

A hybrid ML-physical modelling approach for efficient approximation of tsunami waves at the coast for probabilistic tsunami hazard assessment

Naveen Ragu Ramalingam, Kendra Johnson, Marco Pagani, and Mario Martina PhD Student at IUSS Pavia, Italy









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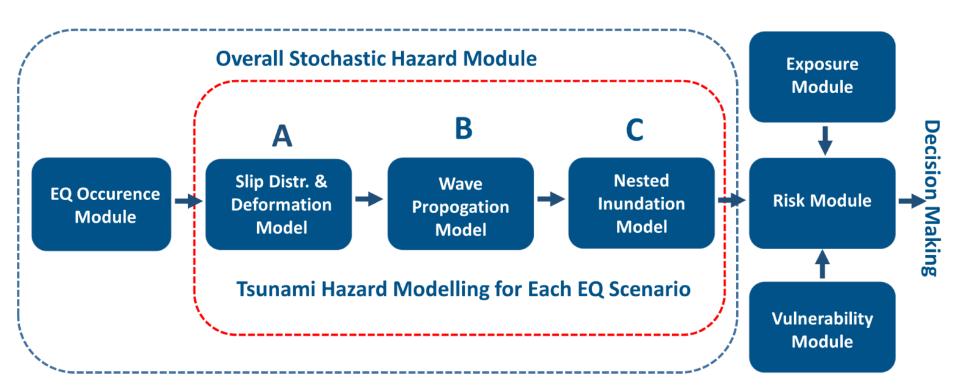
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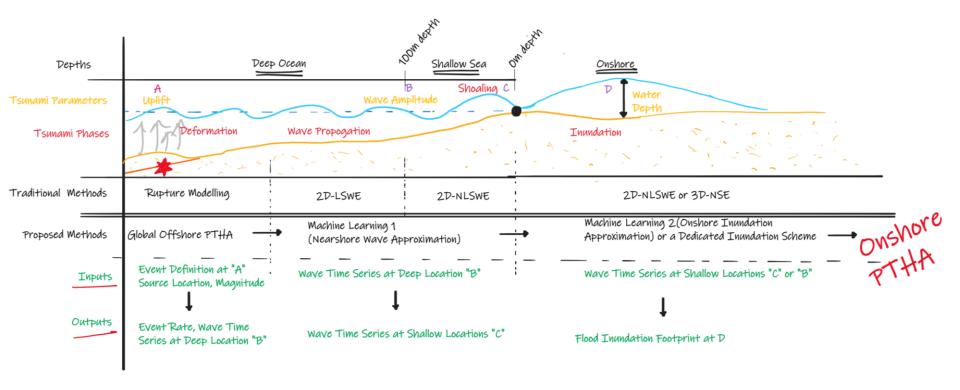




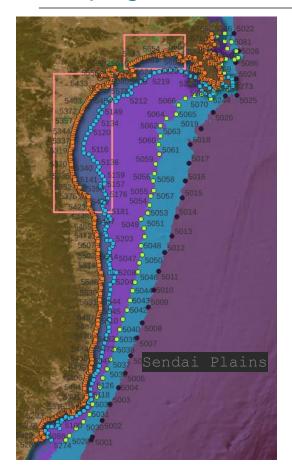
Workflow of probabilistic tsunami risk assessment(EQ sources)



