Towards Data-Driven Evaluation of Site Effects From Coda of Strong Motion Timeseries Using Recurrent Neural Networks

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Title page:

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Abstract

It is known that coda of strong motion records are products of numerous scatterings of body and surface waves within the subsurface soil structure. Several studies have successfully simulated coda wave envelopes by modelling the energy decay. However, due to limitations of quantifying soil heterogeneities, deterministic simulation of scattered wavefields is much more challenging. Therefore, the reverse problem of estimating non statistical properties of subsurface structure from coda waves remains a theoretical potential. On the other hand, machine learning techniques have proven useful in dealing with problems of similar nature, where a theoretical solution is imaginable yet hard to achieve due to a great number of unknown variables. This study utilizes artificial neural networks to propose a new approach of evaluating site effects from coda waves, with the future prospect of obtaining the similar results from microtremor records. A Long Short-Term Memory recurrent neural network is designed using Tensorflow 2 library in Python language. The study utilizes a strong motion dataset consisting of about 60000 3-component records as well as borehole data at 464 stations of Kiban-Kyoshin Network across Japan. The prediction input is coda wave timeseries of strong motion records, defined based on a parametric energy criterion, and all 3 seismograph components EW, NS and UD are used as parallel

sequential features. In the first step, the prediction target is a vector of 3 site effect proxies namely, time-averaged shear-wave velocities for the upper 30-m depth V_{s30} and the upper 10-m depth V_{s10} and predominant frequency f_0 . In this step, different model parameter combinations are tested to ensure the basic model's ability in extracting site-specific information from the input coda waves. One of the combinations is then used in the second step, in which the prediction target is surface to downhole ratio of Fourier Amplitude Spectra. For each of the 3 components EW, NS and UD, 100 identical networks are trained to each predict the desired ratio at a certain target frequency. Accuracy of test sample predictions confirms applicability of the proposed approach as well as its potential for future works on microtremor timeseries instead of coda waves.

Keywords

Coda waves, Site effects, Fourier analysis, Neural networks, Time-series analysis, Computational seismology, Earthquake ground motions

Main Text

Introduction

In the recent years, machine learning (ML) techniques, especially multilayer Artificial Neural Networks (ANNs) have gained growing attention in all fields of science and engineering. Due to

great advances in the flexibility and performance of algorithms as well as programming and computational efficiency, machine learning techniques are already in use for many real-life applications such as medical diagnosis or engineering defect detection. However, one of the fields in which machine learning remains to be limited to research level is seismological and earthquake engineering.

From physics-based ground motion prediction to building response analysis and deterministic seismic hazard analysis, a wide variety of seismological procedures demand an accurate estimation of the site effect as a crucial analytical component. Traditionally, the site effect is accounted for via either averaged parameters such as peak ground acceleration (PGA) and time-averaged shear wave velocity to 30 m depth (V_{s30}) or spectral evaluations based on deconvolution of waveforms.

Both above methods have their respective demerits when it comes to engineering applicability. For instance, single parameter evaluation neglects time-dependent and/or frequency-dependent characteristics and spectral evaluations still contain uncertainties regarding directionality as well as nonlinear behavior of subsurface structure.

64 Considering the availability of a great number of strong motion records, it is not inconceivable
65 that there may be an advantage in adopting ML algorithms such as ANNs to better understand
66 and evaluate site effects and directly extract as much information as possible from past recorded
67 data. Furthermore, as opposed to full waves, the coda of strong motion records is known to contain
68 fully scattered body and surface waves, which makes them an immediate candidate for extraction
69 of site-specific information.

70 A review of literature by Mignan *et al.* (2019) reveals that ANNs have been increasingly adopted
71 in seismological studies in a range of topics such as ground motion prediction, aftershock
72 prediction and seismic waveform analysis. Although, in some cases, the results seem satisfactory
73 compared to conventional predictive methods, for example, prediction of aftershock patterns by
74 DeVries *et al.* (2018) or large earthquake magnitudes by Huang *et al.* (2018), it seems there is not
75 enough justification yet to adopt the proposed methods in engineering or risk assessment practice.

76 Therefore, besides obtaining satisfactory results, a persistent challenge regarding the use of ML
77 methods is to validate the formulation by theoretical explanation.

78 In this research, strong motion datasets are used to train an ANN to ultimately estimate a spectral
79 distribution of site amplification for any arbitrary site inside Japan. Strong motion records from

Kiban Kyoshin Network (KiK-net) stations operated and maintained by the National Research Institute for Earth Science and Disaster Resilience (NIED) (Aoi *et al.*, 2004) are obtained and a Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) cells is trained on the coda window of time-series data to predict site effect proxies and site amplification ratios for each station. In the following sections, after the introduction of utilized data and method, analysis approach and results are discussed, followed by indications regarding applicability of the method as well as physical interpretation of the results.

It is worth noting that the future prospect of this study is to train networks on available coda waves but make predictions from observed microtremor timeseries on sites where earthquake records are not available. This expectation is based on observed evidence of fully scattered waves and energy equipartition in both microtremors and coda of strong motions, indicating that both may reflect similar information on subsurface structure at specific sites. Indications of the current stage of the study in relation to this prospect are also discussed in following sections.

Data processing

Time series data

Strong motion seismographs are used in this study for three purposes. Firstly, for extraction of a large number of coda waves, secondly, for computation of earthquake horizontal-to-vertical (H/V) spectral ratios (EHVRs) and predominant frequencies at each site and lastly, for computation of site amplification ratios for different earthquake events at different sites.

