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Fast Earthquake Magnitude Estimation using HR-GNSS time series: a Deep Learning approach

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Abstract

High-rate Global Navigation Satellite System (HR-GNSS) provides continuous high-frequency measurements of ground motion induced by earthquakes. This can be highly useful for parameter analyses related to the seismic source, in particular for fast magnitude estimation of large earthquakes. The analysis of displacement waveform recorded by HR-GNSS sensors has been adopted as a complementary task for warning systems, especially when the signals of earthquakes recorded in inertial sensors are saturated. Hence, improving algorithms to contribute to the fast analyses of the HR-GNSS data has become a recent challenge.

In this work, we propose a deep-learning-based algorithm for earthquake magnitude estimation, which was trained by thousands of synthetic displacement waveforms corresponding to Mw > 6.5 earthquake signals. We adapted the model to a variable number of stations and lengths of the time series as input. Thus, it is possible to apply the algorithm without any restriction on the number of stations, and the flexibility in the length of the input time series facilitates the inclusion of data not only from local stations but also from regional stations if required. The influence of attributes such as noise, magnitude, number of stations, epicentral distance, and length of input time series on the model performance was evaluated. We aim to generalize this approach to the magnitude estimation of earthquakes from different tectonic regions. The robustness of the model was tested with both synthetic and real earthquake signals.

1. Deep Learning Architecture

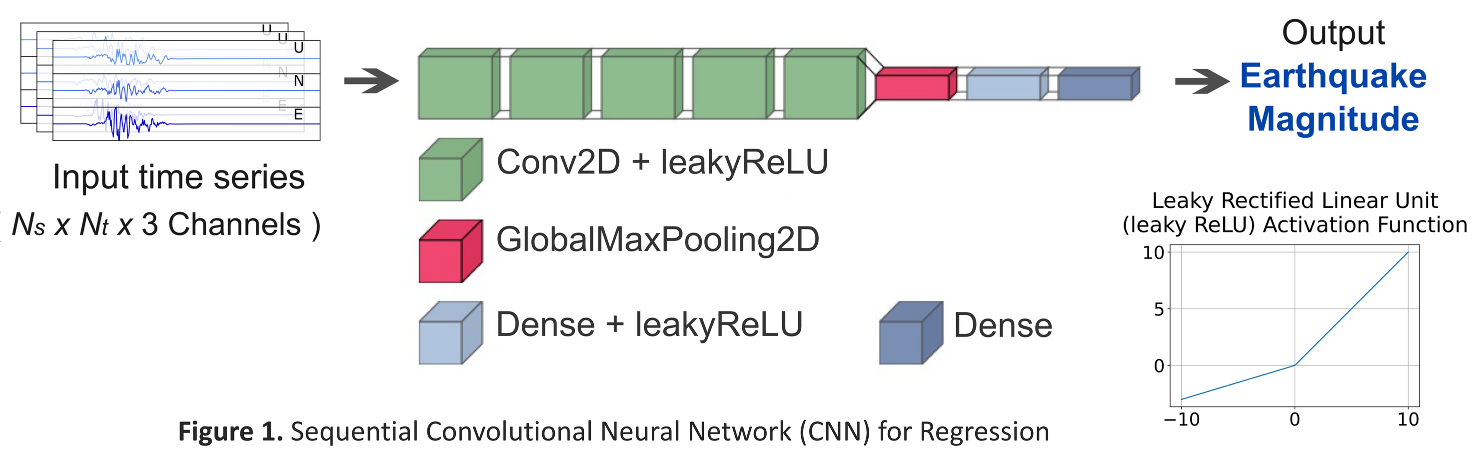

Figure 1. Sequential Convolutional Neural Network (CNN) for Regression

The input consists of time series from N_s number of stations, with N_t number of samples in time, and three channels: the up (U), north (N), and east (E) directions of the GNSS sensor. For each convolutional layer, we used different numbers of filters with kernel size (1, 3) and stride (1, 1). A zero-padding was only used in the first. The kernel is regularized in each Conv layer. The two dense layers consist of 64 and 1 neuron, respectively. The weights of the kernels for the two first dense layers are initialized using a normal distribution and constrained by max-norm regularization with a maximum norm value of 3. We obtain a target variable in the output layer whose value is equivalent to the earthquake moment magnitude Mw.