Hazard Module



Propagation/Inundation database

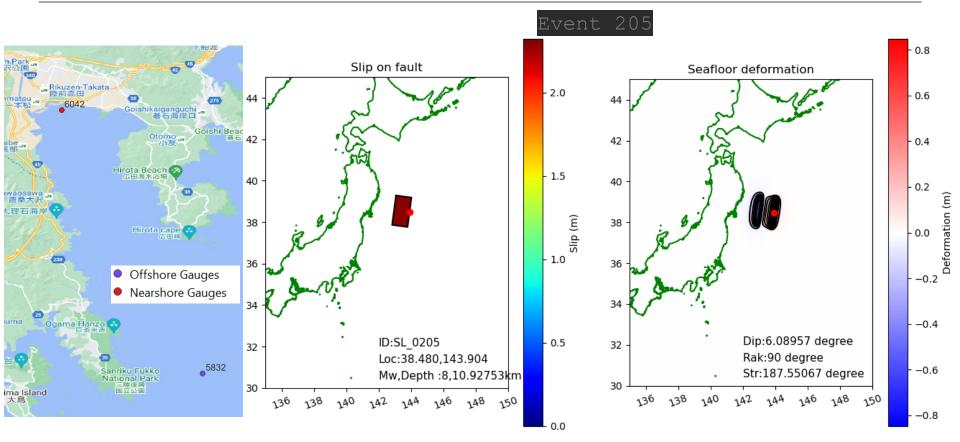




- 1133 locations for observing waveform at different depths (5,25,50 and 100m)
- 3 selected AOI selected to record the max flood depths highlighted by pink rectangles.
- 594 events of varying location and magnitude are simulated for 6 hours of duration
- Homogenous slip events for rectangular fault whose dimensions are scaled based on Mw(7.5, 8, 8.5, 9,9.5)
- Fault parameters(angles) defined using SLAB.2 data and deformation modelled using Okada solution

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Range	Mw	Lat	Lon	Dep	Rak	Str	Dip
min	7.5	35.73	141.15	10.2	90	187.20	5.54
max	9.5	39.48	143.90	45.7	90	225.78	17.0

Preprocessing – Feature design



Preprocessing – Feature design

Rikuzen-Takata 陸前高田 Goishikaiganguchi 碁石海岸口 Hirota Beach Hirota cape Offshore Gauges Nearshore Gauges Ogama Hanzo (1) 5832 Sanriku Fukko National Park ima Island 大島

Event 205

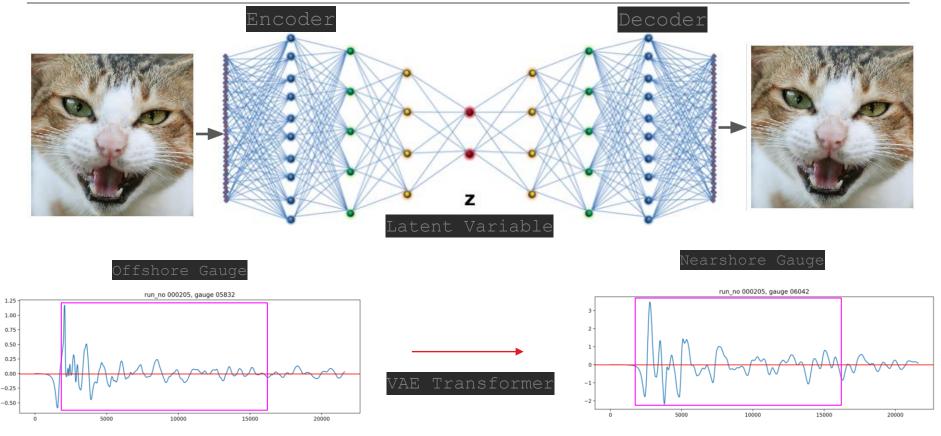


Nearshore Gauge



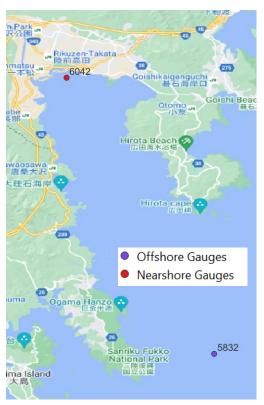
Offshore Gauge

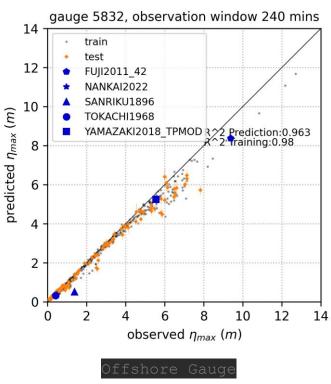
Time to feed a ML model - VAE(variational autoencoder)