The initially selected dataset contains EW, NS and UD components of strong motion acceleration timeseries with PGAs below 100 cm/s^2 and above 10 cm/s^2 , recorded at all KiK-net stations between 2000 January first and 2020 January first (Aoi *et al.*, 2004; NIED, 2019). Records with PGAs below 10 cm/s^2 tend to have short durations, making it difficult to detect coda time windows and thus were not considered for convenience.

The original sampling rate of all the timeseries data is 100 Hz. Because the RNN algorithm performs better with shorter sequences, all timeseries had to be resampled at the smallest frequency possible. Considering that the frequency range of engineering interest is generally up to 10 Hz, without losing any information in this range, the smallest Nyquist frequency would be 10 Hz. Therefore, all timeseries used in this study were resampled at 20 Hz. Next, in order to eliminate unwanted high frequency noise, all timeseries were filtered by a 0.1-10 Hz bandpass Butterworth filter.

In order to ensure that only records within the linear soil response range are included, the higher limit of PGA was adjusted per station, based on the variance of predominant frequencies. First, the predominant frequency (f_0) was calculated from the EHVR of each strong motion record. At each site, mean and standard deviation (SD) values of the estimated predominant frequencies were computed. Those records with f_0 within the mean $\pm$ SD range were kept as linear samples and those with exceeding values were eliminated.

Site effect proxies

Initially five site proxies were calculated for each station, Vs30 and time-averaged shear-wave velocities for the upper 10-m depth (Vs10), depth of engineering bedrock (D_b), surface to bedrock ratio of S-wave velocity (R_v) and f_0 . However, when multiple trial networks were trained on the dataset and all showed poor performances for two of the proxies, namely D_b and R_v , the two were removed from further investigations. The final site effect proxies' vector for each station was built from the remaining 3 proxies, which are Vs30, Vs10 and f_0 .

f_0 at each station was calculated as the first peak frequency of average EHVRs of all earthquake seismographs within the selected strong motion dataset. For this purpose, each EHVR curve was

smoothed using a Parzen window with bandwidth of 0.1Hz. The prominent peaks were then selected as all local maxima points where peak prominence is larger than 1, excluding frequencies that are smaller than 0.1 Hz and thus outside the engineering interest range. In this case, peak prominence is defined as the vertical distance between a peak point and its lowest contour line.

Fig. 1 shows examples of EHVR plots and selected predominant frequencies at six KiK-net stations.

As seen in the figure, in cases like MIEH05 where no peaks in the lower frequency range pass the criteria, inevitably, f_0 is detected in higher frequency range. This means that the same site proxy or RNN feature contains certain information (lower frequency content) at some data points and different information (higher frequency content) at others. Although this inconsistency in a feature vector is far from optimal for training a neural network, any proper solution would have compromised fast and automatic calculation of the proxy values. Furthermore, estimation of practical proxies is not the main goal in the first step of this study and so the issue was considered negligible.

Coda wave extraction

A known characteristic of coda waves is decaying energy content. Since it was first discussed by Aki (1969), several studies have formulated the theory behind this behavior, through various models such as multiple scattering or radiative transfer function. Utilizing a dense array of seismographs, Shapiro *et al.* (2000) have shown that while deformation energy continuously decays following the S-wave arrival, shear to compressional energy ratio stabilizes for a while before largely fluctuating again. Their findings were in agreement with diffuse wave field theory, indicating energy is equipartitioned during the coda window. Using this same method, Margerin *et al.* (2009) have observed equipartition in coda waves and successfully applied it to model a layered media in Pinyon Flats. Although this method is promising, it relies on accurate estimation of divergence and curl of the wave field through observations of a dense array. Therefore, in order to determine the coda time window from single station records in this study, H/V energy ratio was considered instead, as an indicator of equipartition. Energy envelopes were computed for each seismograph by Eq. (1) following Mayeda & Walter (1996):

$$env(t) = \sqrt{(v^2(t) + h^2(t))} \quad (1)$$

in which $v(t)$ and $h(t)$ denote velocity timeseries and it's Hilbert transform respectively.

First, an initial onset t_1 was defined as the time stamp where mean H/V energy ratio (r_{mean})

over its following 5s time window dropped below 2. This step is done to ensure that S-wave

window is eliminated. This criterion is represented by the following equation,

$$r_{\text{mean}} = \text{mean} \left(\frac{\int_{t_1}^{t_1+5} env_{\text{smooth}_h}(t)}{\int_{t_1}^{t_1+5} env_{\text{smooth}_v}(t)} \right) < 2 \quad (2)$$

in which $env_{\text{smooth}}(t)$ is the envelope function smoothed by a Hanning window of 10s width.

Since the parameters are evaluated only in relation to threshold values, the smoothing window

width has negligible effect on the outcome. $env_{\text{smooth}_h}(t)$ and $env_{\text{smooth}_v}(t)$ refer to

average energy envelope of the two horizontal components and energy envelope of the vertical

component, respectively. Fig. 2 shows an example of applying this criterion to EW components

of a M3.7 event (sample record 1) and a M6.5 event (sample record 2) observed at the surface of

MIEH05 station in Mie prefecture. As seen in Fig. 2b, the H/V energy ratio in a lot of records

does not show a clear decline. In such cases, this step is not applicable and the initial onset t_1 is

set as 0.

