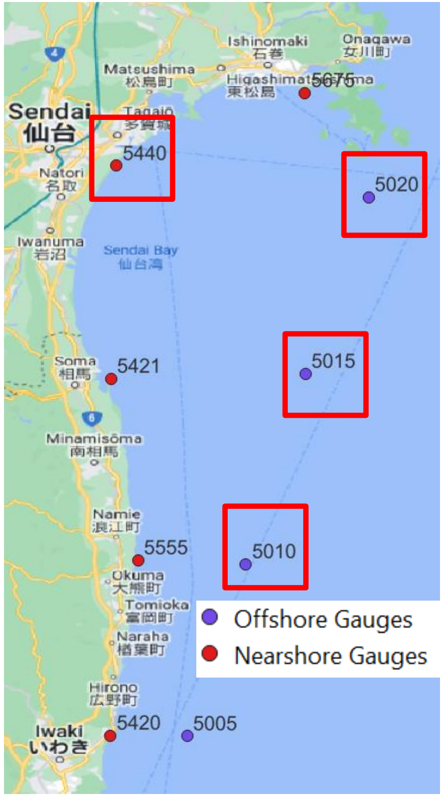


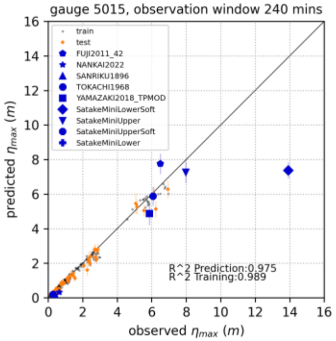
Tohoku like event(Part of Satake 2013 source model with Shift)

