Deep Learning Approach to Tsunami Early Warning Predictions and Probabilistic Hazard Assessment

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Abstract

We present a deep learning model for generating efficient, accurate tsunami early warning information and conducting probabilistic tsunami hazard analysis (PTHA). Traditional numerical solvers that use the shallow water equations to model tsunami propagation are computationally intensive and involve intermediate calculations that are irrelevant to both of these applications. To achieve rapid, efficient generation of run-up information, we trained a neural network on simulated earthquakes and the subsequent tsunamis along the coastline of Japan.

The model input is the amount of slip along a non-planar 3D fault surface. Graph convolution layers are used to encode the irregular geometry of the subfaults. Standard convolutions capture the nearby spatial relationships in the slip distribution, while transformer blocks learn long-range dependencies inherent in this complex wave propagation. The model produces its predictions for the maximum wave height and arrival time at a pre-determined set of coastal locations. Once trained, the network reduces the time (from minutes to under a second) required to compute the maximum wave height and arrival time of each event while maintaining accuracy in its predictions.

We finally used the model to evaluate thousands of independent rupture scenarios and construct well-informed hazard curves for points along the Japanese coast. This approach demonstrates the utility of artificial intelligence in accelerating the work done by numerical models, empowering probabilistic hazard analysis at scales previously restricted by computational limits.

Introduction

- Improvements in tsunami early warning systems and probabilistic hazard assessment are critical for reducing the costs and damages associated with tsunamis.
- Our model uses finite fault models to capture source heterogeneity and generates high-resolution predictions along Japan's eastern coastline.

