SUBDUCTION MEGATHRUST RECORD SELECTION ASSISTED WITH A DEEP-LEARNING-BASED MODEL

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ABSTRACT

High-quality large-magnitude subduction earthquake ground-motion records are needed as inputs for response history analysis of dams in regions adjacent to the Cascadia Subduction Zone. Quality assessment of candidate ground-motion records is time consuming if done manually and poorly handled by automation with conventional mathematical functions; therefore, a supervised deep-learning-based model was developed in a previous study to estimate the quality and minimum usable frequency of ground-motion records through training on 1,096 records from earthquakes in New Zealand, which is an active tectonic environment with crustal and subduction earthquakes. In that study, the model was found to perform well for small-to-moderate magnitude earthquake records from active shallow crustal, subduction slab, and subduction interface earthquakes; however, the model's performance for large-magnitude earthquake records was not investigated. In this study, we evaluate the performance of the model for assessment of records from the 2010 **M**8.8 Maule and 2011 **M**9.1 Tohoku subduction interface earthquakes. We utilize high-quality processed subduction records and then superimpose various amplitudes of artificial background noise to degrade quality and then apply the model quality for quality classification. Eleven high-quality ground-motion records were selected based on the model results and then linearly scaled to a target spectral acceleration for a hypothetical site in British Columbia to produce a suite of large-magnitude subduction interface earthquake ground-motions suitable for structural response history analysis.

INTRODUCTION

Recorded ground-motion time histories from large-magnitude subduction earthquakes are required for response history analysis of dams adjacent to subduction zones; however, quality screening of candidate records is time-consuming if done manually and poorly automated by mathematical algorithms.

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A deep-learning based model was previously developed for estimation of the quality and minimum usable frequency (i.e., the lowest frequency with a signal-to-noise ratio greater than 3) of small-to-moderate magnitude earthquake ground-motion records from crustal, interface, and slab earthquakes (Dupuis et al., 2023). This model provides estimation of quality on a continuous scale from 0 (lowest quality) to 1 (highest quality) and minimum usable frequency from 0.01 Hz to 10 Hz. The model can be applied to 3-component records and provides quality and minimum usable frequency estimates for each component, i.e., 6 estimates total per 3-component record.

Although the model was found to perform well for small-to-moderate magnitude earthquake records by Dupuis et al., 2023, prior to this study it has not been applied to large-magnitude earthquake records. We investigate the performance of the model on large-magnitude earthquakes by applying it to low- and high-quality records from the 2010 **M**8.8 Maule (herein referred to Maule) and 2011 **M**9.1 Tohoku (herein referred to Tohoku) subduction interface earthquakes to select a suite of eleven high-quality ground-motion records which are then linearly scaled to a target hazard for structural response history analysis.

SEED RECORDS

Seed records (22 in total) were retrieved from the NGA-Subduction (NGA-Sub) catalogue of subduction ground-motion records (Mazzoni, 2022): eleven Maule records and eleven Tohoku records, as shown in Table 1. These records were selected to include sites with a range of time-averaged shear wave velocities in the upper 30 m, V_{S30}, and a range of rupture distances, R_{rup}. There is a large range of maximum as-recorded peak ground accelerations, PGAs, in the horizontal direction: 0.002 g to 0.774 g. The seed records have different time steps between samples: 0.005 s, 0.01 s, 0.02 s, and 0.05 s, which result in computable spectral frequency content up to 100 Hz, 50 Hz, 25 Hz, and 10 Hz, respectively. The minimum useable frequency of the filtered and processed records is also provided in Table 1 (Bozorgnia et al., 2020).

Table 1. Seed record metadata from the 2010 **M**8.8 Maule and 2011 **M**9.1 Tohoku subduction interface earthquakes as provided by NGA-Sub (Mazzoni, 2022).