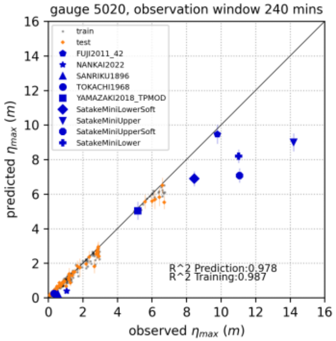


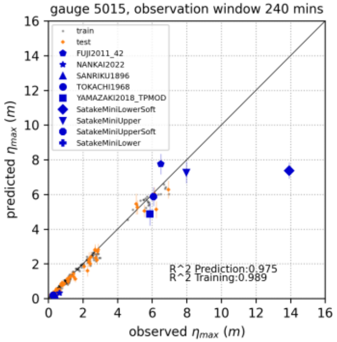


But does it work? For a more complex coastal configuration– Sendai Plain

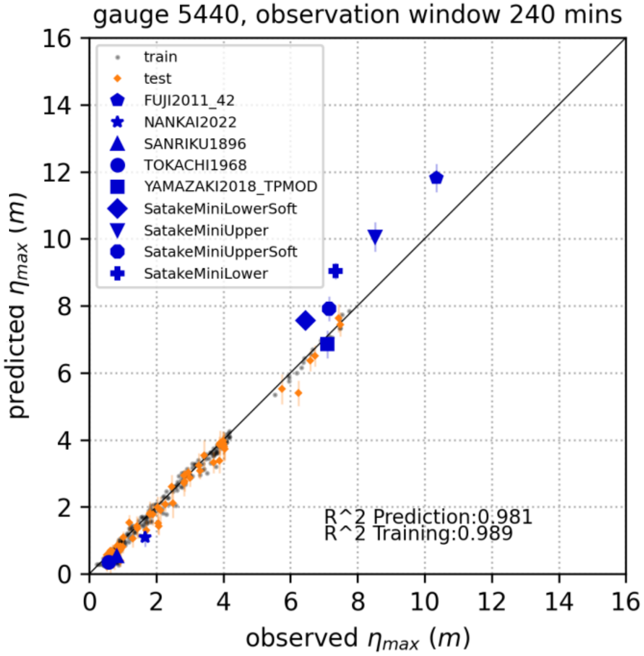








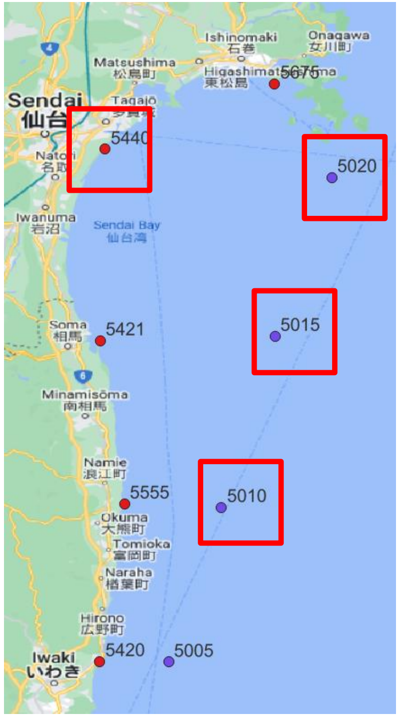
Offshore Gauge



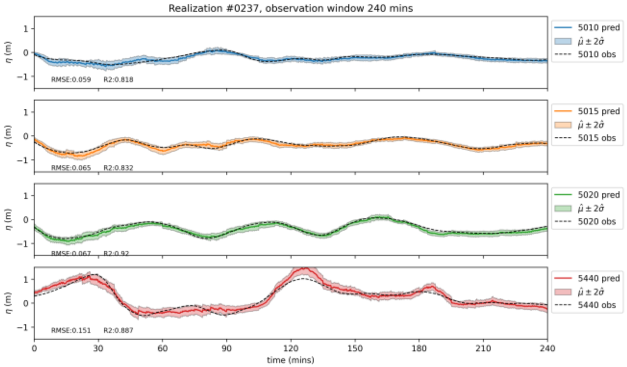
Nearshore Gauge

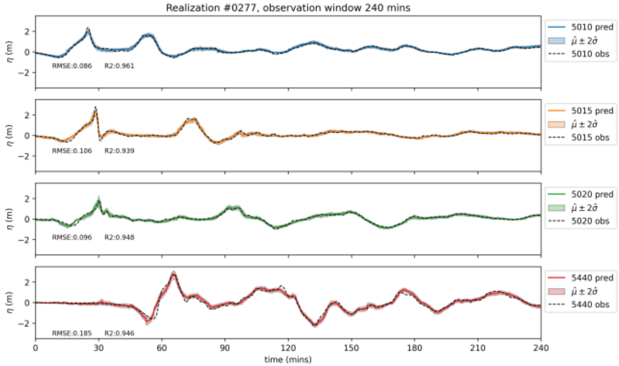
Sample size: Events passing threshold – 289, Training set – 231 , Test set – 58 , Historical Set - 9

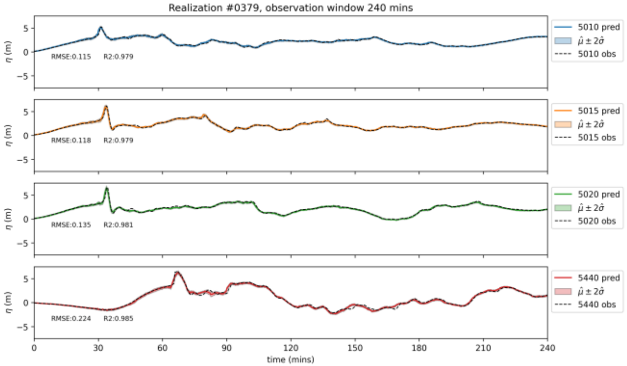
Predicting the test events – are similar to training events but unseen