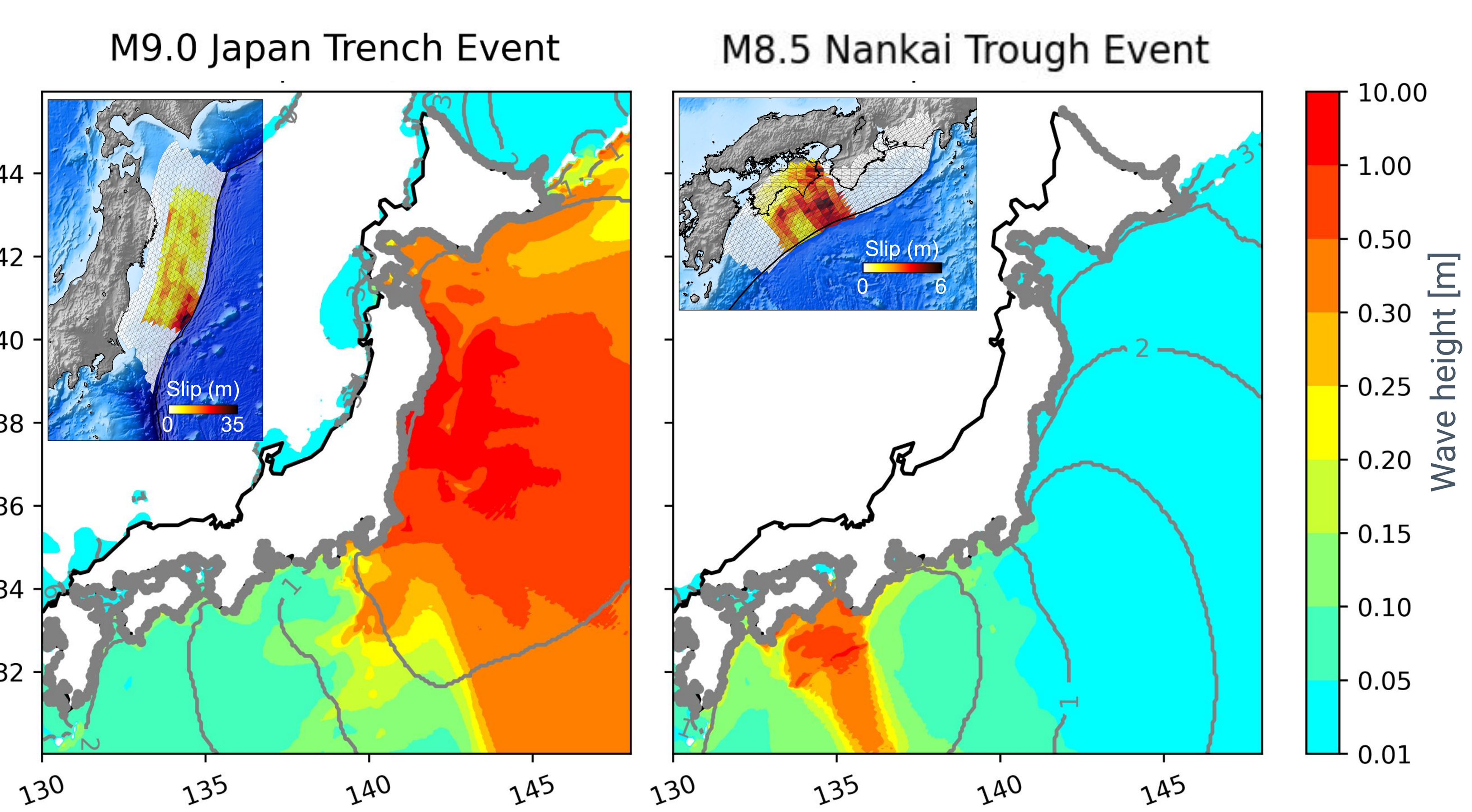


Figure 1: Example stochastic slip distributions (inset) and the maximum wave heights and arrival times for the resulting tsunami, computed by a numerical model. Grey contours indicate wave arrival times in hours. Grey coastal points are those whose metrics are predicted by our neural network.

Synthetic Data Generation

- We generated 2,500 stochastic slip distributions, Mw 7.5-9.0 along 2 separate fault planes, the Japan Trench and Nankai Trough (5,000 events in total), using MudPy
- We used GeoClaw as a numerical solver to model tsunami propagation, recording maximum wave height and tsunami arrival time across a fixed grid

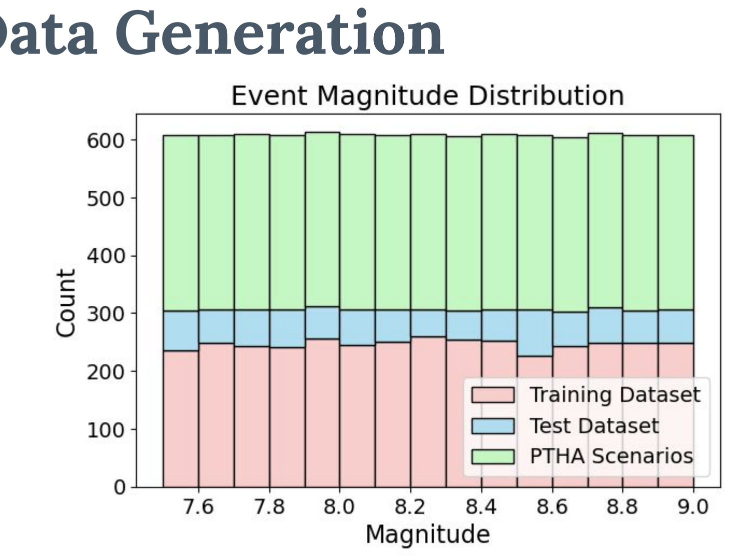
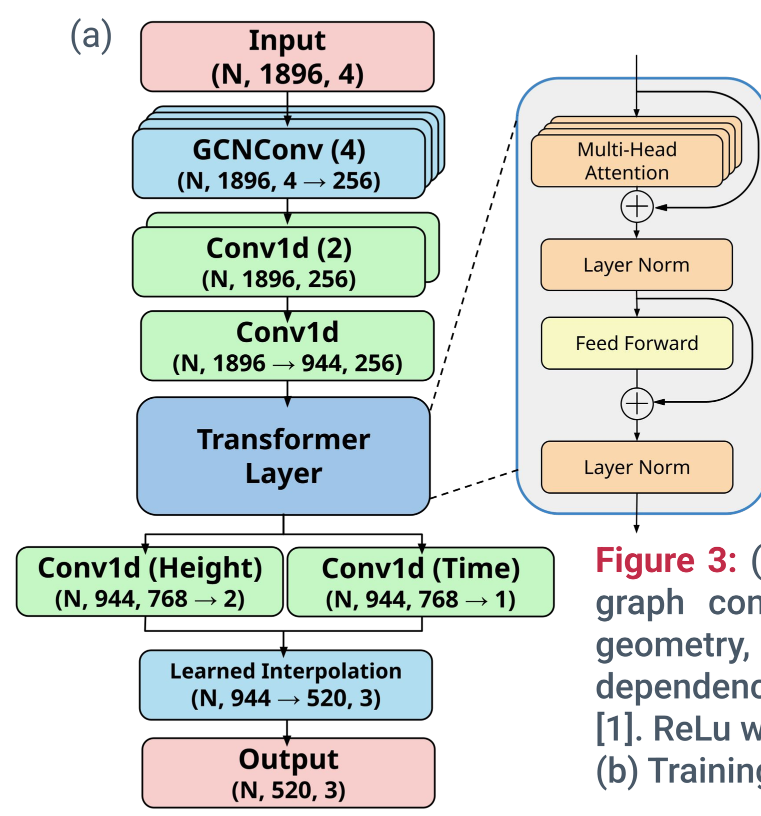