Event	NGA-Sub RSN	Station ID	Rupture distance, R_{rup} (km)	Shear wave velocity, V_{S30} (m/s)	Time step (s)	Duration (s)	Peak ground acceleration, PGA (g)	Minimum usable frequency (Hz)
Tohoku	4000001	40307	259	497	0.01	299.98	0.015	0.006
	4000011	41110	303	299	0.01	359.98	0.015	0.010
	4000012	41202	200	192	0.01	359.98	0.034	0.010
	4000019	41210	210	230	0.01	359.98	0.034	0.017
	4000042	41322	114	370	0.01	359.98	0.112	0.016
	4000043	41323	136	279	0.01	244.98	0.112	0.036
	4000044	41324	158	323	0.01	325.68	0.081	0.005
	4000045	41325	146	211	0.01	359.98	0.134	0.017
	4000082	42113	256	319	0.01	359.98	0.030	0.012
	4000086	42204	125	339	0.01	359.98	0.290	0.020
	4000087	42205	120	359	0.01	359.98	0.151	0.032
Maule	6000785	LVC	1300	1087	0.05	1563.9	0.002	0.023
	6001801	ROC1	142	1951	0.01	361.44	0.133	0.013
	6001802	SJCH	135	495	0.01	167.86	0.481	0.047
	6001804	ANTU	117	622	0.02	399.32	0.269	0.009
	6001806	CSCH	97	315	0.01	89.98	0.328	0.047
	6001807	MELP	75	598	0.01	89.98	0.774	0.047
	6001808	OLMU	135	391	0.01	89.98	0.354	0.048
	6001809	CONC	32	241	0.005	141.67	0.403	0.103
	6001821	CRMA	111	439	0.01	99.96	0.562	0.028
	6001828	VALP	118	926	0.005	69.075	0.306	0.082
	6003554	PB05	1244	745	0.01	1540.8	0.002	0.003

CANDIDATE RECORD DEVELOPMENT

High-quality records, which have been manually reviewed (i.e., without the use of a deep-learning-based model) as part of the NGA-Sub project, were obtained from the NGA-Sub catalogue of subduction ground-motion records (Mazzoni, 2022); however, to validate the performance of the model, low-, intermediate-, and high-quality candidate records were required. Low- and intermediate-quality records were created by adding various amplitudes of artificial background noise to the 22 (high-quality) seed records.

Background noise, in theory, could be modelled with pure Gaussian white noise — however, in the real world, noise comes from high frequency vibrations of nearby objects (i.e., trees, buildings, etc.) or low frequency vibrations from natural phenomena such as tides and wind. Thus, real-world background noise has a characteristic "U" shape from 0.1–10 Hz (Peterson, 1993). Therefore, background time series matching the spectral shape of the United States Geological Survey (USGS) low level background noise model, as shown in Figure 1 (McNamara and Buland, 2004), was synthesized.

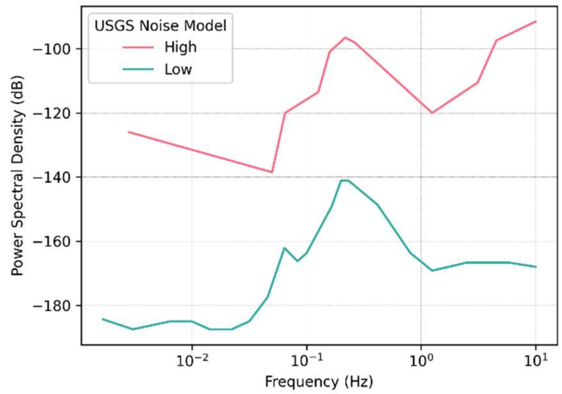

Figure 1. Background noise models for the United States developed by the United States Geological Survey (USGS) (McNamara and Buland, 2004).

Six different amplitudes of the synthetic background noise were added to the seed suite, with noise amplitudes scaled relative to the PGA of each seed record component: 0, 0.01, 0.03, 0.1, 0.3, and 1; where 0 corresponds to the unaltered, high-quality, seed record from the NGA-Sub catalogue. One example record is shown with added noise amplitudes of 0, 0.1, and 1 in Figure 2. In total, 132 3-component candidate records were generated: 6 amplitudes of background noise applied to the 22 seed records.

