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STUDY ON SITE-SPECIFIC GROUND MOTION MODELS UTILIZING MACHINE LEARNING CONSIDERING EPICENTRAL DIRECTIONS

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Abstract

Aiming at acquiring the knowledge of the earthquake motion evaluation of the new point of view, trial evaluations of site-specific ground motion models are performed utilizing machine learning methods. Horizontal ground motion records in and around the Kanto plains in Tokyo metropolitan area are used as the training data for machine learning. At each site where the site effect is common to all the records, the machine learning method is applied to the feature parameters of source and seismic wave propagation characteristics and applied to the target variables of the earthquake motion indexes derived from the records.

The "Gradient Boosting Decision Tree" is used as the machine learning method. As the target variables of machine learning, the peak ground acceleration PGA [cm/s^2], the pseudo velocity response spectra $_{\mathrm{P}}S_{\mathrm{V}}$ [cm/s] and the velocity response duration time spectra TS_{V} [s] (damping factor h=0.05, parameter $p1$=0.03, $p2$=0.95) of several periods T [s], are examined, respectively. Since there are few large data of PGA and $_{\mathrm{P}}S_{\mathrm{V}}$, both are changed into common logarithmic input data ($\log_{10} PGA$ and $\log_{10} {}_{\mathrm{P}}S_{\mathrm{V}}$) for machine learning to raise the precision of the evaluation models. As the input feature parameters of machine learning, the moment magnitude M_{W}, the hypocentral depth H [km], the hypocentral distance X [km] and the epicentral direction Λ [degree] are selected. Λ is set 0 degrees to due north and is defined clockwise. Then, sin Λ and cos Λ are inputted for the machine learning models because Λ is discontinuous at due north. The feature impact on the evaluation model is defined as the degree of that the evaluation precision has been aggravated, when one of data sequence of the feature parameters has been shuffled and the model has been revalued by machine learning.

In particular, the impact of Λ is large on TS_{V}. In many cases it is almost as large as the impacts of M_{W}, H and X, or larger. The averages of the ratios of the evaluated earthquake motion indexes to the observed ones are almost 1.1. The common logarithmic standard deviations of the ratios are more than 0.2 regarding PGA and $_{\mathrm{P}}S_{\mathrm{V}}$ and are more than 0.1 regarding TS_{V}. Most of the evaluated values are within double to half of the observed values. These evaluation models consider the epicentral direction and the response duration time which have not been considered in the conventional prediction equations. It can help the qualitative and quantitative analyses of various characteristics of ground motions which depend on site locations and periods. There is a possibility in future that the differences of three-dimensional seismic wave propagation characteristics can be reflected in such semi-automatic evaluation models.

If the Artificial Intelligence and the so-called Big Data could be utilized for earthquake ground motion evaluations, there is a big advantage in constructing a site-specific ground motion model at each recording site where large amount of data and information with high quality could be obtained. Huge training data and further ideas of interpolation and extrapolation of data are necessary for machine learning. Especially it is necessary for evaluating large earthquakes, very strong ground motions and long duration ground motions.

Keywords: earthquake, ground motion, record, site, machine learning, spectrum, duration time, epicentral direction

1. Introduction

In Japan recently, earthquake observation stations have been deployed nationwide [1], and high-quality and enormous data can be obtained in real time. At the same time, remarkable advances in computers have enabled high-speed arithmetic processing thereof. Such rapid changes in the environment of data, information and computers, have great potential to improve both quality and quantity of knowledges, of earthquakes and ground motions. On the other hand, looking at the earthquake ground motion evaluation models, many general and practical attenuation relation formulas [e.g.2] have been developed and utilized. However, the data and information on which these models are based, have biases in the number of earthquakes depending on the region and biases in the number of records depending on the observation stations, so that imbalance occurs in their reflection on the models. The rapid increase in data and information in recent years is expected to greatly improve this problem, but the subdivision and advancement of specialized fields have limited the time and effort that can be spent by experts. In order to overcome this situation, we will leave everything that can be automatically processed to the computer thoroughly, so that we can devote enough time and effort to advanced and detailed examinations and various judgments that only humans need to bear.

From such a viewpoint, a desirable form of future earthquake motion evaluation models will be automatically generated and verified by the Artificial Intelligence (AI) as needed, using so-called Big Data such as observation records which will be constantly upgraded every time an earthquake occurs. Recently, pioneering efforts to build earthquake motion evaluation models using machine learning [3] have begun [4 to 8]. In this paper, as a clue to acquire new knowledge about earthquake ground motions in the future when such an environment is acquired, a preliminary study on the construction of earthquake ground motion evaluation models using machine learning is performed.