Figure 2: Distribution of earthquake magnitudes in the training and test datasets, as well as the hazard assessment. Test data was 25%, while validation data was 20% of the entire dataset.

Neural Network Architecture



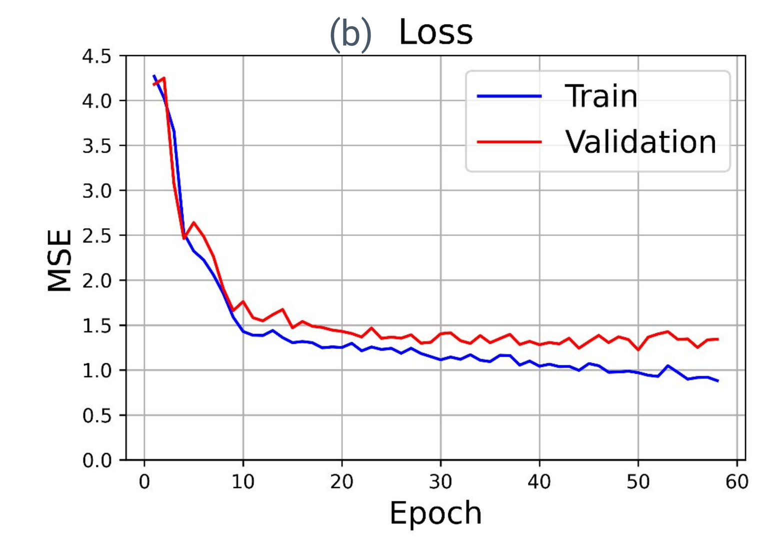


Figure 3: (a) Neural network architecture: Our model employs graph convolution layers to learn from the irregular fault geometry, standard convolution layers to capture spatial dependencies and transformers for long-range relationships [1]. ReLu was used as an activation function.
(b) Training and validation loss curve over 58 training epochs.