Since samples with varying PGA values exhibit varying energy compositions of S-wave time-window, relying on the decline of H/V energy ratio is not enough to detect a coda onset. To create a unified parameterized criterion for all samples, the ratio of energy prior to coda onset to the total energy of the seismograph (ER) was defined as a control parameter. Based on this parameter, an alternative onset was defined as the timestep t where $er(t)$ drops to a certain value (e.g., $er_{thres} = 0.8$). Between the initial and alternative onsets computed for each sample, the later one of the two was chosen as final onset to avoid high amplitudes as much as possible. On the other hand, in order to determine the end of coda, coefficient of variation (CV) for remaining portion of seismograph following coda was used as a control parameter and the end of coda was determined as the timestamp t where $cv(t)$ reaches a certain lower limit (e.g., $cv_{thres} = 0.05$). The following two equations sum up this procedure.

$$cv(t) = \frac{\text{std}(env_{smooth}(t))}{\text{mean}(env_{smooth}(t))} \leq cv_{thres} \quad (3)$$

$$er(t) = \frac{\int_0^t env_{smooth}(t)}{\int_0^\infty env_{smooth}(t)} \geq er_{thres} \quad (4)$$

The values of er_{thres} and cv_{thres} can be optimized during the RNN training, for highest prediction accuracy. Figs. 3 and 4 show examples of applying this coda extraction criteria to sample records 1 and 2 of Fig. 2, respectively. In each figure, the top row shows the extracted coda time-window with the criteria $er_{\text{thres}} = 0.8$ and $cv_{\text{thres}} = 0.1$ (C1), and the bottom row shows the extracted coda time-window with the criteria $er_{\text{thres}} = 0.9$ and $cv_{\text{thres}} = 0.2$ (C2). Compared to C2, C1 picks an earlier onset and a later more stabilized end point. By this method, coda time-windows with different lengths are extracted from each record sample. In order to create fixed length input vectors for training RNNs, only the last 10 seconds of each extracted coda wave was used for extracted time-windows longer than 10 seconds, and 10-second vectors were created by zero padding the vector head for extracted time-windows shorter than 10 seconds. In the end, each sample input consists of three timeseries (EW, NS and UD) with 200 timestamps at a 20Hz sampling rate. As RNNs have a better performance on shorter timeseries data, the 10-second length was chosen because it is the minimum duration necessary to contain the lower limit of our frequency range of interest in this paper which is 0.1Hz.

Site amplification ratios

At each observation point of KiK-net, a pair of seismographs are installed at ground surface level and bedrock level inside a borehole. All boreholes are 100m deep or more, in order to assure that the seismographs are minimally affected by any shallow structures and surface waves (Okada et al., 2004). Although the ground at these downhole levels is mostly hard rock, it is still located at depth and affected by reflected waves. On the other hand, downhole depths are not strictly standardized, and downhole S-wave velocities differ from station to station. For these reasons, unlike records at a nearby reference outcrop rock, the downhole records are not explicitly controlled by just source and path characteristics. In order to account for this discrepancy when computing site transfer functions based on downhole data, some studies have suggested correction functions for surface to downhole spectral ratios (Héloïse *et al.*, 2012). However, since the purpose of this study is not to predict the transfer function but to examine the capability of an RNN model in predicting site effects from coda timeseries data, such procedures were deemed unnecessary. It was assumed for the purpose of this study that KiK-net downhole records are ground motion at engineering bedrock, containing main characteristics of earthquake source and propagation path which can be implicitly recognized by a data-driven model. This means that our reference bedrock ground motion is not recorded at a unique outcrop and is affected by varying

local sedimentary layers at each station. Nevertheless, this divergence from ground motion at outcrop is a function of the same shallow subsurface structure which we expect to be represented by the coda waves. Therefore, although this divergence is not explicitly quantified and corrected for each station, the RNN model is expected to implicitly capture and generalize it to all stations, thus learning consistent patterns. If the model is proved to work using downhole data, it can be used on corrected ground motion at engineering bedrock for practical use.

In literature, several deterministic methods exist to calculate ground motion at engineering bedrock from appropriate parameters to account for source mechanism as well as path attenuation.

An early example is the approach of Boore (1983) which is a stochastic approximation of ground motion envelope based on two most basic parameters of magnitude and distance. Another example is the method by Satoh (2004) which utilizes inversion of group time delay to improve Boore's envelope approximation and simulate full length time series with much higher precision.

Once any such technique is employed, in order to simulate ground motion characteristics at surface level, only site amplification effects remain unaccounted for.

In the second step of this study, RNNs are used to predict ground motion Fourier amplitude spectra (FAS) from an input of coda waves representing site effects. The prediction targets in this

case are surface to bedrock (downhole) ratios (SBRs) of FAS (rsb_{FAS}). These ratios are calculated from surface and downhole records of each event at the same KiK-net station. In order to create vectors of 100 components as the prediction targets, SBRs are computed from FAS for every 0.1Hz bin. For each of the three components, the FAS is first calculated from the preprocessed timeseries, then smoothed using a Parzen window of width 0.2Hz. The reason for choosing this bandwidth instead of 0.1Hz as used before, is to capture a smoother shape as accurately as possible, considering amplitudes are extracted only at every 0.1Hz in the final representative vector. The rsb_{FAS} vectors are thus calculated as follows. Subscripts s and b denote surface and bedrock respectively.

$$rsb_{FAS} = \frac{FAS_s(\omega)}{FAS_b(\omega)} \quad \forall \omega \in [0.0, 0.1, \dots, 10.0] \quad (5)$$

Method

Modelling sequential data with RNN

Based on the information flow, ANN architectures can be broadly divided into two types, feed-forward and recurrent neural networks. Feed-forward refers to architectures in which output of

each layer serves as the input to the next layer without loops. In contrast, by utilizing an information flow different from feed-forward architectures, recurrent type architectures are intended to account for the order in sequential data. In this case, the input to each hidden layer is not only the previous layer's output, but also the output of the same hidden layer from the previous time stamp. This way, during training, the updating of weights automatically depends on the order of the data. In graph notations, this order-dependency or sequential nature of weights in hidden layers is represented by a loop (Figs 5 and 6), also called a recurrent edge (Raschka & Mirjalili, 2017).