The authors aim to acquire new knowledge of the earthquake motion evaluation from the following new perspectives. The author considers the merits of effectively utilizing AI and Big Data and tries to construct an earthquake motion evaluation model for each observation station where high-quality large-volume records and site-specific information have been obtained. It has also been pointed out that observation records show differences in earthquake ground motion characteristics depending on the epicentral directions [e.g.9,10], although they have not been reflected in the conventional attenuation relation formula. In this paper the epicentral direction is also considered. Although duration times of earthquake ground motions are important factors as well as amplitudes and periodic characteristics (e.g. response spectra) not only in understanding phenomena but also in earthquake engineering [11], it has hardly been considered in the conventional attenuation relation formula. In this paper, the epicentral direction dependency of characteristics of earthquake ground motions and the response duration time spectra of earthquake ground motions [9,12] will be also evaluated.

2. Approach and subject of study

It is attempted to create site-specific ground motion evaluation models utilizing machine learning methods [3] using past ground motion observation records as training data. The parameters describing the source and propagation characteristics are used as the input feature parameters. The earthquake motion indexes obtained from the observation records are used as the target variables. Then the machine learning models that associates those are created.

2.1 Outline of method for creating earthquake motion evaluation models

The "Gradient Boosting Decision Tree" [13] is used as the machine learning method.

The "Gradient Boosting" is a method of constructing a strong classifier (high-performance machine learning model) by combining plurality of weak classifiers (low-performance machine learning models). The "Decision Tree" is a method of creating a machine learning model that can perform classification and regression by performing conditional branching using a branch structure of a tree. A method of combining weak classifiers created by the Decision Tree by applying Gradient Boosting is called the Gradient Boosting Decision Tree. Fig. 1 shows the concept of the Gradient Boosting Decision Tree. In this study, the Gradient Boosting Decision Tree is implemented using XGBoost (eXtreme Gradient Boosting) [14] which is an open source library.