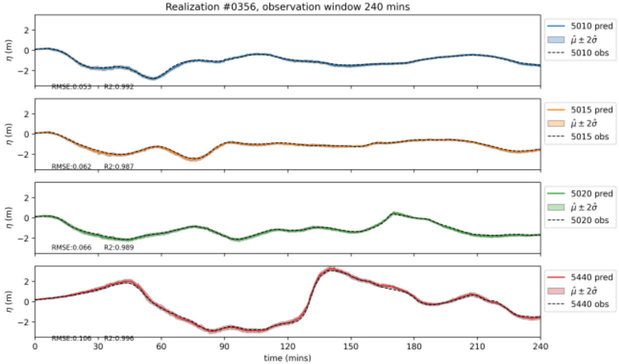


- Offshore Gauges
- Nearshore Gauges



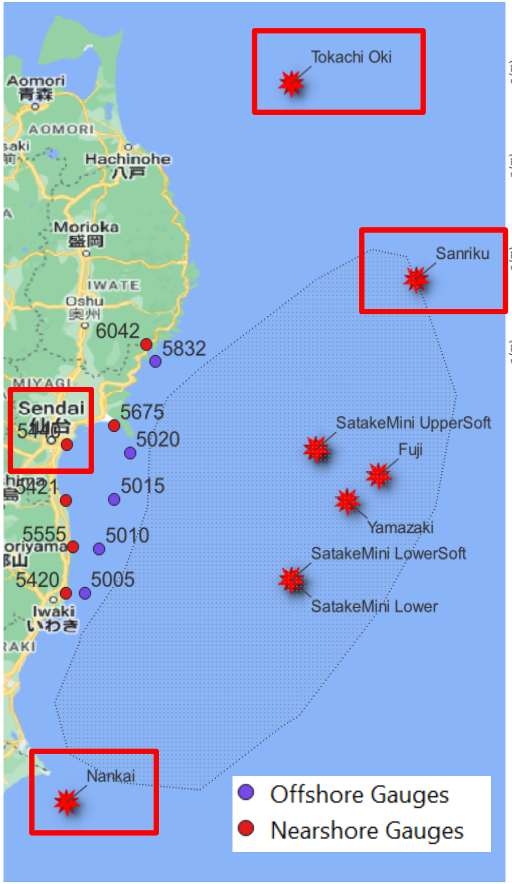


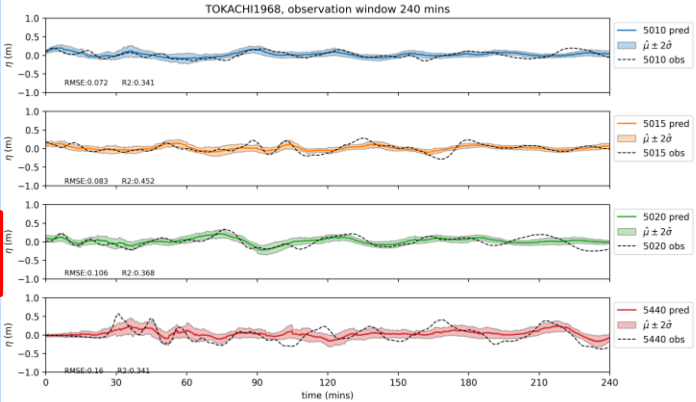


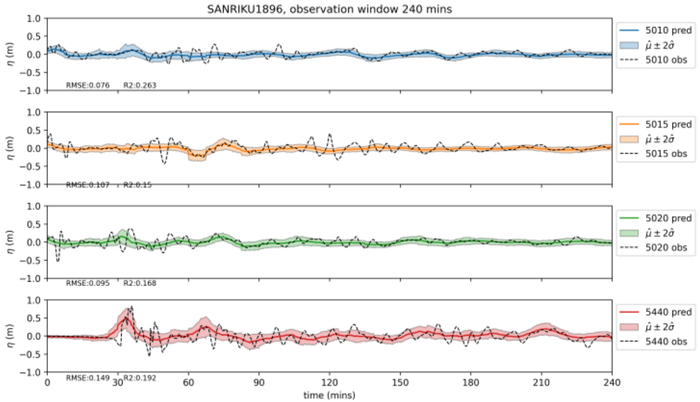


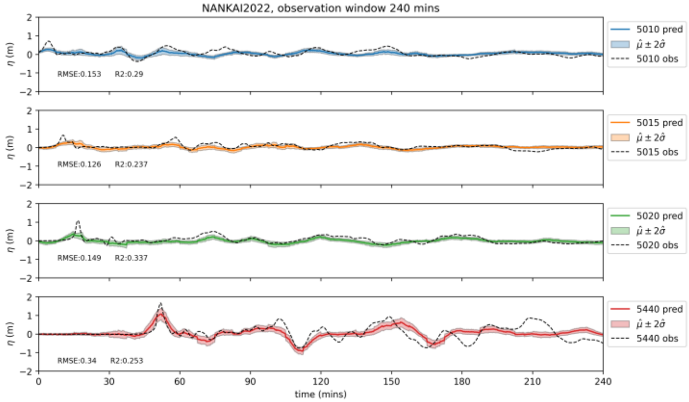
ML works very well and gives exact match – few training reference for the type