The training process of machine learning models requires the definition of an error function as well as an efficient method to minimize the error generated by this function in each training epoch. Since the error minimization involves calculating weight derivatives and due to large weight matrices in ANN models, training these models was long a challenge compared to simpler machine learning techniques. Since its introduction by Rumelhart *et al.* (1986), back-propagation has been the best solution for this challenge and the most powerful and widely used method of training feed-forward ANNs.

However, the same back-propagation techniques do not work as favorably on RNNs. Since in RNNs the hidden layer contains terms from all previous timestamps, its loss computation requires multiplication of many weight values corresponding to adjacent timestamps. This means back-propagation of errors generates weight derivatives powered by large values, especially in RNN models with long range dependencies. Therefore, very large or very small weight derivative values arise the problem of vanishing or exploding gradient.

To overcome this challenge several techniques have been introduced, amongst which the use of LSTM networks, introduced by Hochreiter & Jürgen (1997), is currently most efficient and popular. The building blocks of these networks are LSTM cells, which contain a memory of the cell state upon the introduction of each new sample. These cell states are designed in a way that generate weight matrices with determinant values of nearly 1 to avoid the vanishing or exploding gradient problem. The network is then trained by backpropagating the error to these support matrices and updating them instead of the original weight matrices.

RNN for single output regression

The initial model is an LSTM network with two or three recurrent hidden layers with 64 to 32 LSTM cell units, and one feed-forward dense hidden layer with 32 units at the end to generate

the output value. The input data is a three-dimensional (3D) tensor standard to all RNNs,

containing a sequence of feature vectors for each sample.

A sigmoid or tanh activation function is used in order to obtain a continuous predicted value for

the site proxies or amplification ratios, against which, the prediction loss and errors of the network

are calculated. The target value is the min-max scaled true value of site proxies and amplification

ratios. A visual annotation of this network is shown in Fig. 5.

The intuitive goal of this study is to let the RNN learn a timeseries of ground acceleration data

and predict site effect proxy or site amplification values of the associated station and each of the

three ground motion components EW, NS and UD are treated as independent features. Therefore,

the input 3D tensor is designed with dimensions $n_s \times 100 \times 3$; n_s being the number of training

samples, 100 and 3 being the number of timestamps in each input timeseries (sequential sample)

and the number of components (sequential features), respectively.

Outlier detection via autoencoder RNN

A significant factor that affects the performance of machine learning models is the quality of data.

Specifically, in problems involving big data of any sort, ensuring this quality becomes more

significant and more challenging, because this type of data is usually automatically generated and thus its robustness cannot be manually verified. To overcome this issue, ML methods rely on outlier analysis algorithms that automatically detect atypical or outlying data points and eliminate them from the training dataset.

While there are many well established methods such as the principal component analysis for accurate detection of non-sequential outlier data points, handling sequential outliers is not as straightforward. The problem of detecting anomalous timeseries in a timeseries dataset is either an unsupervised one, relying only on input data, or a supervised one, employing the target information as well. In both approaches, outlier analysis could be done by either clustering data points via similarity functions or parametric approaches which do not specify anomalous data but instead assign an anomaly score to each data point (Gupta *et al.*, 2013). In the latter approach, a threshold score can be defined as a control parameter to be adjusted and find just the right borderline between good and bad data points.

In this study, the input timeseries are coda waves extracted from earthquake seismographs, through the energy-based procedure explained in the previous section. Among these generated timeseries data points, outlying points are those minimally correlated with others. This may

include timeseries that passed the coda wave criteria but are dominated by non-scattered body waves or consist of mainly device noise. But even the desired coda waves are supposed to be fully scattered waves and thus noisy data. In this case, clustering algorithms may not be able to precisely map the innate correlation among data points. Therefore, it is preferred to take a parametric approach rather than determining the outliers by strictly modelling correlations.

Following a similar method to Malhorta *et al.* (2016) and Kieu *et al.* (2018), an autoencoder RNN is utilized as the outlier analysis method in this study. The autoencoder RNN is trained to take an input signal, learn and encode it via LSTM hidden layers and reconstruct and decode it to return the same signal as the output. The anomaly score of each input signal is then defined as its reconstruction error.

The autoencoder model is an LSTM network with two recurrent hidden layers each composed of 72 LSTM cell units, and one feed-forward dense hidden layer. Since an autoencoder is a model to encode the input data and decode it back to the same data, input and output data have the same dimensions, in this case three-dimensional tensors containing three component coda wave timeseries. A visual annotation of this network is shown in Fig. 6.

Firstly, a coda sample containing three component timeseries is fed into the RNN encoder and the model is trained over 200 epochs to reconstruct the input signal. After the training is complete, mean squared errors (MSE) of reconstructed signal against the original signal is calculated. This value is assigned to the coda time window as its outlier score. This procedure is independently repeated for every coda sample. Since the outliers are expected to be device noise or S-wave dominated, the timeseries should exhibit relatively stationary fluctuations with regular shapes. Therefore, the autoencoder is expected to be more successful and return smaller MSE values when reconstructing the outliers rather than the actual noisy coda waves.

To decide the threshold outlier score, microtremor data was used as reference because of its more reliable content of scattered seismic waves. The microtremor used for this purpose is a data set by Kawase *et al.* (2015). Fig. 7 shows some example comparisons between original and reconstructed signals for three components of random coda timeseries with high and low reconstruction errors, as well as a random microtremor timeseries. It can be confirmed that coda samples with smaller reconstruction errors have long periods and regular fluctuations while those with larger errors have higher frequencies and more complicated amplitudes, similar to microtremor timeseries. Based on visual inspections, threshold outlier score was initially set to

0.3. All coda samples with lower scores were eliminated. This means that in some stations like EHMH04 of Fig. 7, no coda samples passed the criteria, thus such stations were not represented in the final learning dataset.