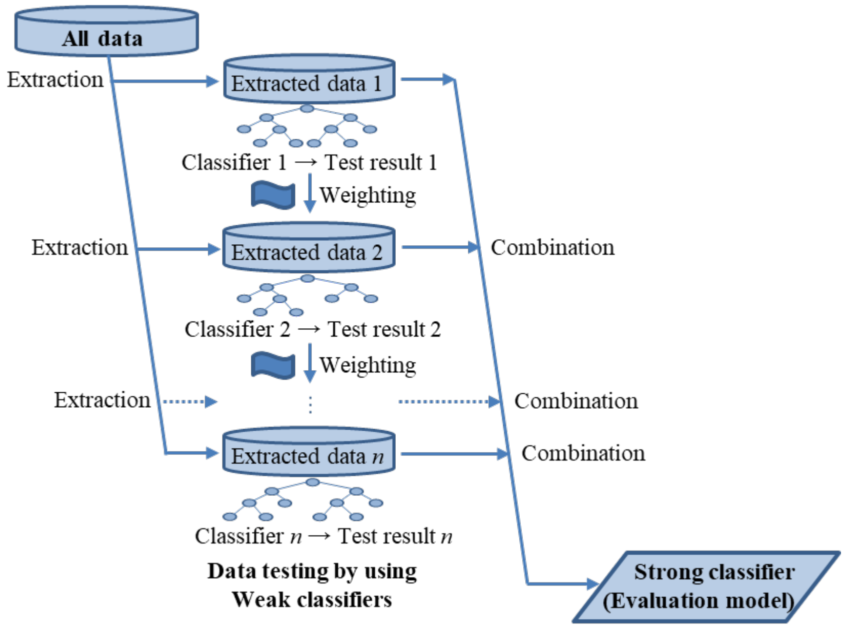


Fig. 1 – Schematic explanation of the Gradient Boosting Decision Tree

2.2 Earthquake motion records and earthquake motion indexes for target variables

In this paper, among the observation stations in Tokyo metropolitan area of the strong motion seismograph network K-NET of the National Research Institute for Earth Science and Disaster Resilience (NIED) [1], SIT006 (Chichibu) which is located on a shallow bedrock and on hard surface ground, and TKY028 (Etchujima) which is located on a deep bedrock and on soft surface ground, are selected and earthquake ground motions at these sites are studied. From the data search and download website of K-NET [1], the earthquake ground motions recorded at the above-mentioned stations from 1996 to May 31, 2019 are selected for the training data of machine learning. Among the earthquakes whose moment magnitude M_W was obtained by the broadband seismograph network F-net of NIED [1], every horizontal ground motion whose combined three-component maximum acceleration displayed on the website is 1 cm/s^2 or more is selected. Fig. 2 shows the epicenters of the target earthquakes with the locations of both observation sites used in this study. The selected horizontal ground motions have a total of 1468 time histories (2 components of each observation record of 734 earthquakes) at SIT006 and a total of 1314 time histories (of 657 earthquakes) at TKY028.

As the "earthquake motion indexes" for the "target variables" of machine learning, the peak ground acceleration PGA [cm/s^2], the pseudo velocity response spectra $_{P}S_V$ [cm/s] and the velocity response duration time spectra TS_V [s] (period T=0.1, 0.5, 1, 3, 5 [s], damping factor h=0.05, parameter $p1$=0.03, $p2$=0.95 [12]), are examined, respectively. Since there are few large data of PGA and $_{P}S_V$, they are changed into common logarithmic data ($\log_{10} PGA$ and $\log_{10} {}_{P}S_V$) for the input target variables of machine learning to raise the precision of the evaluation models. As the loss functions used in the analyses, the least squares method (the normal distribution) is applied to PGA and $_{P}S_V$ and the Poisson distribution is applied to TS_V.