Some historical events – Unseen because of location and type

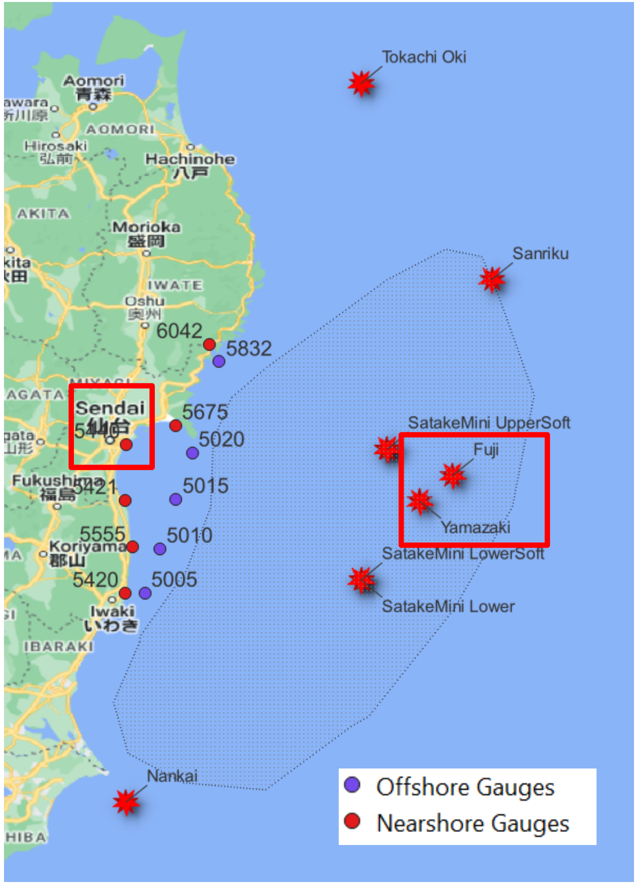


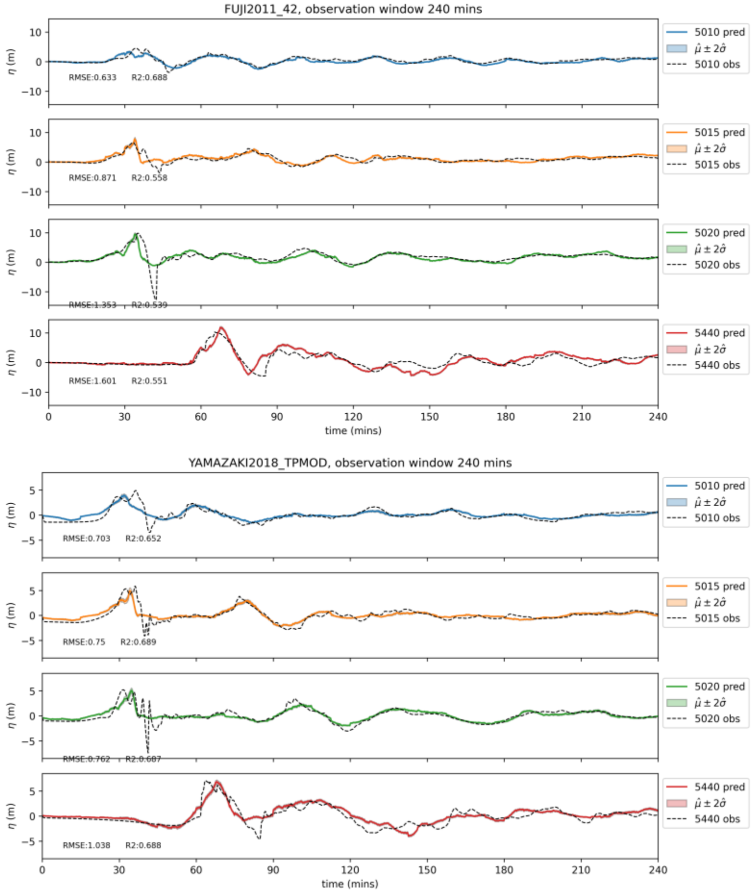




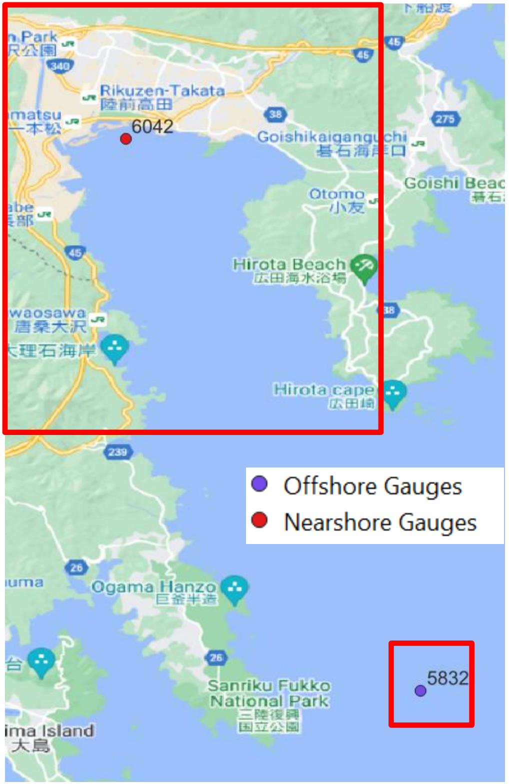


Some historical events – Tohoku Types(static and dynamic slip)