Satoh *et al.* (2001) have shown that at soft soil sites the HVRs calculated from earthquake coda are contaminated by Rayleigh waves. Therefore, in frequencies lower than 3, maximum peaks of HVRs for coda waves lie somewhere between those for microtremor and earthquake S-wave. This was observed in our investigations as well. To evaluate the possible effects of outlier analysis on the average properties of our coda dataset, HVRs were compared at 105 stations, where microtremor records were available. Fig. 8 shows examples at three stations, in which bold lines show average HVRs calculated from coda dataset (blue), outlier-removed coda dataset (black), segmented microtremor dataset (red) and selected earthquake dataset (green) and light-colored lines show standard deviations.

As evident from the example plots, the elimination of outliers makes no significant difference in EHVRs. It can be concluded that the detected and eliminated outliers are indeed noise dominated stationary signals and have no apparent relation with site effects or even S-wave content.

Analysis and results

Prediction of site effect proxies

This first step of the study, namely prediction of site effect proxies, seeks two main purposes.

First, to construct an RNN model and enable it to extract information on site effects directly from coda wave timeseries. Second, to evaluate the similarity between coda waves and microtremor waves regarding the reflection of site-effects in each of the two timeseries. Therefore, a parametric investigation was conducted to find suitable coda wave extraction parameters on one hand, and best model parameters on the other.

Coda waves were extracted from strong motion timeseries according to the steps described in the previous section. The parameters er_{thres} and cv_{thres} were given two combinations of values, one with a loose energy criterion (C1) in which, $er_{\text{thres}} = 0.8$ and $cv_{\text{thres}} = 0.1$, and another with a stricter energy criterion (C2) in which $er_{\text{thres}} = 0.9$ and $cv_{\text{thres}} = 0.2$.

RNN models were designed with four different parameterized structures as shown in Table 1. The two structure parameters are number of LSTM hidden layers (n_{LSTM}) and activation function, resulting in four different models.

For training the models, both C1 and C2 coda datasets were constructed and divided into training and test sets. To have all stations represented in both training and test sets, only stations with 10 or more coda waves were kept in the dataset and from each station, 10 percent of coda samples were put in the test set and remaining 90 percent in the training set. After each of the four models were trained on the training set, MSE of predictions against the true values and SD of errors were computed for test and training sets for all three proxies. The results are summarized in Table 2. For each proxy, the values are color coded from blue to white, for smallest to largest errors and deviations. As expected, training samples derive smaller errors than test samples. For all three proxies, all eight combinations have yielded very similar performances and converged at similar rates, after about 400 epochs. This means that for a better selection of the coda definition criteria, more hyperparameter combinations should be evaluated through a more vigorous tuning method such as Grid Search. Since all combinations examined in this step were equally successful at learning site effect proxies from coda waves, only one combination (model B trained on C1 dataset) was utilized in the second step for the prediction of site amplification ratios.

In order to exhibit the overall performance of this method, prediction results of model B trained on C1 dataset are shown in Fig. 9. Figures show true values against predicted values for each proxy, with light blue dots corresponding to output of each sample and dark blue dots, corresponding to average output of all samples from the same station. As shown in the figure, predictions have a relatively high accuracy, and the general trend is captured by the networks.

Prediction of site amplification ratios

The second step of this study attempts to predict site amplification ratios for a given strong motion event at a given site, from an input of three coda timeseries representing site effects. For simplicity, site amplification ratios are defined here as SBRs of FAS.

To achieve equal representation of all stations, 40 coda waves were randomly chosen for each station. Because of the varying number of coda waves that passed the C1 criteria and the outlier analysis at each station, some stations in the dataset had less than 40 coda waves. For these stations, the randomly ordered coda wave set was duplicated until it reached 40 waves. For each target value (amplification ratio at a unique time or frequency bin), a separate single output regression RNN was constructed, using the same structure parameters as model B in the previous section.

406 That means 300 RNN models were used in total to predict FAS ratios of EW, NS and UD
407 components at 100 time or frequency bins (300 target values).

408 Prior to training the models, the dataset was divided into training and test sets with the ratio of
409 0.9 to 0.1. In order to assess the generalization ability of the network with more coherence, two
410 separate cases with different test set definitions were considered. In the first case (Cs from this
411 point on), about 10 percent of stations were defined as test stations and all their coda waves were
412 kept out of training. Results of this test set are to exhibit the networks performance on unseen
413 locations. In the second case (Cc from this point on) 10 percent of the coda waves from each
414 station, meaning four samples, were kept out of training. The results of this test set are to help
415 interpret Cs test results by exhibiting the networks performance on unseen coda samples at seen
416 locations.

417 Table 3 shows average Mean Absolute Errors (MAEs) and SD of MAEs for test and training sets
418 of both cases, with cells color coded from dark blue to white indicating lowest to highest errors.

419 As expected, Cc test samples derive closer errors to training test samples, confirming that similar
420 to the first step, the network is able to generalize coda samples recorded at the same station to
421 derive same relevant targets, in this step, amplification ratios.