3. Model Training

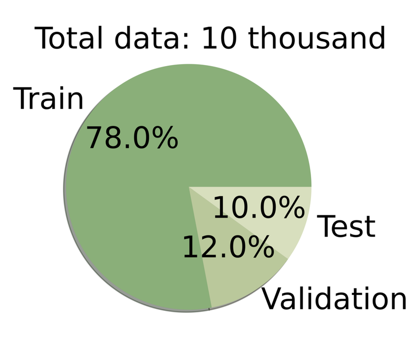

Figure 2. Data distribution. The database was split into a training, validation, and testing set

We optimized the model using the Adaptive Moment (ADAM) estimation method to reduce the losses and used a learning rate schedule with a standard decay function:

decay rate = learning rate/epochs

We set the initial learning rate to 0.01, the decay to 0.1/maximum number of epochs, the maximum number of epochs to 500, and the batch size to 128. We used early stopping when the minimum validation loss was reached, with a patience of 10 epochs.

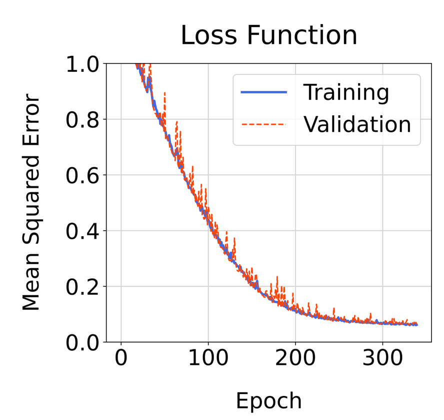

Figure 3. Loss values during the training and validation

2. Data & Preprocessing

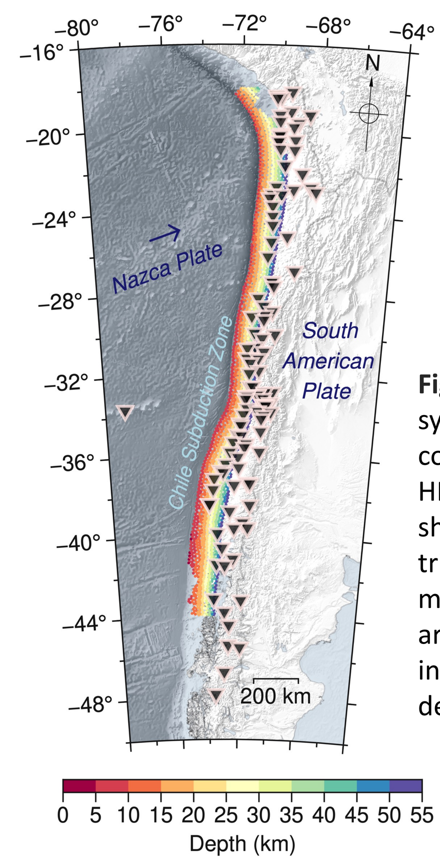

Figure 4. The synthetic data correspond to the HR-GNSS stations shown as black triangles on the map. Hypocenters are shown as dots in color scale by depth.

Owing to the lack of noise in the synthetic data, we generated synthetic noise using the Mudpy software (Melgar, 2020) . We randomly included different levels of noise in the waveforms to make the data as realistic as possible.