Inputs: the coordinates of a subfault centroid (latitude, longitude, depth) as well as the amount of slip on the subfault, for subfaults in both fault planes (total 1896)
Outputs: maximum wave height and arrival time for 520 points along Japan's coast, in addition to a binary feature determining run-up status

Results

- After 58 epochs, the best model achieved an R2 value of 0.945 for the arrival time 0.717 for the maximum wave height predictions.
- Height predictions may match general trends in the target values, but are less accurate when predicting large wave amplitudes. Wave height is a complicated function of the bathymetry and our dataset is zero-inflated, making this feature particularly difficult to learn.

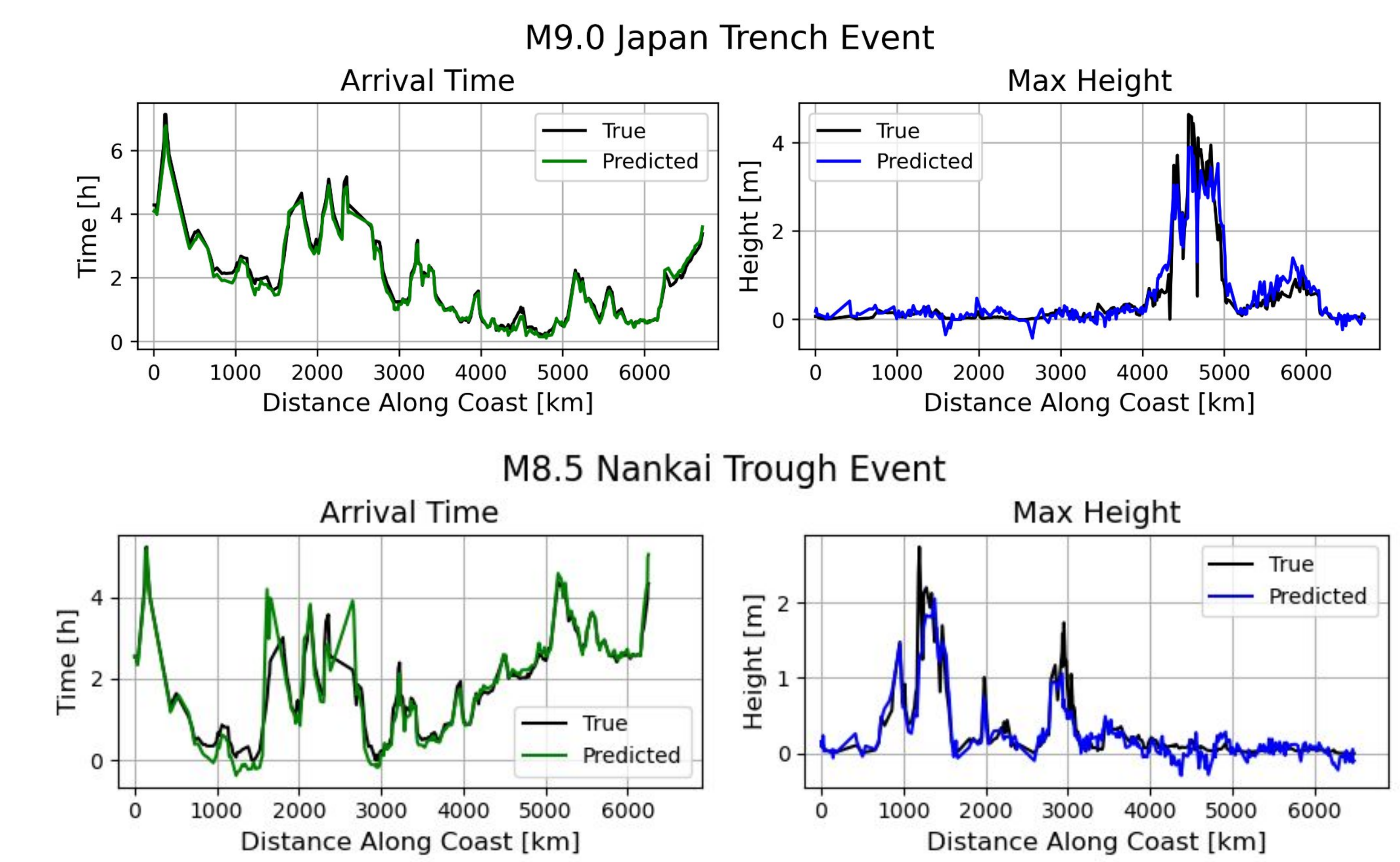


Figure 4: Model outputs for the earthquake/tsunami scenarios in Figure 1. The x-axis represents the projected distance of each point along the coastline from south (0 km) to north (6,700 km), counter-clockwise around the island of Shikoku.