Fig. 10 shows average MAE and SD of prediction errors per station. Although test set of case Cc includes samples from all stations, only results of 54 stations in test set of case Cs are illustrated in the figure, for the purpose of comparison. The bars are sorted by the difference between Cc and Cs errors divided by the Cs error, in a decreasing order from left to right. The following three observations can be made regarding this figure: 1. The stations with medium Cs accuracies (medium length bars) are scattered from left to right, showing varying degrees of Cc outperforming Cs. 2. The lower Cs errors are towards the left side, meaning Cc has a much better performance at stations with better accuracies. 3. The biggest Cs errors tend to be towards the right side, meaning the Cc and Cs performances do not differ much in stations with lower accuracies.

Fig. 11 shows examples of three stations with similar Cs as well as Cc errors. It can be observed that most of these stations do not have distinct peaks and although Cc in general outperforms Cs, both predictions are almost within the uncertainty range of true values. It shows that in absence of extreme variations, the model trained on current dataset exhibits sufficient predictive accuracy on unseen locations.

Fig. 12 shows examples of three stations with relatively low Cs errors and highest difference between Cc and Cs errors (left hand bars on Figure 10). We can see from Cs figures on top that although the networks can detect the overall trend at new stations, the peaks are not coherent. On the contrary, the Cc case shows much more precision with coherent peaks as well as amplitudes except for the lower frequency peak at AICH06. This shows that only in cases where the model can generalize learnt trends to unseen locations (low Cs error), presence of more closely related data in training set increases coherence of peaks and variation of amplitudes.

Fig. 13 shows examples of three stations with highest Cs as well as Cc errors (right hand bars on Fig. 10). Both high and low frequency peaks in these cases have high amplitudes and are vastly underestimated by the model in Cc case. The Cs case also, despite detecting the peaks, equally underestimates the amplitudes. It shows that although the presence of closely related samples in dataset, enables the network to detect coherent peaks, estimation of amplitudes relies on the general trend learnt from all training samples. This is most clear in case of lower frequency peak at MYGH01 which is not well detected by Cs case. Thus, for more accurate results on unseen locations, the presence of representative training data alone is not enough but the number of representative samples must suffice as well.

These observations can be confirmed with more confidence by examining scatter plots of prediction results at different frequencies. Fig. 14 shows predicted values for training and test sets of both Cs and Cc cases, plotted against true values for three example frequencies 9.8Hz, 4.8Hz and 0.8Hz. At each frequency, in middle range amplitudes where training samples are most populated, predictions of Cc test samples are as good as those of Cs test samples. These values correspond to stations without distinct peaks such as example stations in Figure 12. As the amplitudes get larger and training samples sparser, Cs test results deviate from true values faster than Cc test results. At amplitudes larger than about 10 for high and 3 for low frequency ranges, the trend of Cs test sample predictions starts to flatten, but for Cc test samples this does not happen until much larger amplitudes. At these amplitudes, overall pattern of Cs test samples is still captured but with lower definition than Cc, as previously displayed by examples in Figure 13. On the other hand, in amplitudes that are much larger than median and training samples are remarkably sparse, values of both Cs and Cc test samples are equally underestimated. These amplitudes correspond to underrepresented stations similar to examples in Figure 14.

It can be concluded that accurate estimation of amplitudes depends on sufficient representation of samples with similar amplitudes at associated frequencies. If given enough training samples at

certain amplitude ranges, the network can generalize learnt trends to the same ranges at unseen locations. Therefore, it is necessary to adjust the dataset and decrease the bias on different subsurface structures from the different number of samples, by selecting more high amplification basins and reducing the number of low amplification hard rock sites in the dataset, for example. Furthermore, detection of coherent peaks depends on the presence of representative samples from closely related geological settings. This can be achieved by increasing data locations or utilizing data from denser points over a smaller region.

Conclusions and Discussions

In this study, recurrent neural networks were utilized to predict site effects from earthquake coda timeseries. In the first step, MSE values were relatively small on both training and test coda sets on all site proxies. Although the scatter of predicted values against true values are somewhat large on predictions of unique samples, it is much smaller on average for predictions at unique stations. SD values in the case of Vs30 lie between 20m/s and 200 m/s which is comparable with geomorphologic mapping methods (Matsuoka *et al.*, 2005). This indicates that RNNs were successful at extracting site specific information from coda waves. Nevertheless, a neural network

485 should be able to minimize this scatter.

486 The scatter occurs mainly due to the outlier data, degrading the network's performance. Since the
487 dataset is so large, it is crucial to deal with outliers and increase data quality as much as possible.

488 Among the many methods to tackle this issue, an RNN autoencoder was utilized in this study, to
489 detect and rule out least correlated samples. Additionally, tuning network hyperparameters and
490 optimizing data processing parameters could improve results which is yet to be done in this study.

491 A third reason causing scattered predictions is possibly the LSTM architecture. The conventional
492 LSTM networks are meant for classification tasks as opposed to regression. This means the
493 structure of memory cells is most suitable for outputs closer to 0 or 1 as possible, making it less
494 sensitive to uniformly distributed continuous values. Therefore, a more robust way to utilize
495 RNNs in a regression problem and achieve continuous value targets from sequential data is
496 through a hybrid model. In a hybrid model, the RNN acts as a feature extraction algorithm and a
497 separate regressor is used to infer the target value from those features. Lastly, as a general rule,
498 adding more data samples helps improve the performance of machine learning models. In this
499 study, this can be achieved by utilizing earthquake records with lower PGAs, while maintaining
500 robust coda definitions to avoid increasing uncorrelated outlier samples.