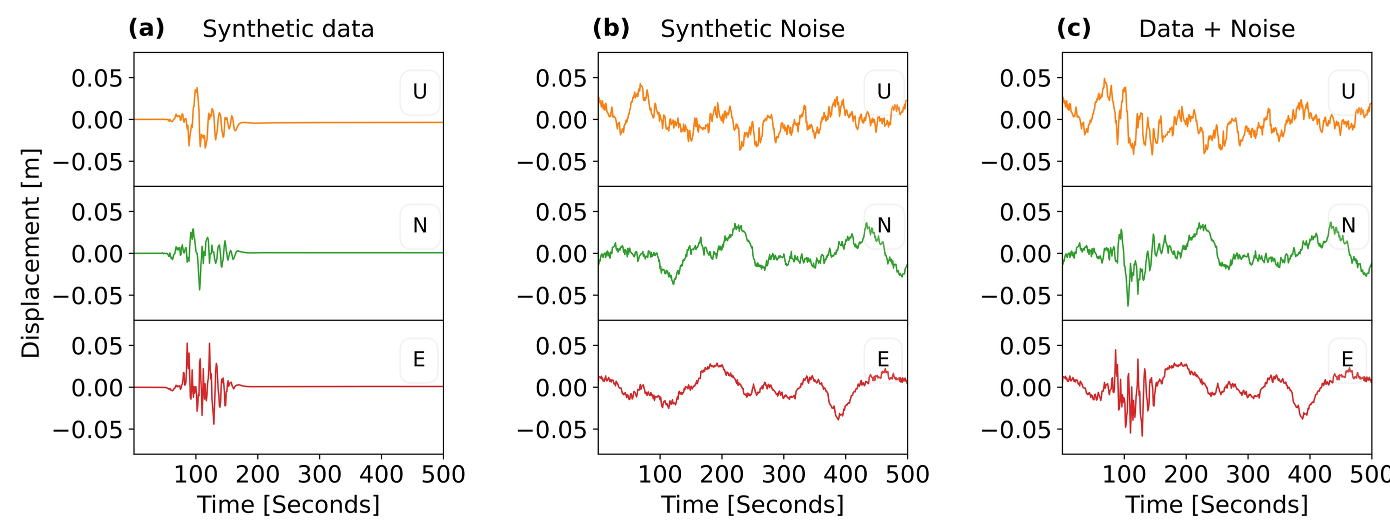

Figure 5. (a) Synthetic displacement waveforms of an earthquake Mw 8.1 and the final waveforms from the synthetic signal with noise. Signals with 1 Hz rate sampling.

We used synthetic HR-GNSS data for the model training, validation, and testing.

These synthetic displacement waveforms were previously generated by Lin et al. (2020), containing 36,800 earthquakes associated with rupture scenarios specifically modeled for the Chile subduction zone. We include those earthquakes with Mw > 6.9.

Furthermore, we evaluated the model's performance using real data (Melgar & Ruhl, 2018) of five large earthquakes from diverse regions.