Possible ML and training configuration



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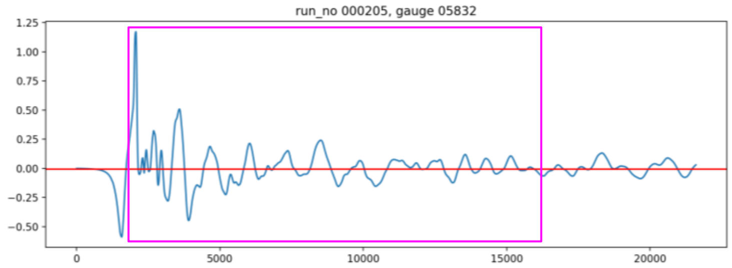
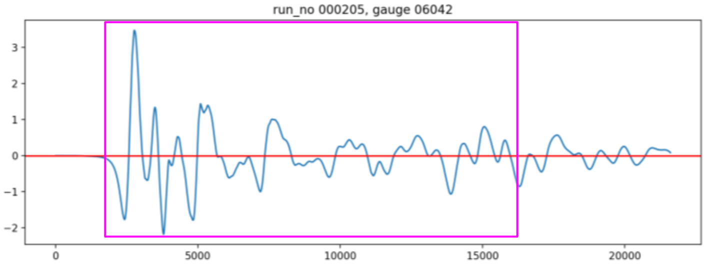
Time to feed the ML model - VAE(variational autoencoder)

