Attempts to detect tsunami-induced electromagnetic fields using machine learning methods: Towards tsunami early warnings

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Summary

Tsunamis possibly cause significant damage to our lives. With significant tsunamis, it is known that observable tsunami-induced electromagnetic (TEM) variations arise. The electromagnetic fields are generated when conductive sea water moves in the Earth's main magnetic fields as the tsunami propagates. Recent research findings indicate that the initial rise of TEM fields occurs prior to the variation in the tsunami wave height in deep sea cases. This phenomenon could contribute to tsunami early warnings. However, there are some obstacles to detecting TEM fields immediately. TEM phenomena are rarely reported because TEM detection is limited to the cases where the signal-to-noise ratio is large enough. So far, previous studies have been attempted to detect TEM visually in the time or frequency domain. In this study, we propose a new approach using a machine learning method. We developed 1-D CNN models composed of three convolutional layers. We set up a classification problem to categorize the input data as either containing TEM data or not containing TEM data. As input data, we prepared three components of magnetic fields, three components of the Earth's main magnetic fields and ocean depth at the observation site. We employed several seafloor observation sites in the Philippine Sea and in the northwest Pacific Ocean. Our model was trained well, as evidenced by a significant decrease in the loss value. Currently, our experiments with real data imply difficulties in application of machine learning for detection of TEM variation in real data.

Keywords: Tsunami, Tsunami-induced electromagnetic fields, Machine learning
Give 1 to 5 keywords

Introduction

When the tsunami waves propagate, it is known the tsunami-induced electromagnetic (TEM) fields are generated. The TEM fields arise when the conductive sea water moves in the Earth's main magnetic fields as a tsunami wave propagates (e.g., Tyler, 2005). It has been revealed that tsunami electromagnetic fields are observed prior to the arrival of tsunami wave heights, which is useful for estimating tsunami wave heights and the direction of tsunami propagation (e.g., Lin et al., 2021). Therefore, if we can detect the TEM signal prior to the tsunami wave heights, we would make some progress in the tsunami early warning systems.

However, there are some challenges: Observing TEM fields is limited to significant tsunami events because the signal-to-noise ratio must be high enough to detect the signals. Additionally, it takes persistence to visually identify TEM signals in either the time or frequency domain (e.g., Schnepf et al., 2016). To address these problems, we attempted to apply machine learning methods to detect TEM signals. In this study, we report on how accurate our. Machine learning model is in detecting signals by comparing the reported TEM arrival time with the detection time by our model.

Methods

We use machine learning methods to detect tsunami-induced magnetic fields. In this attempt, we set up a classification problem to categorize the input data as either containing TEM data or not containing TEM data. The input datasets have two types: one is TEM data, and the other is non-TEM data.

For data preparation, we use simulation results and seafloor observation data. For the data that doesn't contain TEM variations, we use real seafloor observation data. We extracted periods when the tsunamigenic events didn't occur and filtered them to match the bandwidth of the tsunami magnetic fields. For the data that contains TEM, we performed numerical simulations of TEM fields. We used COMCOT (Wang and Liu, 2006) to obtain tsunami wave velocities, and then we fed the results into the TEM simulator, TMTGEM(Minami et al., 2017) to obtain TEM fields. After obtaining the TEM signals, we added seafloor observation data, which was filtered to match the bandwidth of the tsunami magnetic fields, to the results. The seafloor observation sites used in this study and the wave origins we set are shown in Figure 1.

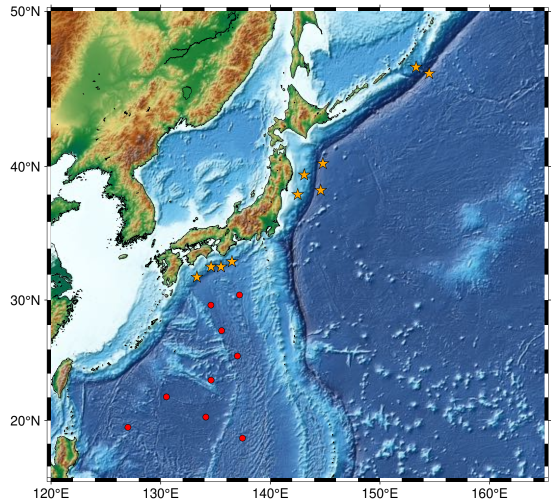

Figure 1. Map of the observation sites and wave origins: Red circles indicate seafloor observation sites and stars indicate wave origins.

As a machine learning model, we adopted an 1-D CNN model. The model architecture is shown in Figure 2. The model consists of three convolutional layers. The loss function is binary cross entropy loss and the output is constrained to values between 0 and 1. A value near 0 indicates non-TEM data, while a value near 1 indicates TEM data. The threshold is set at 0.5. We trained our model through multiple training loops to minimize the loss values.