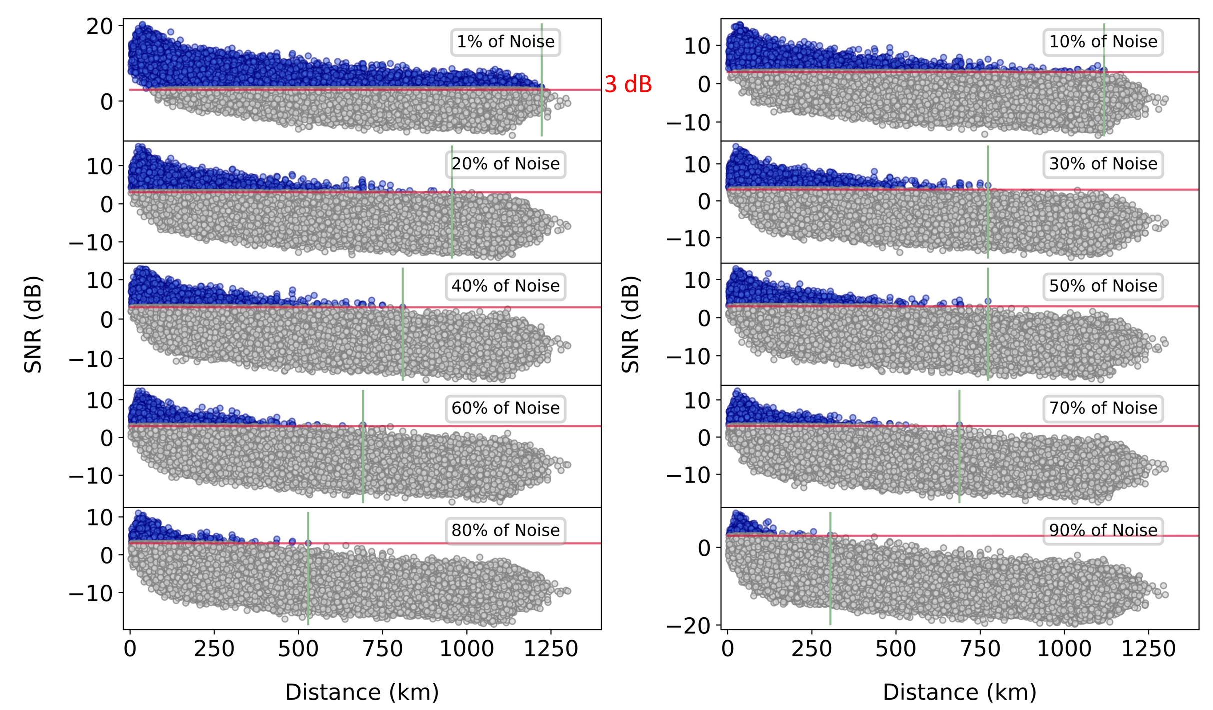

Figure 6. Signal to noise ratio (SNR) vs epicentral distance, using different levels of noise. Example for signals of earthquakes with Mw 7.5. Only those data with a SNR higher than 3dB (dots in blue), are included training process.

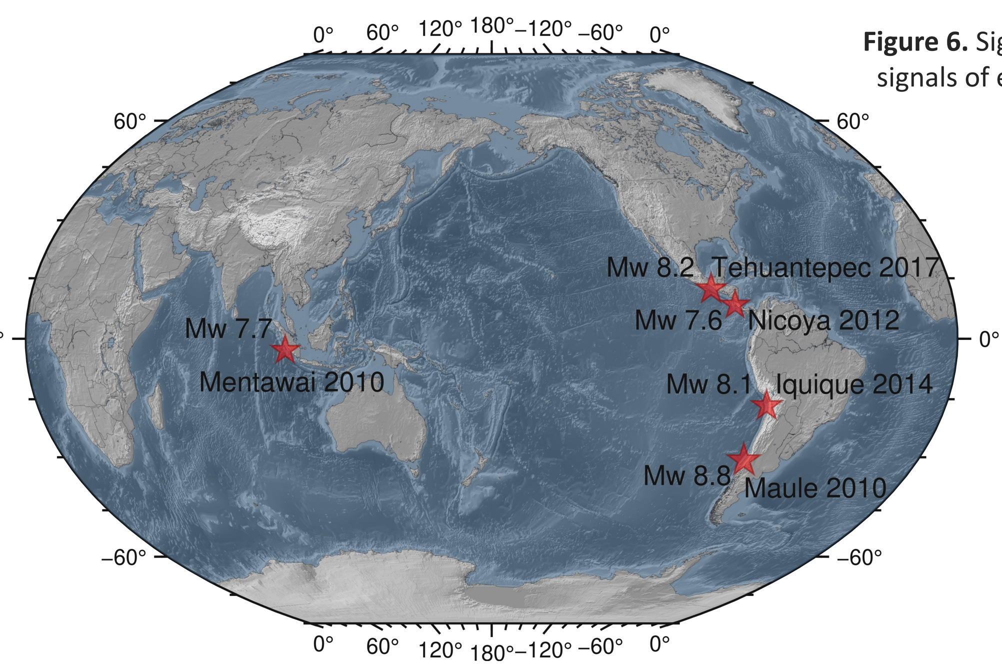

Figure 7. Epicenter of the earthquakes used for the testing with real HR-GNSS signals