Offshore Gauge



VAE Transformer

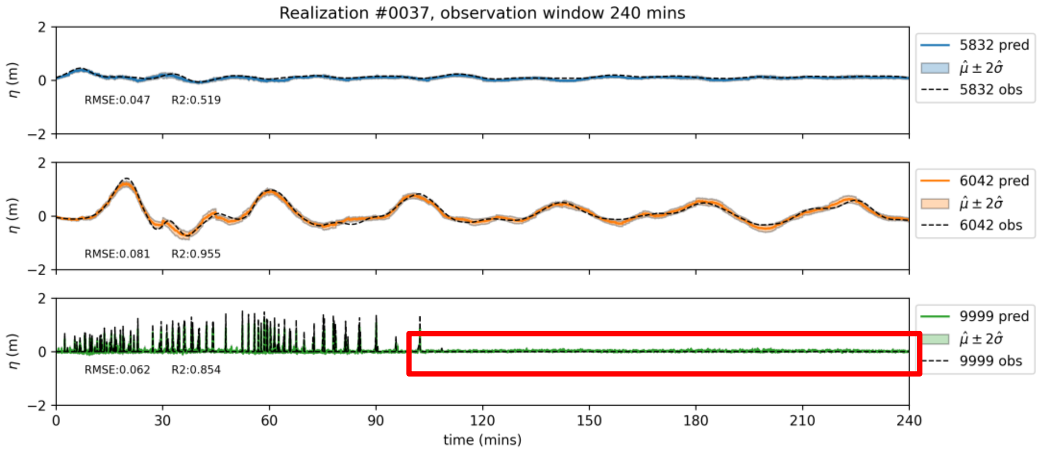


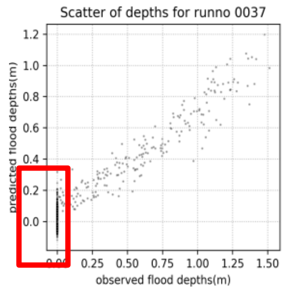
Nearshore Gauge

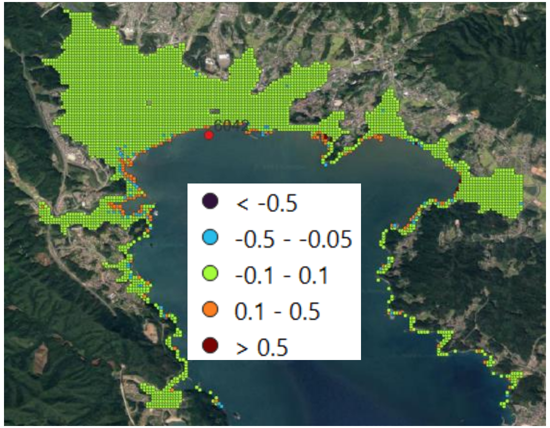
Onshore Inundation

VAE Transformer

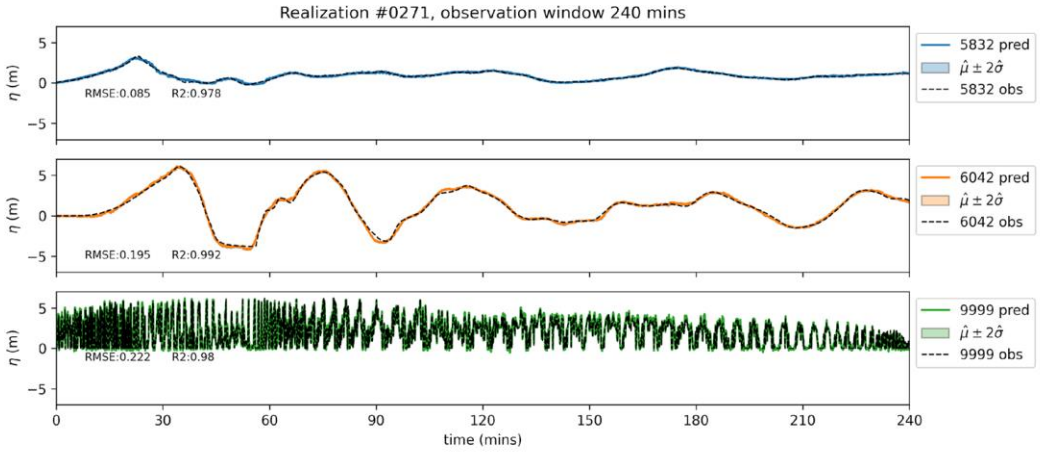
Pre-pre alpha example for Rikuzentakata(Low/High Inundation Events)