In the second step, site amplification ratios were computed as surface to bedrock ratios of FAS of the strong motion record at KiK-net stations. In both Cs and Cc cases, MSE values were lower than 3 for all three components of all samples and frequency peaks as well as overall amplitudes were detected in all samples. In the samples with higher MSE values, prediction deviated from true value mainly in higher frequency range, where amplitudes tend to be underestimated yet the peaks align well. Comparing different events at a given station, even in stations with large inter-event inconsistencies, predictions remained consistent. This indicates that irregular events did not degrade the model's capability in predicting average site amplification properties, and models were able to extract the correct factors from the coda timeseries whereby to amplify bedrock ground motion. However, from investigating event and site characteristics of these inconsistent examples, it was evident that the RNN models were not able to account for directionality and topographical irregularities.

The future prospect of this study is to utilize easily obtainable microtremor timeseries instead of coda time-series and predict site effects at any arbitrary site in Japan. Both waves are believed to consist mainly of fully scattered surface and body waves, thus reflecting shallow subsurface structure and site-specific amplification characteristics. While single station microtremor

observations can be easily conducted anywhere, currently there is not enough observed data to directly use for training a machine learning model. On the other hand, there is an abundant earthquake dataset available, from which thousands of coda wave time windows can be extracted. Intuitively, one can attempt to train RNN models on coda timeseries, and using the same models, make predictions on microtremor timeseries. To investigate this idea, a few tentative tests were run in both steps of the study. However, on the microtremor dataset, the MSEs were higher and the predictions were as good as a random normal distribution with almost identical mean prediction values and similarly large standard deviations for all stations. This indicates first and foremost, that RNNs fail to simply treat microtremor and coda time windows as equivalents. Although by visually inspecting the HVR plots at multiple stations, S-wave, coda wave and microtremor wave seem to exhibit rather identical shapes, there are still differences, for example in the exact peak frequencies and peak amplitudes. Considering the limited duration of earthquake records, it is unlikely that any coda wave with no S-wave influence can be extracted. One solution would be to minimize the S-wave to coda wave power ratio by utilizing lower PGA records. Another solution would be to erase S-wave traces through deterministic procedures such as procedures by Sánchez-Sesma *et al.* (2012) or Froment *et al.* (2011). Another imaginable

approach is a simple additional step to map coda timeseries to their counterpart microtremor timeseries. That is to say, if another sub model is trained to map between coda input and microtremor input utilizing the 27 stations where both records are available, a larger network can be trained on data from all KiK-net stations and make predictions from microtremor, by either implementing the sub model prior to creating the training samples or prior to making predictions. Another future prospect of the study is to tackle nonlinearity and directionality, which are the most challenging aspects of evaluation of site effects. Although the current results are only a first step in this direction, with proper datasets categorically sorted to, it should be possible to deal with such challenging aspects in a similar manner. The main takeaway from the study is that RNN algorithms can offer a fast and simple method of extracting site specific information from scattered wavefield timeseries. In future, we expect to use microtremor time-series in a similar manner and achieve reliable knowledge on the effect of subsurface structure by non-invasive means.

549 **List of Abbreviations**

550 Artificial Neural Network (ANN)

551 Coefficient of Variation (CV)

552 Earthquake Horizontal-to-Vertical (H/V) Spectral Ratios (EHVR)

553 Energy Ratio (ER)

554 Fourier Amplitude Spectra (FAS)

555 Kiban Kyoshin Network (KiK-net)

556 Long Short-Term Memory (LSTM)

557 Machine Learning (ML)

558 Mean Absolute Error (MAE)

559 Mean Squared Error (MSE)

560 National Research Institute for Earth Science and Disaster Resilience (NIED)

561 Peak Ground Acceleration (PGA)

562 Recurrent Neural Network (RNN)

563 Root Mean Squared Error (RMSE)

564 Standard Deviation (SD)

565 Surface to Bedrock Ratio (SBR)

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567

Declarations

Availability of data and materials

The strong motion data underlying this article are available at K-NET/KiK-net database of NIED (NIED, 2019) at <https://www.doi.org/10.17598/NIED.0004>.

The microtremor data will be shared on reasonable request to the corresponding author.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

M.I. and S.M. designed the study, M.I. processed the data and conducted the analysis and M.I. and S.M. wrote the manuscript.

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Table 1. RNN model parameters

models	n_LSTM	activation
A	2	tanh
B	3	tanh
C	2	sigmoid
D	3	sigmoid

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Table 2. Prediction root mean squared errors (RMSE)

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RMSE		Vs30[m/s]		Vs10[m/s]		f_0 [Hz]	
coda parameters	model	train	test	train	test	train	test
C1 (CV=0.1, ER=0.8)	A	186.7	299.3	127.7	197.6	0.4	1.3
	B	185.5	299.6	123.7	190.3	0.4	1.2
	C	187.7	306.4	124.2	195.1	0.5	1.3
	D	219.0	303.8	123.2	192.5	0.4	1.2
C2 (CV=0.2, ER=0.9)	A	187.2	296.8	123.1	191.7	0.4	1.3
	B	184.2	301.8	159.4	190.2	0.4	1.3
	C	186.0	307.6	124.9	192.6	0.4	1.3
	D	188.7	296.0	129.6	194.2	1.1	1.2

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Table 3. Prediction results for two cases for the EW component

	Cs_test	Cs_train	Cc_test	Cc_train
MAE	4.31	3.32	3.78	3.39
SD	4.93	7.80	7.67	7.50

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673

674 Figure 1. Examples of EHVRs and selected predominant frequencies. Grey lines show the H/V
675 spectral ratios calculated for unique earthquake events, black lines show average EHVR of all
676 events recorded at the station and automatically detected first peaks are shown by orange circles.

677 Figure 2. H/V energy ratios for 2 sample events at MIEH005. a) sample event 1 and b) sample
678 event 2. Grey line indicates the threshold value ($=2$).