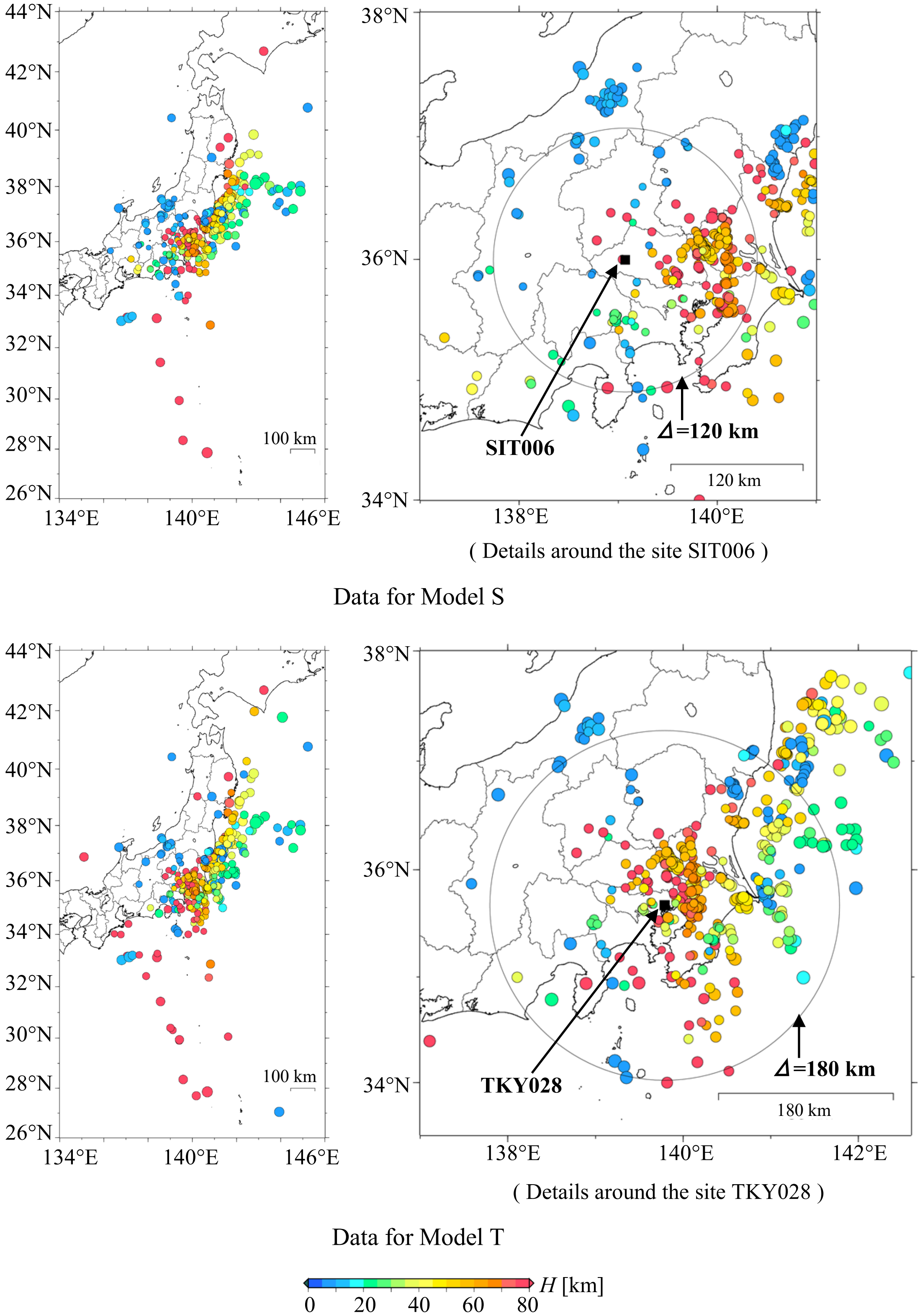


Fig. 2 – Epicenters of the target earthquakes with the locations of observation stations used in this study

2.3 Feature parameters of earthquake motion evaluation models

At each site where the site effect is common to all the records, the machine learning method is applied using the "feature parameters" of source and seismic wave propagation characteristics and the target variables of earthquake motion indexes derived from the records as the training data. As the input feature parameters of machine learning, the moment magnitude M_W, the hypocentral depth H [km], the hypocentral distance X [km] and the epicentral direction Λ [degree] are selected. M_W values are obtained from F-net data [1], the locations of epicenters necessary to determine H, X and Λ are obtained from the Japan Meteorological Agency (JMA) data [15], and the locations of observation stations are obtained from K-NET data [1]. Λ is set 0 degrees to due north and is defined clockwise. Then, sin Λ and cos Λ are inputted for the machine learning models because Λ is discontinuous at due north.

A "feature impact" on an evaluation model, which is called "impact" by the machine learning tool DataRobot [16], is defined as the degree of decrease of the evaluation precision when a model has been revalued by machine learning with a set of re-shuffled feature parameter data. It is used in order to investigate the effect of each feature on the target variables. When the evaluation accuracy is greatly deteriorated, that feature parameter is important. Conversely, when the evaluation accuracy does not change, that feature parameter does not affect the evaluation and is useless.

2.4 Machine learning model and input dataset

The earthquake motion evaluation models for SIT006 and TKY028 are named "Model S" and "Model T", respectively. The data of the feature parameters and the target variables necessary for machine learning are named "Data Set S" and "Data Set T", respectively.

Fig. 3 shows examples of relationship between the obtained data for feature parameters of the earthquake ground motion evaluation models. There are few records of distant small earthquakes. Even if the epicenters are near, there are few earthquake data of short distance considering their hypocentral depths. Although the epicenters extend in all directions, many of them are in the northeastern direction (around 45 degrees).