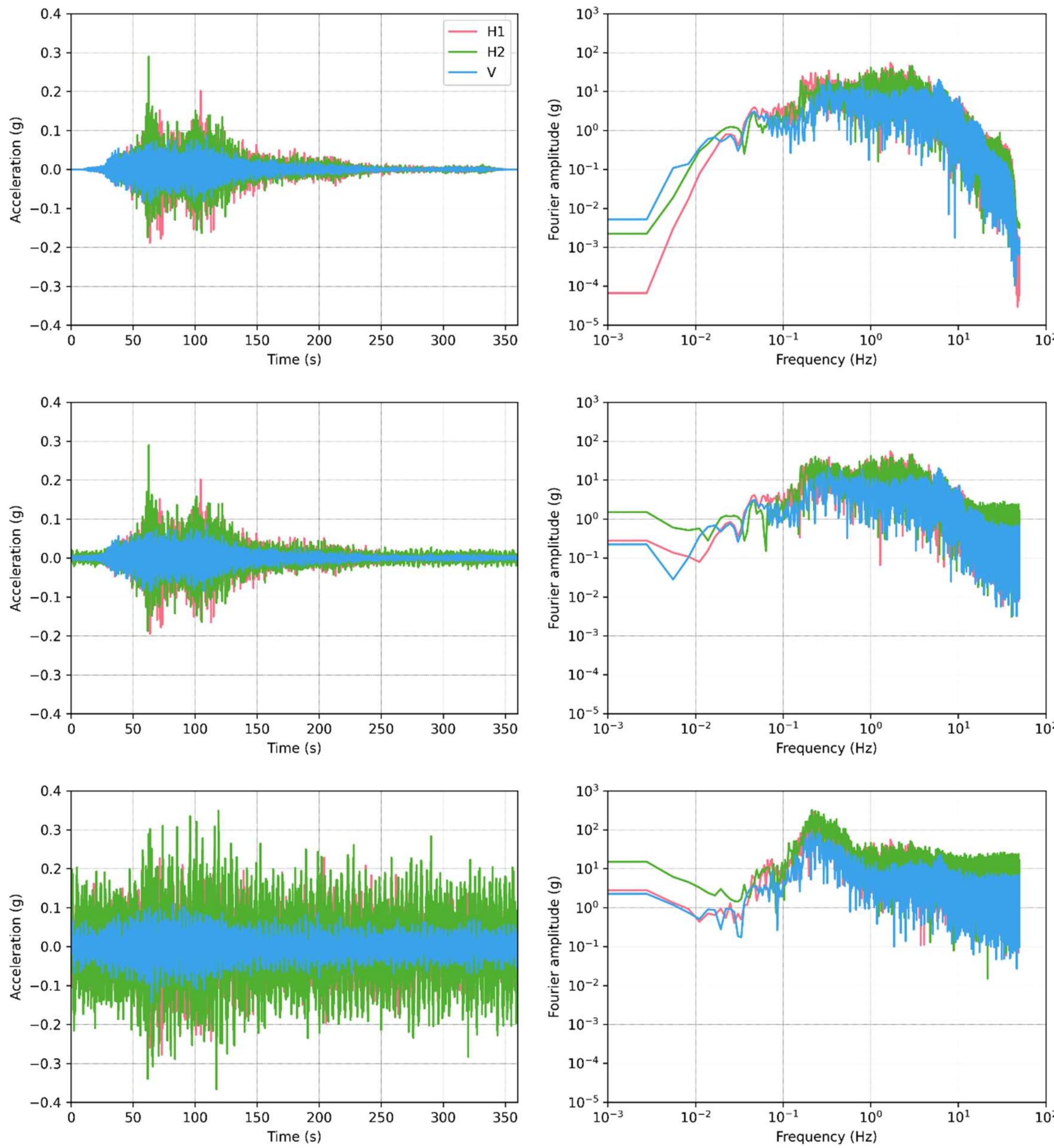

Figure 2. Candidate records developed from seed record 4000086 (Tohoku, Station 42204) with added noise of relative amplitude of 0 (top), 0.1 (middle), and 1 (bottom). Left: acceleration time-series; right: Fourier amplitude spectra.

MODEL QUALITY AND MINIMIM USABLE FREQUENCY ESTIMATES

The model was applied to the 132 candidate 3-component records (396 components total) to estimate the component quality score (0–1) and the component minimum usable frequency (0.01–10 Hz). High-quality records correspond to a quality score of 1; low-quality records correspond to a quality score of 0. The minimum usable frequency corresponds to the lowest frequency with a signal-to-noise ratio greater than 3.