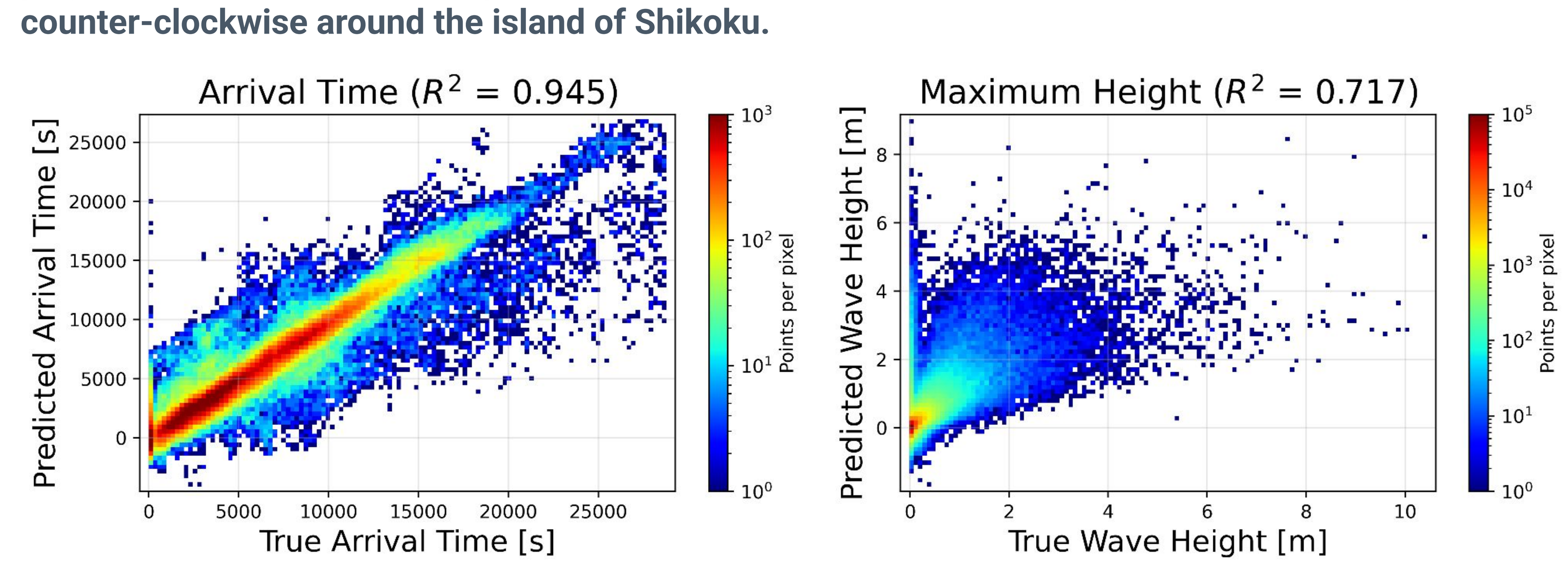


Figure 5: Density scatter plots comparing model predictions to the targets for the entire test dataset.

Probabilistic Tsunami Hazard Assessment

- We used the National Earthquake Information Center catalog to determine the occurrence rate of earthquakes along the studied fault planes according to the Gutenberg-Richter law.
- Given the probability of each event and the number of events that exceed a certain maximum wave height (computed by the trained neural network), we may compute hazard curves for each coastal location expressing the exceedance rate (in events per year).