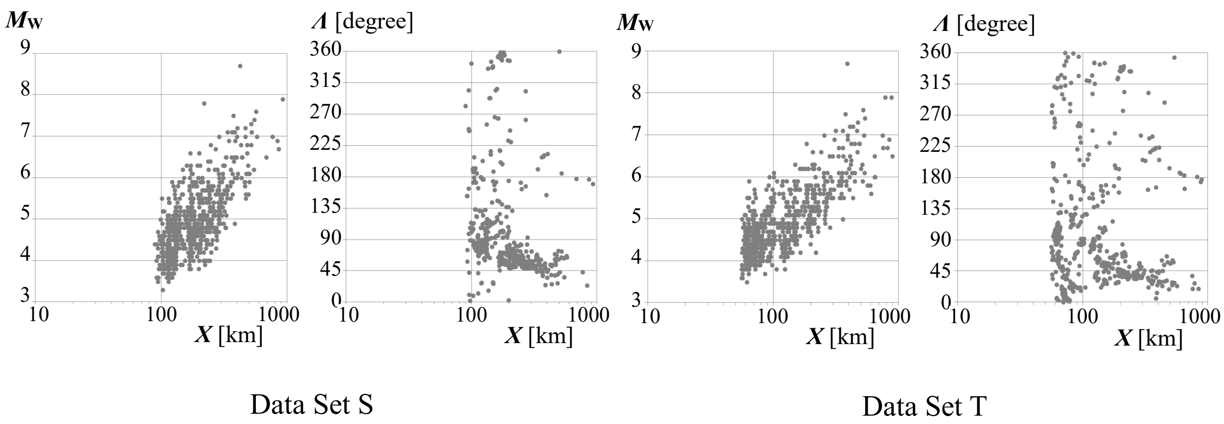
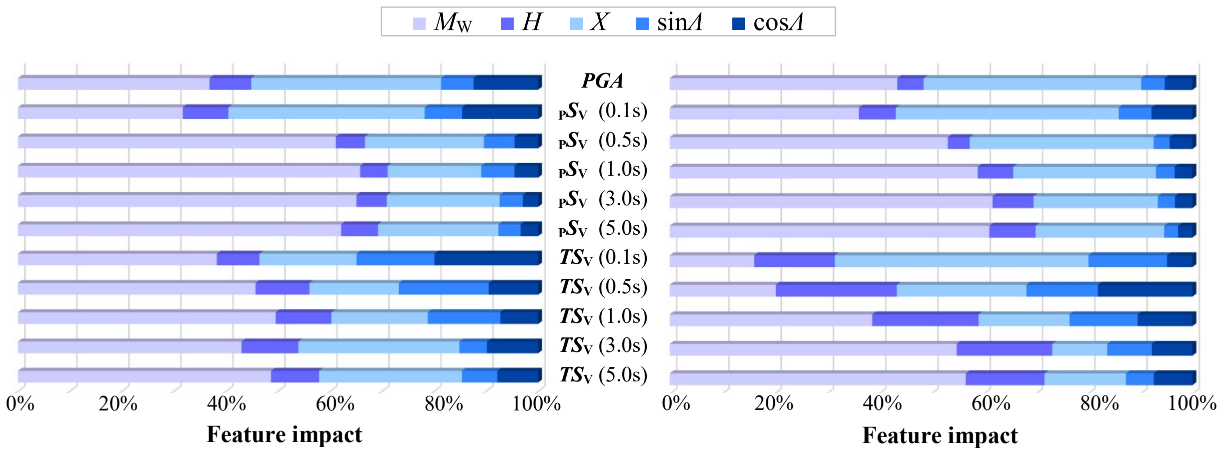


Fig. 3 – Examples of the relationship between the obtained data for feature parameters of the earthquake ground motion evaluation models

3. Results

Model S and Model T are created by machine learning using Data Set S and Data Set T, respectively.

The left of Fig. 4 shows the feature impacts on the earthquake motion indexes (the target variables) of Model S. M_W and X have comparable impacts on PGA and short-period ${}_{p}S_V$ (impacts of X is slightly higher), but M_W has the greatest impacts on other variables. The feature impacts of H are small. The feature impacts of Λ are greater in short periods than in long periods. These impacts on TS_V are greater than the ones on ${}_{p}S_V$, surpassing those of X. The right of Fig. 4 shows the feature impacts of Model T. In short periods, the impacts of X are dominant, and in other cases, the impacts of M_W are dominant. Generally, the feature impacts of M_W increase with period and the ones of X decrease with period. The feature impacts of H are small. The feature impacts of Λ are larger in short periods, especially on TS_V, larger than the ones on PGA and ${}_{p}S_V$, exceeding those of X for periods other than 0.1 second, and exceeding M_W in short periods. The impacts of M_W on short-period TS_V at Etchujima where the bedrock is deep is relatively smaller than the ones at Chichibu where the bedrock is shallow. It is necessary to examine this point in detail by selecting more records of earthquakes at more stations.



Model S (SIT006)   Model T (TKY028)

Fig. 4 – Feature impacts on the earthquake motion indexes (the target variables) of the earthquake ground motion evaluation models

Fig. 5 shows examples of the relationship between the observed target variable values and the evaluated ones ($\log_{10} PGA$, $\log_{10} {}_{p}S_V$, TS_V) and histograms of the ratios of the evaluated earthquake motion indexes to the observed ones (PGA, ${}_{p}S_V$, TS_V). In the figures concerning ${}_{p}S_V$ and TS_V, T [s] denotes the period and the damping factor is 0.05. Looking at each scatterplot, there is no significant difference between the distribution of the training data shown in black and the distribution of the validation data shown in red. As a whole, observed values are well evaluated and modeled, and most of the evaluated values are within double to half of the observed values. Looking at each histogram, the ratios of the evaluated earthquake motion indexes to the observed ones have relatively uniform distribution centered at about 1, and the variations in response duration time are smaller than the ones in amplitudes (maximum values and response spectra). Table 1 shows the ratios of the evaluated earthquake motion indexes (PGA, ${}_{p}S_V$, TS_V) to the observed ones. The averages of the ratios of the evaluated earthquake motion indexes to the observed ones are almost 1.1. The common logarithmic standard deviations of the ratios are more than 0.2 regarding PGA and ${}_{p}S_V$ and are more than 0.1 regarding TS_V.