Example estimates for the first horizontal component (H1 direction) of selected records are shown in Figure 3 for the six relative amplitudes of added background noise. Detection of P-wave arrival is required to compute input features for the model and is done with PhaseNet (Zhu and Beroza, 2019). For some records, which are not shown in Figure 3, the model incorrectly identified P-wave arrival and therefore failed to return estimates. In total, the model failed on 25 of the 132 candidate records; these components were removed from the analysis.

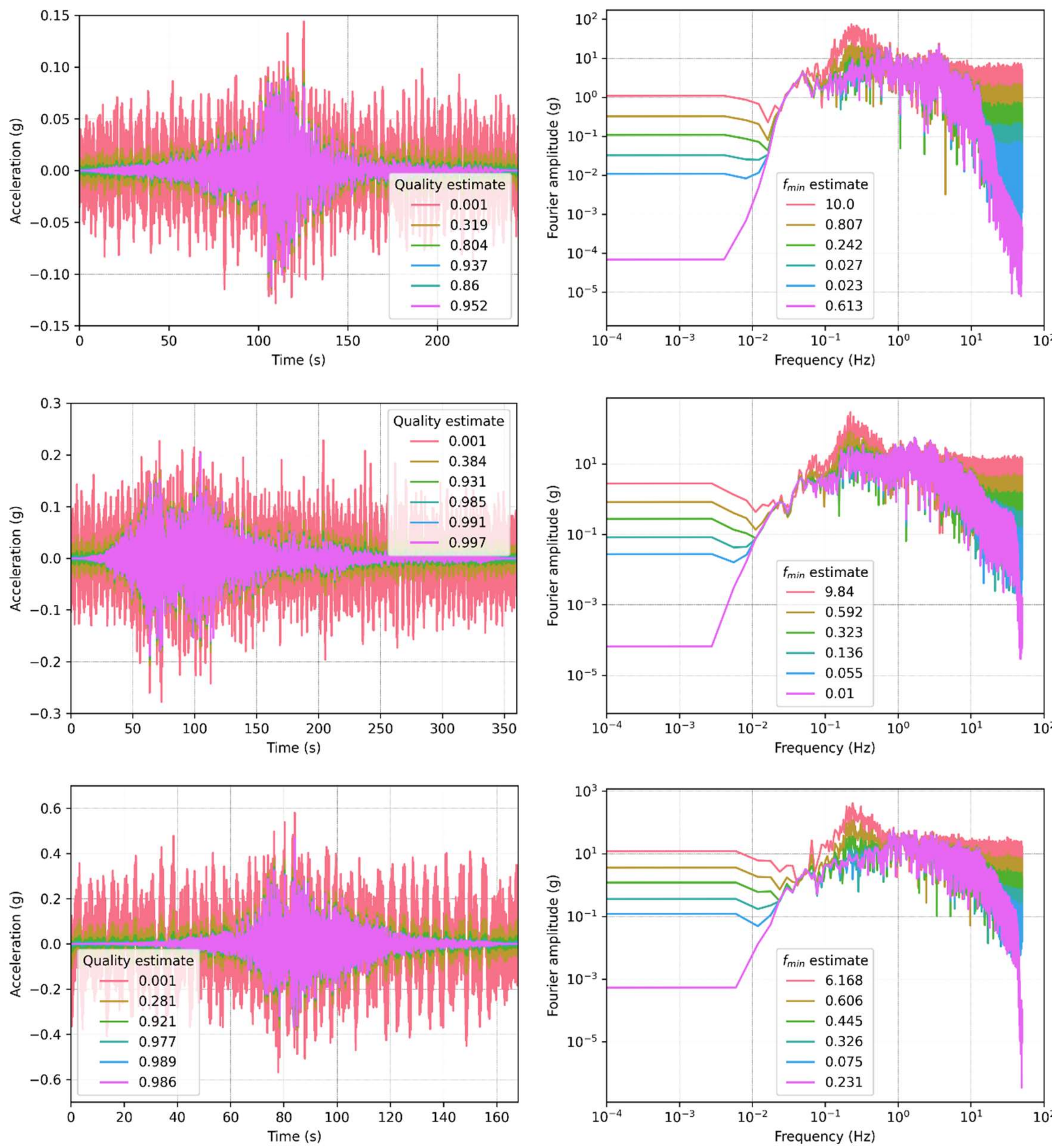

Figure 3. First horizontal component of record 4000043 (top), 4000086 (middle), and 6001802 (bottom) with six relative amplitudes of background noise added: 1 (pink), 0.3 (bronze), 0.1, (green), 0.03 (turquoise), 0.01 (light blue), and 0 (purple). Left: acceleration time-series labelled by estimated quality score; right: Fourier amplitude spectra labelled by estimated minimum usable frequency, f_{min} (Hz).