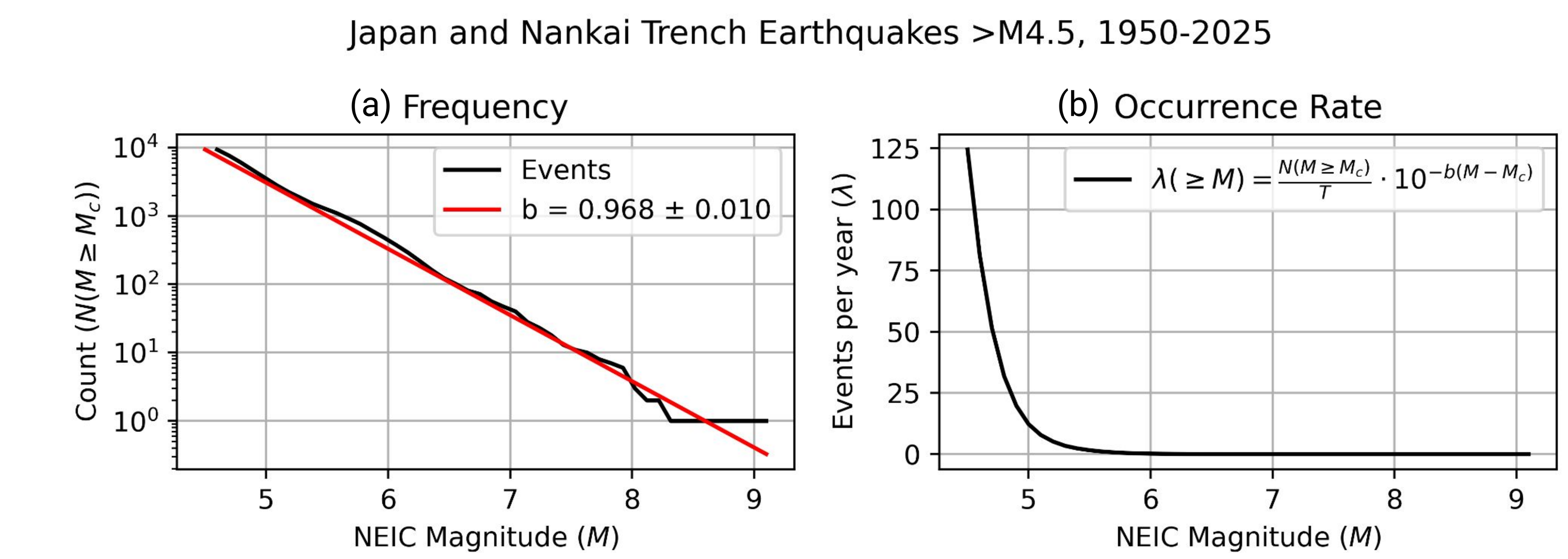


Figure 6: (a) Gutenberg-Richter relation between the frequency of earthquakes within the study area and their magnitude reported by the NEIC Earthquake Catalog, with a b-value of 0.968 ± 0.010 determined with the maximum likelihood estimation method [2]. (b) Occurrence rate as a function of magnitude over 75 years, using the calculated b-value.