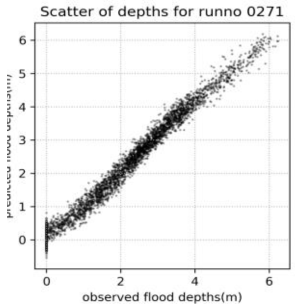


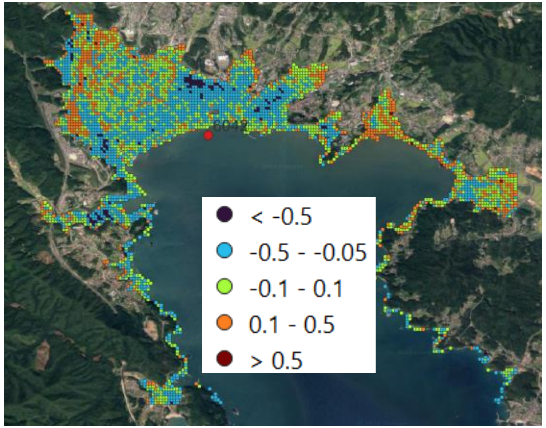




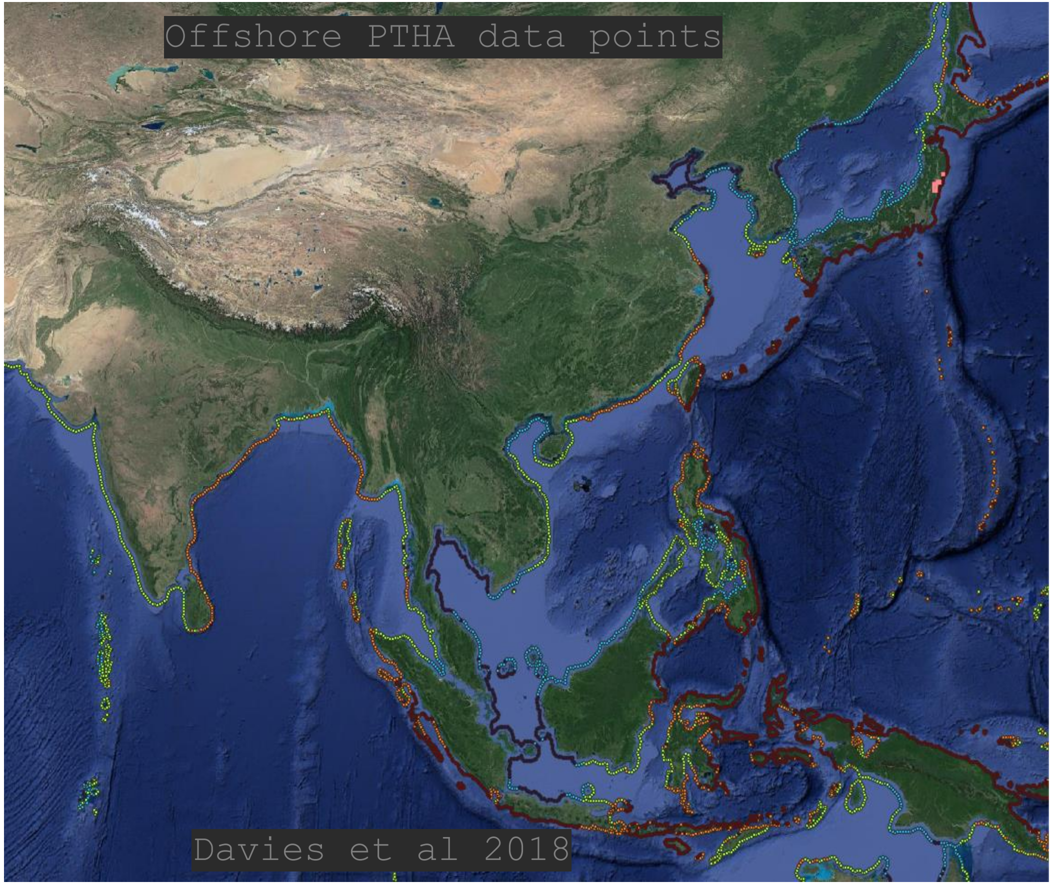
Absolute Error in Predicted Depth(m)