The estimates for the three selected components shown in Figure 3 are representative of the model performance on the overall dataset of candidate records. In general, the model provided high quality score estimates for background noise amplitudes of 0 and 0.01; the model usually failed, or provided low quality score estimates for noise amplitudes of 0.3 or 1. Similarly, for the minimum usable frequency estimates, the frequencies returned for the model were very low for noise amplitudes of 0 and 0.01, with a significant increase, or model failure, at larger noise amplitudes.

The minimum usable frequency estimates without added noise (e.g., 0) agree well with the values provided by NGA-Sub. However, for a relatively small portion of the records, the model made inaccurate estimates, e.g., the minimum usable frequency estimates for record 400043 and 6001802 with no added noise shown in Figure 3. There does not appear to be a common attribute between records which resulted in inaccurate estimates. These occasionally inaccurate estimates, and their apparent lack of explanation, is a limitation of the current model and is attributed to the limited set of input features and relatively small training dataset.

The estimates for the entire dataset of candidate records are shown in Figure 4. The behavior of the model estimates is consistent with expectations based on experience with previous applications of the model for small-to-moderate magnitude records: high quality score and low minimum usable frequency estimates are made for records with little added noise and low quality scores and high minimum usable frequency estimates are made for records dominated by background noise, especially for the noise-dominated records with relative noise amplitudes of 0.3 and 1 which have signal-to-noise ratio of 3 or lower. A signal-to-noise ratio of 3 is often used as an acceptance criterion for strong ground-motion records (Boore and Bommer, 2005).

As shown in the top of Figure 4, for a small portion of records with very little or zero added noise, the model erroneously produces very low quality or very high minimum usable frequency estimates. The model estimates appropriately high minimum usable frequency estimates for records with added noise with a very large relative amplitude of 1 (Figure 4, top right).