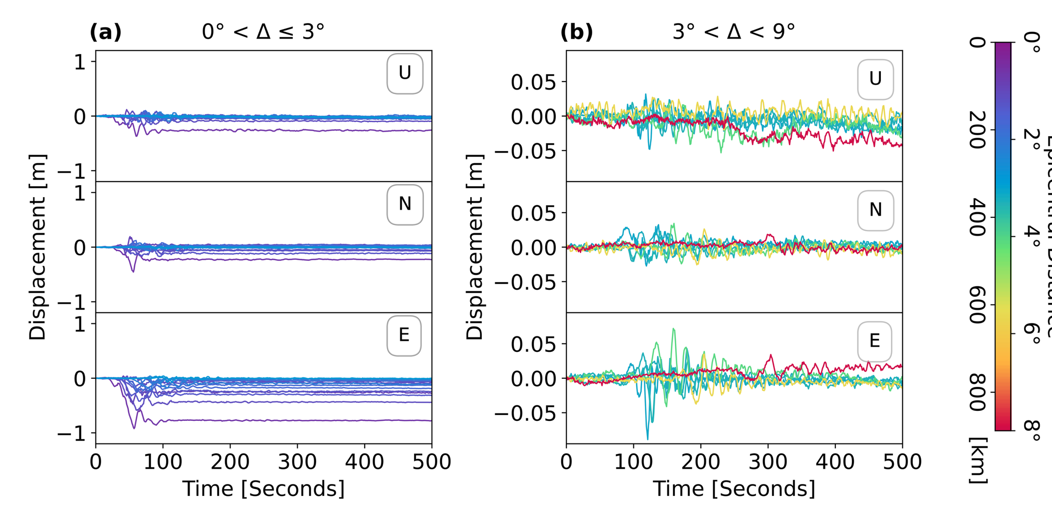

Figure 8. An example of real displacement waveforms from the Iquique Earthquake 2014, Mw 8.1.

4. Model Testing: Synthetic Data

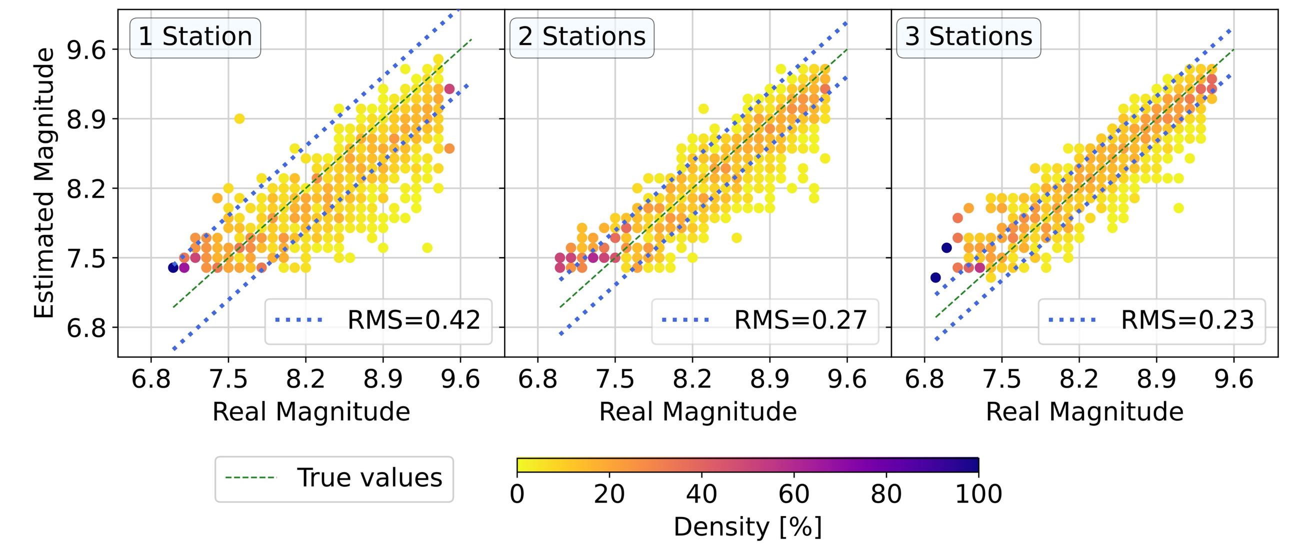

Figure 9. Error of magnitude estimation using synthetic HR-GNSS data from Chile Each circle corresponds to one bin whose color represents the percentage of tests done for each real magnitude. Plots (a), (b), and (c) are the fits of the magnitude estimations, where the RMSs are shown by the dotted lines. The results are binned on a 0.1 magnitude grid.

We evaluated the performance with different data from those used for training or validation. We set the input data with one, two , and three stations, to compare how the model works in these cases.

As we increase the number of stations, the rms decrease.

In general, these preliminary results with synthetic data show a good fitting.

However, it is still necessary for further improvements to avoid the overestimations observed for Mw ≤ 7.2.

5. Model Testing: Real Data

Depending on the number of available stations for each earthquake, we grouped them to obtain up to 500 random combinations of data for testing purposes.

Similar to the results obtained with synthetic data, the best estimations were achieved using two or three stations. The preliminary model provided satisfactory magnitude estimations with real data.

These earthquakes served as the initial testing for the model. However, the next step is to further evaluate the model by utilizing real data from additional earthquakes.