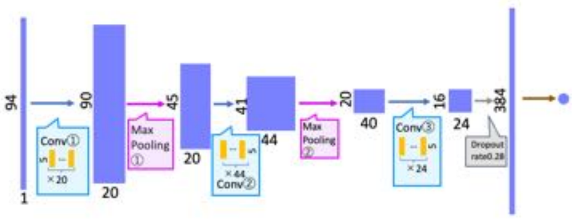

Figure 2. Model architecture: Our model consists of three convolutional layers. Two numbers beside each purple box indicate the input data shape, and the numbers beside each orange box indicate the filter size and the number of filters. In the last layer, we applied the dropout method.

Results

We show the training process in Figure 3. Figure 3 shows how the loss value decreases through 100 Epochs(An epoch refers to a training iteration, and one epoch is completed when all the training data has been used once.). By checking it, we stopped the training loops at 50 Epochs and used it as our model in the following experiments.

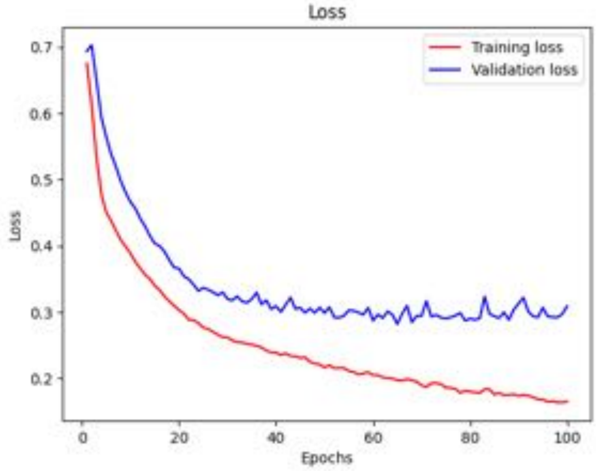

Figure 3. Loss value in training iteration: We split the input data to training data and validation data as 80%:20%. According to this graph, we stopped the training loop at 50 epochs.

We input real observation data into our model to evaluate its performance. Here, we show one example from the 2006 Kuril earthquake case. Figure 4 shows the results the model is input the real observation data. Figure 4 (Top) shows input three components magnetic data and simulated tsunami wave heights. Figure 4 (Bottom) shows model output and simulated tsunami wave heights.

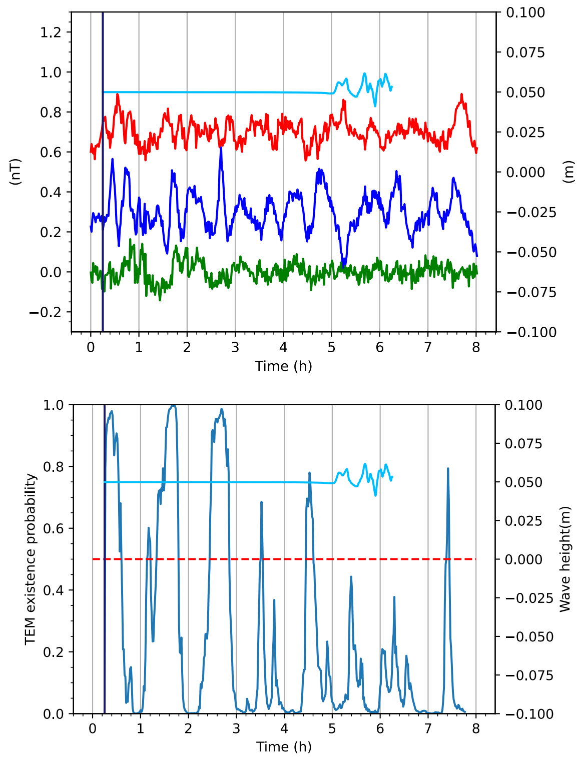

Figure 4 (Top). Input three components of magnetic data (red: bx, blue: by, and green: bz) and simulated tsunami wave heights (sky blue). The horizontal axis represents time for 8 hours between 11:00 and 19:00 on November 15th, 2006. The vertical solid line indicates the time of the earthquake occurrence. **Figure 4 (Bottom).** Output values indicating the probability of TEM existence (light blue) and simulated tsunami wave heights (Sky blue). The horizontal axis is the same as the top panel.The horizontal dotted line represents the 0.5 threshold.

Our model outputted a high probability of TEM existence during certain periods. However, these periods do not necessarily coincide with the arrival of the tsunami waves.

Conclusion

We developed a machine learning model that outputs the probability of TEM existence based on input data. Our model identified periods that may include TEM; however, these periods did not necessarily agree with the arrival of the tsunami waves. To address this issue, we need to conduct more investigation and improvement. It is important to note that the observation data used for evaluation did not report TEM at this moment. We will attempt to evaluate our model with other datasets that include reported TEM signals.

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