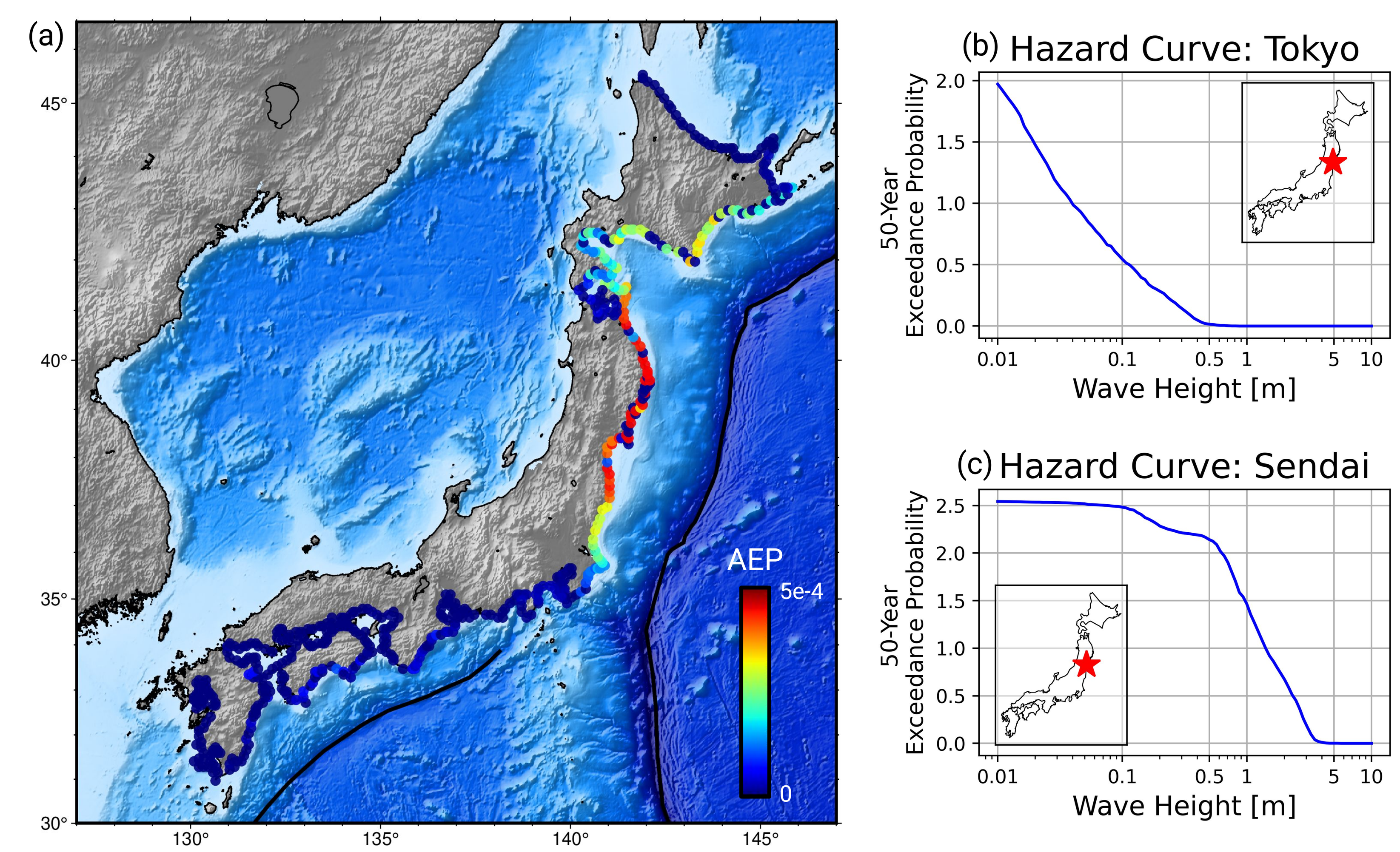


Figure 7: (a) Probability map expressing the annual exceedance probability (AEP) for tsunami waves over 0.5 meters. (b-c) Hazard curves computed using an independent dataset of 4,800 events, evaluated at the locations of major coastal cities, expressing 50-year exceedance rates.

Conclusion & Future Work

While this work demonstrates the potential value of machine learning in determining tsunami hazard metrics, future work is needed to enable operational PTHA:

- **Further model development** to improve maximum wave height predictions
- **Ablation studies** to rigorously test the necessity of elements in the model architecture
- **Uncertainty analysis**, including comparison of different numerical solvers and understanding the effects of both epistemic and aleatory variables on model predictions

References

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