Although the DL model has demonstrated promising results, further improvements are required to enhance the estimation of lower magnitudes.

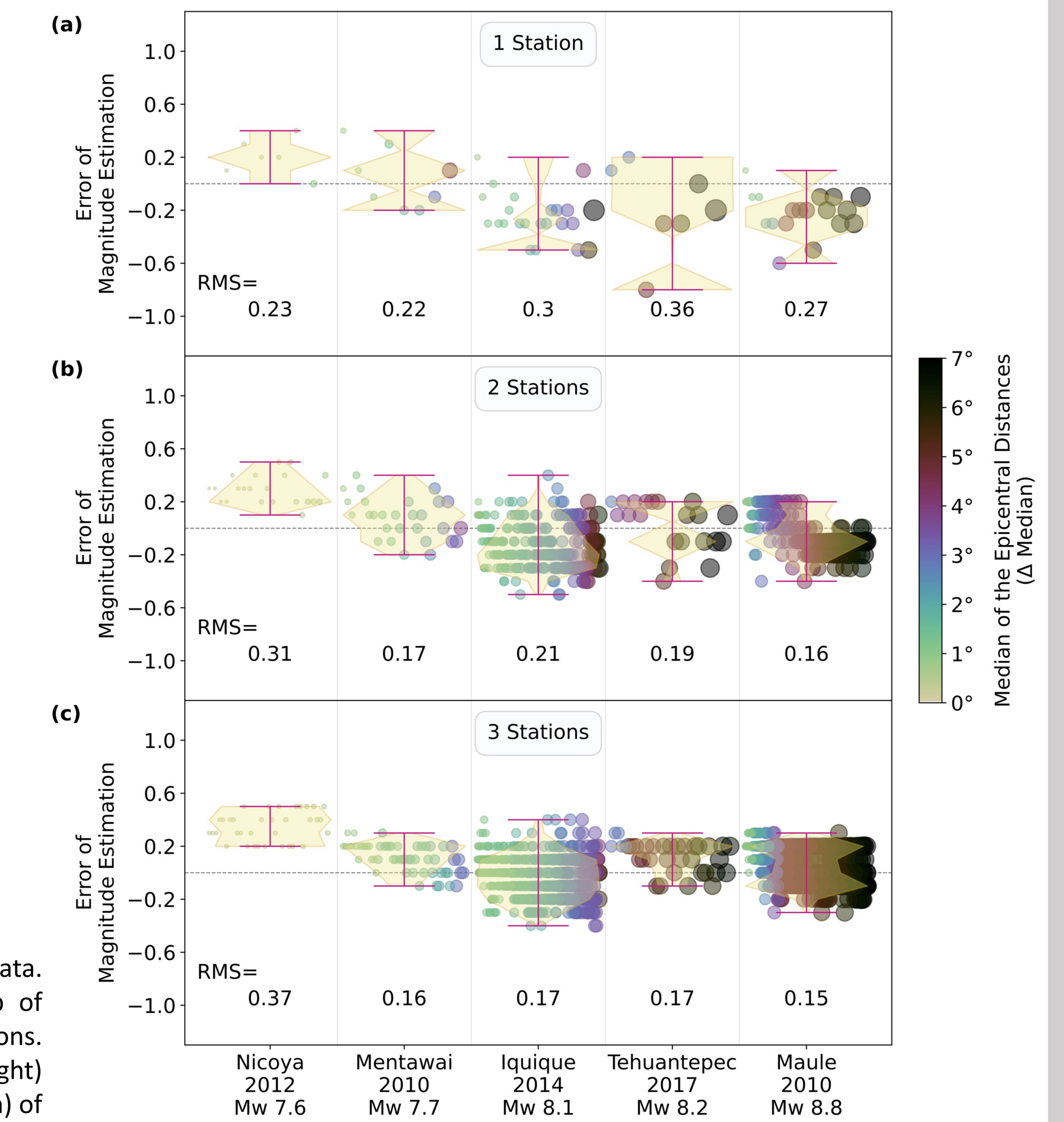

Figure 10. Errors of magnitude estimations using real data. The circles indicate the magnitude error for each group of stations, which were defined by different random combinations. Both the color scale and circle sizes (sorted from left to right) depend on the median of the epicentral distances (Δ Median) of each combination of stations, for each earthquake.

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