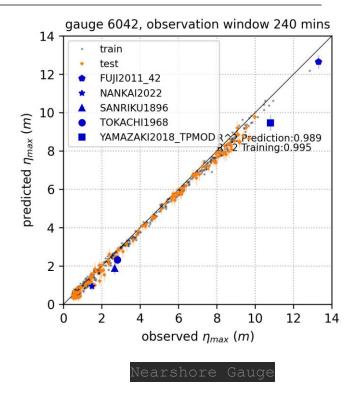


Liu et al 2021

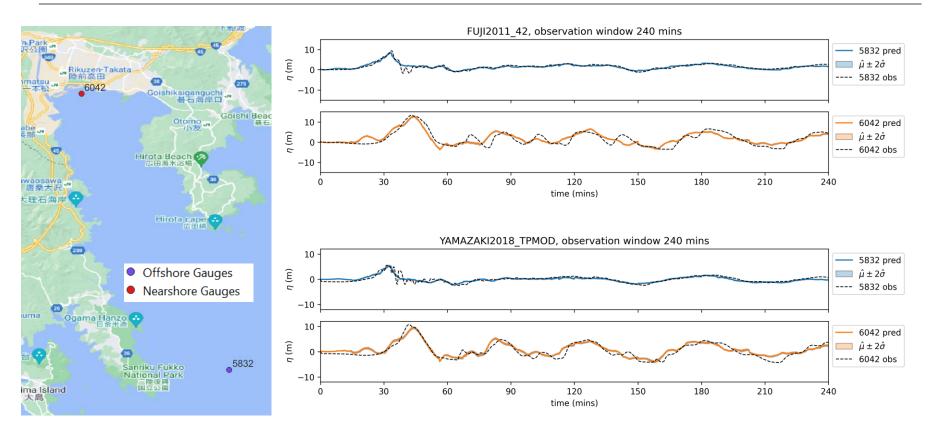
But does it work? Testing at Rikuzentakata



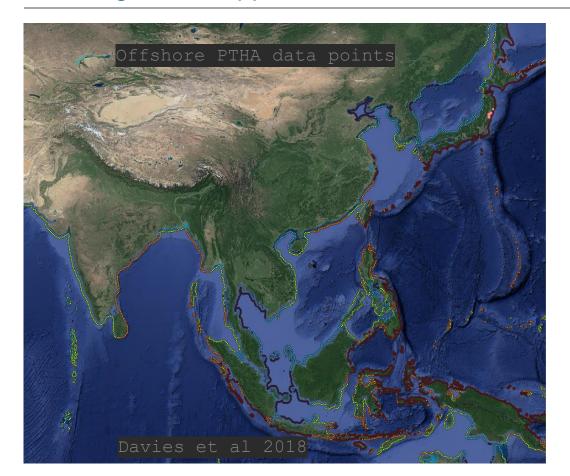




Tohoku 2011 event



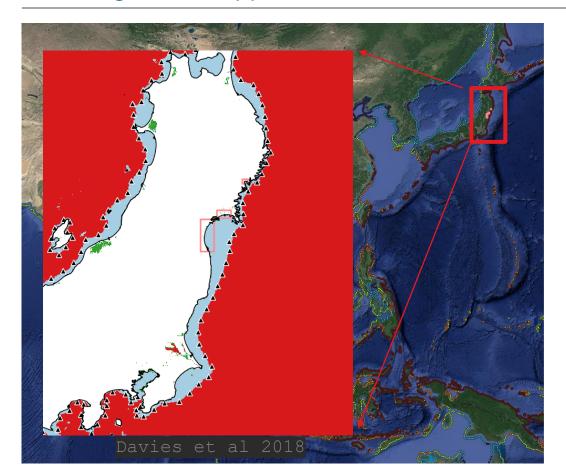
Challenges and Opportunities



- 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 to multi-input architecture, model inundation footprint directly
- Implement smart feature design and training(clustering, batch etc)
- Probabilistic wave or inundation database can be used as BC
- Link with available PTHA model which provides hazard offshore and convert them to hazard or risk onshore

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Thank you for your attention!

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