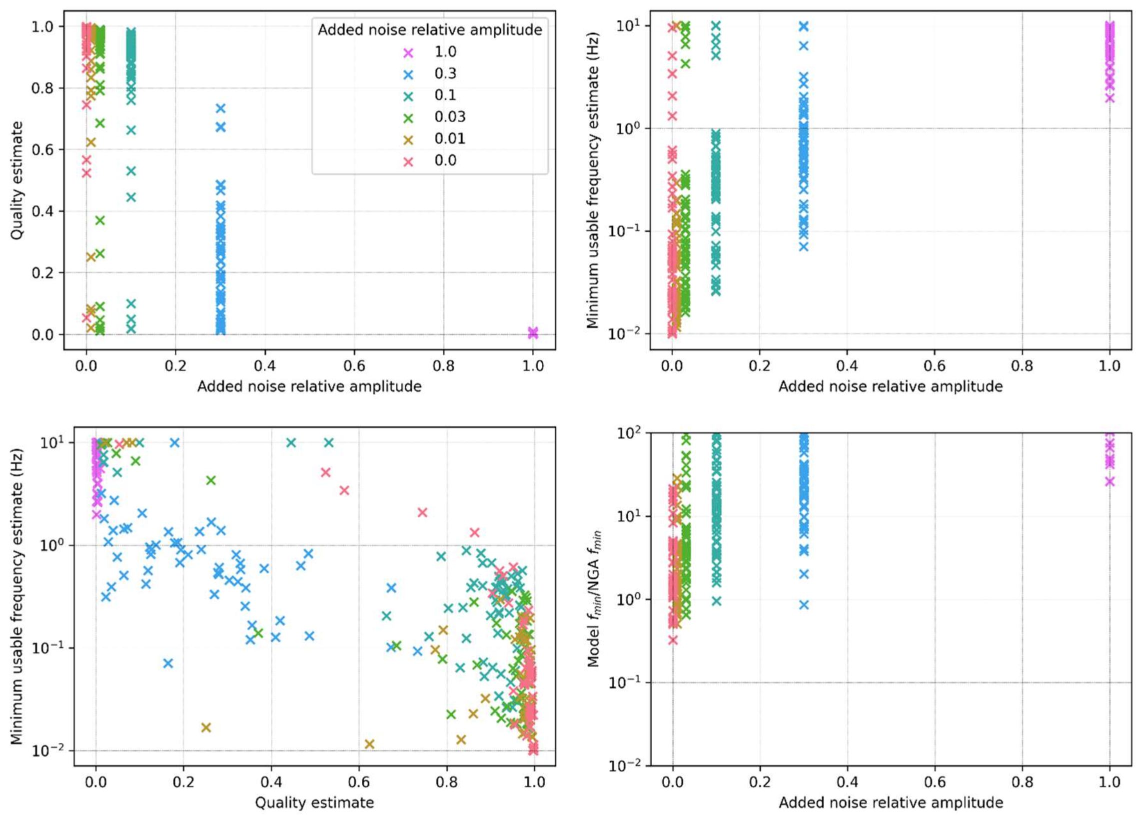

Figure 4. Estimated quality score for all components as a function of the relative amplitude of background noise added (top left) and minimum usable frequency estimate by relative amplitude of background noise added (top right) and by quality estimate (bottom left), and minimum usable frequency estimate relative to that provided by NGA (bottom right).

A brief statistical summary of the estimates for the candidate records at each added noise amplitude is presented in Table 2. The results indicate that the model is effective at correctly estimating quality and minimum usable frequency for very high- and very low-quality records; however, there is very little or no sensitivity in the estimates to addition of small amplitudes of noise (e.g., 0.01).

Table 2. Component quality and minimum usable frequency estimates for the original high-quality NGA records (noise amplitude of 0), and for records with various amplitudes of superimposed background noise.

		Quality estimate		Minimum usable frequency estimate (Hz)	
Relative amplitude of background noise	**Failed P-wave pick**	**Arithmetic mean, μ**	**Standard deviation, σ**	**Geometric mean, μ**	**Standard deviation (log-space), σ**
0	5/22	0.94	0.16	0.06	0.74
0.01	5/22	0.89	0.24	0.06	0.66
0.03	4/22	0.84	0.29	0.12	0.75
0.1	2/22	0.84	0.23	0.30	0.63
0.3	4/22	0.23	0.17	0.69	0.46
1	5/22	0.00	0.00	7.15	0.19

SELECTION OF HIGH-QUALITY RECORDS

To simulate how this model may be applied in practice to develop a suite of earthquake records for structural analysis, eleven horizontal record components were selected from the dataset of candidate records following the steps outlined below. A record is comprised of three orthogonal components: two horizontal and one vertical. Only horizontal components were considered from each candidate record, and records for which the model failed were removed. In total, 25 records were removed due to failed P-wave pick (Table 2), therefore 214 horizontal candidate record components were considered.

Records were selected from the candidate records with the goal to select for high-quality records usable to below 0.5 Hz which are consistent with the target site conditions (shear wave velocity, V_{S30} > 300 m/s) and earthquake source characterization (rupture distance, R_{rup} < 300 km). Records with pseudo-spectral acceleration less than 0.15 g at 0.2 s were removed to avoid using records with scale factors (the ratio of the pseudo-spectral accelerations for the target and the seed) greater than 5, which are problematic as inputs for response history analysis (Du et al., 2019). Although records were selected to obtain high-quality records with minimum usable frequencies satisfying the required threshold, selection was done without consideration of the added noise amplitudes (i.e., blind selection). Versions of a given seed record with different amplitudes of background noise were treated as independent records, therefore some seed records are included more than once.

The following steps were applied to select a suite of high-quality records consistent with the target site metadata and seismic hazard:

1. Removed all candidate records for which the model failed (25 records removed total).

2. Only considered the horizontal components from each candidate record (214 candidate components).
3. Filtered candidate records to only include those with a rupture distance, R_{rup}, less than 300 km, site shear wave velocity, V_{S30}, greater than 300 m/s; estimated minimum usable frequencies less than 0.5 Hz; and scale factors less than 5.
4. Ranked records from highest to lowest by estimated quality score and selected the first 11 record components without regard for the amplitude of added noise (i.e., blind selection).