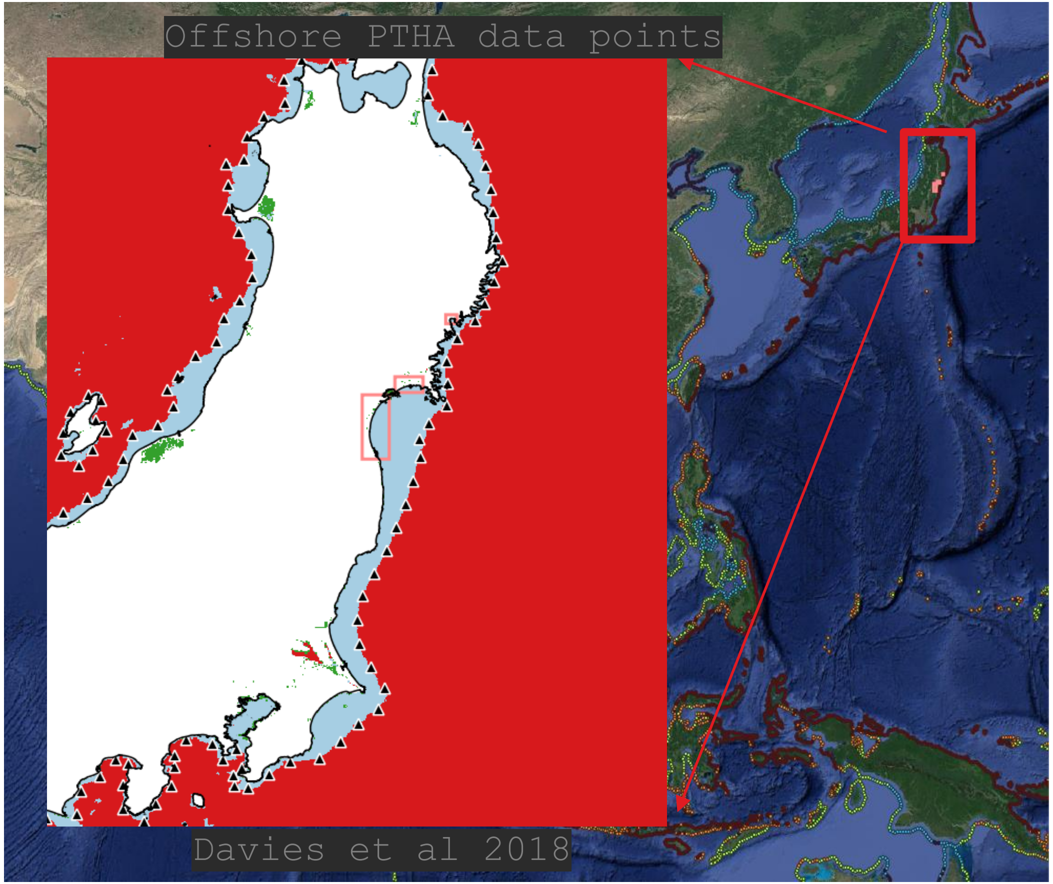


Challenges and Opportunities



- Sparse dataset(balance number of simulation vs accuracy of ML model)
- Fine tuning of ML and transferability – lots of hyperparameters, training configuration, model architecture
- Expand work inundation footprint prediction
- Implement smart feature design and training(pretraining, masking etc)
- Probabilistic wave or inundation database can be used as BC
- Link with available regional PTHA model which provides hazard offshore and convert them to hazard or risk onshore
- Early Warning Identify/optimize location of observation network for a region, based on ML score

Challenges and Opportunities



Final Workflow of PTHA or PTRA

1. Select an event from the stochastic catalogue (gives the probability and location of EQ)
2. Pick tsunami wave offshore from GPTHA or any other offshore model
3. Compute tsunami wave nearshore or tsunami hazard as footprint onshore using ML Model
4. Compute tsunami risk maps for event by plugging in relevant exposure and vulnerability modules
5. Make your decision!!!!

Thank you for your attention!

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