679 Figure 3. Coda wave extraction based on the energy envelope for EW component of sample event
680 1 of Fig. 2. a) Energy envelope with the extracted coda part in orange. b) Timeseries with the
681 extracted coda part in orange. Top: C1 ($er_{\text{thres}} = 0.8$, $cv_{\text{thres}} = 0.1$), Bottom: C2 ($er_{\text{thres}} = 0.9$,
682 $cv_{\text{thres}} = 0.2$).

683 Figure 4. Coda wave extraction based on the energy envelope for EW component of sample event
684 2 of Fig. 2. a) Energy envelope with the extracted coda part in orange. b) Timeseries with the
685 extracted coda part in orange. Top: C1 ($er_{\text{thres}} = 0.8$, $cv_{\text{thres}} = 0.1$), Bottom: C2 ($er_{\text{thres}} = 0.9$,
686 $cv_{\text{thres}} = 0.2$).

687 Figure 5. Implemented RNN model for single output regression, model B parameters.

688 Figure 6. Implemented RNN autoencoder model for outlier detection.

Figure 7. EW component of coda and microtremor records and reconstruction errors at 3 sample stations. a) Coda with small MSE. b) Coda with large MSE. c) Microtremor. Original and reconstructed signals are shown in red and black respectively. Top: KMMH10 station, Middle: MYGH01 station, Bottom: EHMH04 station.

Figure 8 Examples of HVR of earthquakes, coda, and microtremors at 3 sample stations. a) EHMH04 station. b) MYGH01 station. c)FKOH06 station. Average HVR of earthquakes, coda including outliers, coda without outliers and microtremors are shown in green, blue, black and red respectively. SD of calculated HVRs are shown in light shades.

Figure 9. Prediction results on test set, for model B trained on C1 dataset with z-score>3 excluded from training and plots. a) V_{s30} . b) V_{s10} . c) f_0 . Light blue and dark blue dots show unique test sample results, and averaged results per station respectively.

Figure 10. Prediction errors per station for test set, sorted by difference of the two errors divided by C_s error in decreasing order from left to right. a) MAE. b) SD. Error bars for C_c and C_s cases are shown in blue and orange respectively.

703 Figure 11. Examples of fits of SBRs at stations with similar Cs and Cc errors (middle length bars
704 on Fig. 10). a) EHHM10. b) FKOH07. c) HRSH01. d) GIFH25. e) TKCH07. f) NMRH05. Top :
705 Cs, Bottom: Cc.

706 Figure 12. Examples of fits of SBRs at stations with highest difference between Cc and Cs errors
707 (left hand bars on Fig. 10). Predicted peaks are more coherent in Cc. a) AICH06. b) FKOH04. c)
708 MYZH14. Top: Cs, Bottom: Cc.

709 Figure 13. Examples of fits of SBRs at stations with highest Cc error (right hand bars on Fig. 10).
710 a) ISKH05. b) MYGH01. c) TSKH02. Top: Cs, Bottom: Cc. Stations with highest Cc error also
711 tend to have similarly high Cs error.

712 Figure 14. Fits of predicted amplitudes of SBR in three frequency ranges. a) $f = 1.0$ Hz. b) $f = 5.0$
713 Hz. c) $f = 9.0$ Hz. Top: Cs, Bottom: Cc.

Figures

Figure 1

Examples of EHVRs and selected predominant frequencies. Grey lines show the H/V spectral ratios calculated for unique earthquake events, black lines show average EHVR of all events recorded at the station and automatically detected first peaks are shown by orange circles.

Figure 2

H/V energy ratios for 2 sample events at MIEH005. a) sample event 1 and b) sample event 2. Grey line indicates the threshold value ($=2$).

Figure 3. Coda wave extraction based on the energy envelope for EW component of sample event 1 of Fig. 2. a) Energy envelope with the extracted coda part in orange. b) Timeseries with the extracted coda part in orange. Top: C1 ($er_{\text{thres}} = 0.8$, $cv_{\text{thres}} = 0.1$), Bottom: C2 ($er_{\text{thres}} = 0.9$, $cv_{\text{thres}} = 0.2$).

Figure 3

See image above for figure legend

Figure 4. Coda wave extraction based on the energy envelope for EW component of sample event 2 of Fig. 2. a) Energy envelope with the extracted coda part in orange. b) Timeseries with the extracted coda part in orange. Top: C1 ($er_{thres} = 0.8$, $cv_{thres} = 0.1$), Bottom: C2 ($er_{thres} = 0.9$, $cv_{thres} = 0.2$).

Figure 4

See image above for figure legend

Layer input: $n_s \times 3 \times 100$

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Implemented RNN model for single output regression, model B parameters.

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Prediction errors per station for test set, sorted by difference of the two errors divided by Cs error in decreasing order from left to right. a) MAE. b) SD. Error bars for Cc and Cs cases are shown in blue and orange respectively.

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Figure 12

Examples of fits of SBRs at stations with highest difference between Cc and Cs errors (left hand bars on Fig. 10). Predicted peaks are more coherent in Cc. a) AICH06. b) FKOH04. c) MYZH14. Top:Cs, Bottom: Cc.

Figure 13

Examples of fits of SBRs at stations with highest Cc error also tend to have similarly high Cs error (right hand bars on Fig. 10). a) ISKH05. b) MYGH01. c) TSKH02. Top:Cs, Bottom: Cc. Stations with highest Cc

error also tend to have similarly high Cs error.

Figure 14

Fits of predicted amplitudes of SBR in three frequency ranges. a) $f = 1.0\text{ Hz}$. b) $f = 5.0\text{ Hz}$. c) $f = 9.0\text{ Hz}$. Top:Cs, Bottom: Cc.

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