The suite of 11 selected records, levels of added background noise, estimated quality scores and minimum usable frequencies, and associated site metadata are provided in Table 3. In general, the model appears to have performed well; no records with relatively large amplitudes (0.03, 0.1, 0.3, or 1) of added noise were selected. For the suite of selected records, each record is named in the following convention: <Noise Amplitude>_<NGA RSN Component Name>. In total, five records from Tohoku and six records from Maule were selected.

Table 3. Selected "high-quality" records from the 2010 **M**8.8 Maule and 2011 **M**9.1 Tohoku subduction interface earthquakes ordered from highest quality estimate to lowest.

Record name	Added noise relative amplitude	Estimated quality score	Estimated minimum usable frequency (Hz)	Rupture distance (km)	Shear wave velocity, V_{S30} (m/s)
0pt00_NGAsubRSN4000086_89C-EW	0	0.997	0.010	125	339
0pt00_NGAsubRSN4000086_89C-NS	0	0.997	0.011	125	339
0pt01_NGAsubRSN4000086_89C-NS	0.01	0.993	0.026	125	339
0pt00_NGAsubRSN6001801_ROBL360	0	0.992	0.066	142	1951
0pt00_NGAsubRSN6001801_ROBL090	0	0.992	0.022	142	1951
0pt01_NGAsubRSN4000086_89C-EW	0.01	0.991	0.055	125	339
0pt00_NGAsubRSN4000087_89D-NS	0	0.990	0.017	120	359
0pt00_NGAsubRSN6001821_CRMA-EW	0	0.990	0.046	111	439
0pt00_NGAsubRSN6001821_CRMA-NS	0	0.990	0.051	111	439
0pt01_NGAsubRSN6001802_SNJM090	0.01	0.989	0.196	135	495
0pt01_NGAsubRSN6001802_SNJM360	0.01	0.989	0.075	135	495

LINEAR SCALING TO TARGET HAZARD

To complete the record development, the selected record components were linearly scaled to match a target spectral hazard for the hypothetical site: pseudo-spectral acceleration of 0.75 g at a period of 0.2 s. The linearly scaled suite of 11 horizontal record components is shown in Figure 5.

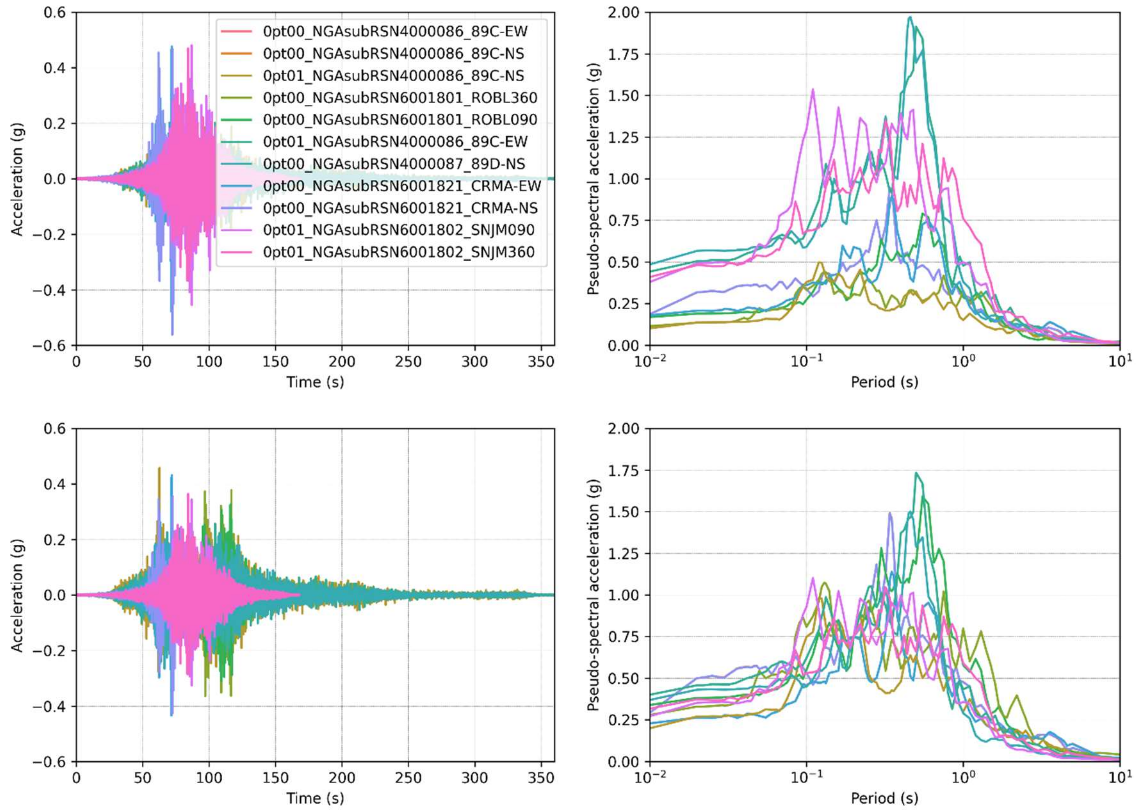

Figure 5. Suite of 11 selected horizontal ground-motion record components, labelled as <Noise Amplitude> <NGA RSN Component Name>. Left: acceleration time series, right: response spectra; top: unscaled; bottom: linearly scaled to 0.75 g at 0.2 s.

CONCLUSION

A deep-learning model, previously developed for ground-motion quality and minimum usable frequency estimation of small-to-moderate magnitude earthquake records, was applied to large-magnitude subduction interface earthquake records. High-quality records were retrieved from the NGA-Sub catalogue for both the 2010 **M**8.8 Maule and 2011 **M**9.1 Tohoku subduction interface earthquakes. These high-quality records were then seeded with varying relative amplitudes (0, 0.01, 0.03, 0.1, 0.3, and 1) of synthetic background noise to create records of high, intermediate, and low quality. In total, 132 records were considered.

The model was found to perform well at correctly estimating high-quality and low minimum usable frequencies for the original high-quality records from the NGA-Sub catalogue. The minimum usable frequency estimates without added noise (e.g., 0) agree well with the values provided by NGA-Sub. Similarly, very low-quality records with relatively large amplitudes of added noise (e.g., 1) were correctly estimated as very low quality and as having high minimum usable frequencies. The model demonstrated little sensitivity to small amplitudes of added background noise (e.g., 0.01); this is appropriate since such small amplitudes of background noise correspond to a signal-to-noise ratio of 100, well above the commonly accepted threshold of 3 (Boore and Bommer, 2005).

Records with added noise amplitudes of 0.03, 0.1, and 0.3 were assigned intermediate-to-low quality estimates and similarly intermediate minimum usable frequency estimates.

The model was used to select a suite of 11 high-quality ground-motion records components from the dataset of 264 horizontal record components without prior knowledge of the added noise amplitudes in each record. The estimated quality scores and minimum usable frequencies from the model were useful for filtering out low-quality records with large amplitudes of added noise. The selected suite of records contained seven records without any added noise and four records with relative noise amplitudes of 0.01. The selected records were then linearly scaled to a target spectral hazard to complete the record suite development. In general, the model performed well for the large-magnitude subduction records considered, which were representative of a large range of rupture distances and site conditions. Therefore, it is reasonable to conclude that deep-learning-based models offer opportunities to make subduction earthquake record selection for response history analysis of dams more efficient and effective than manual selection.

Three main limitations of the model were identified. First, erroneous quality and minimum usable frequency estimates were made for a small portion of high-quality records. Second, the model failed to provide estimates for 25 of the 132 records considered, primarily due to early P-wave pick, and this percentage of failed estimates is expected for other applications to large-magnitude records, for which the model was not developed. Although this limitation is easily remedied by consideration of more candidate records, it may present challenges to studies which require selection of many high-quality large-magnitude earthquake records. Finally, for dams, or other high-frequency structures, the maximum useable frequency of records becomes an important consideration; therefore, automated ground-motion quality classification tools developed in the future should also consider providing maximum useable frequency estimates.

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