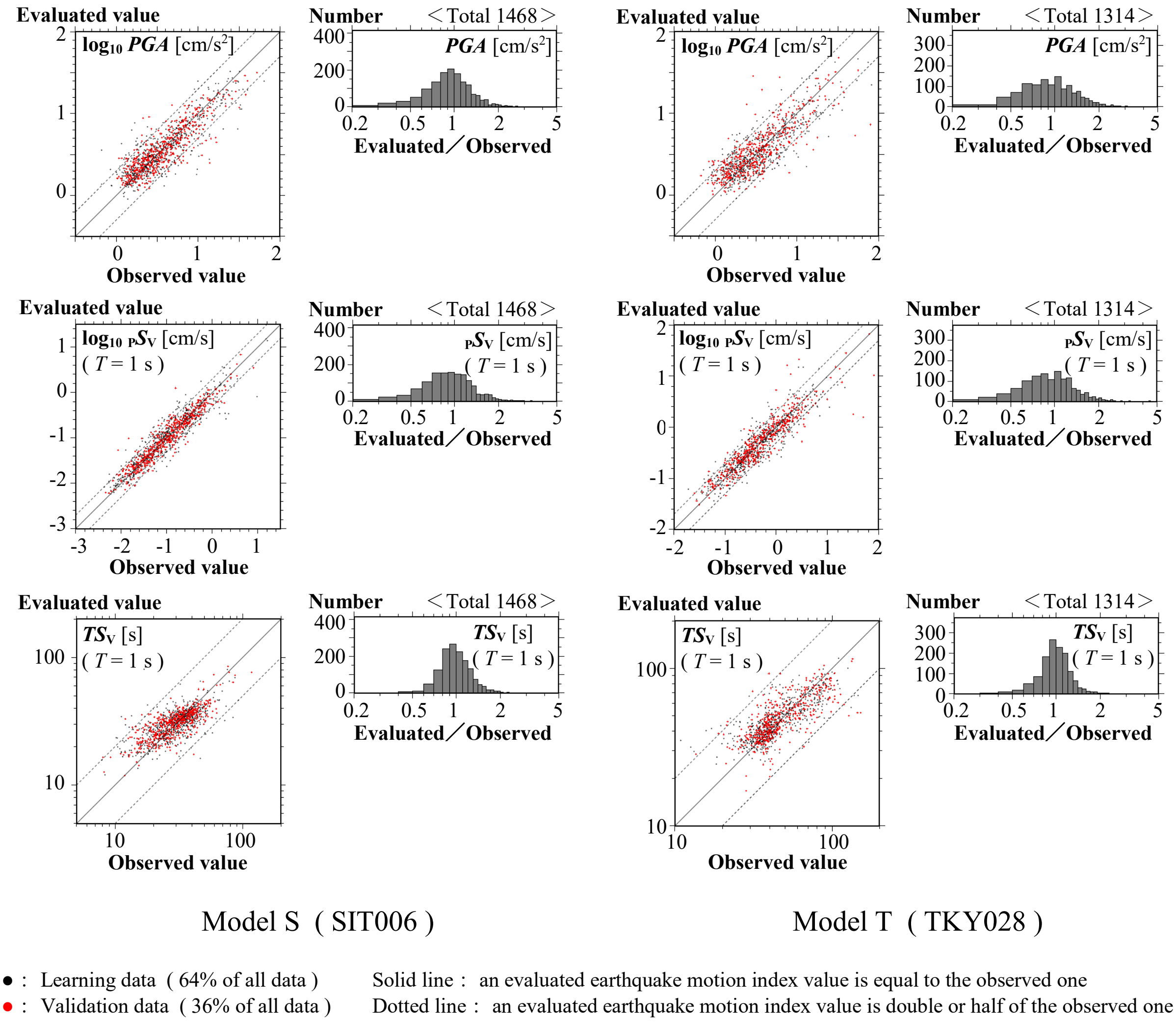


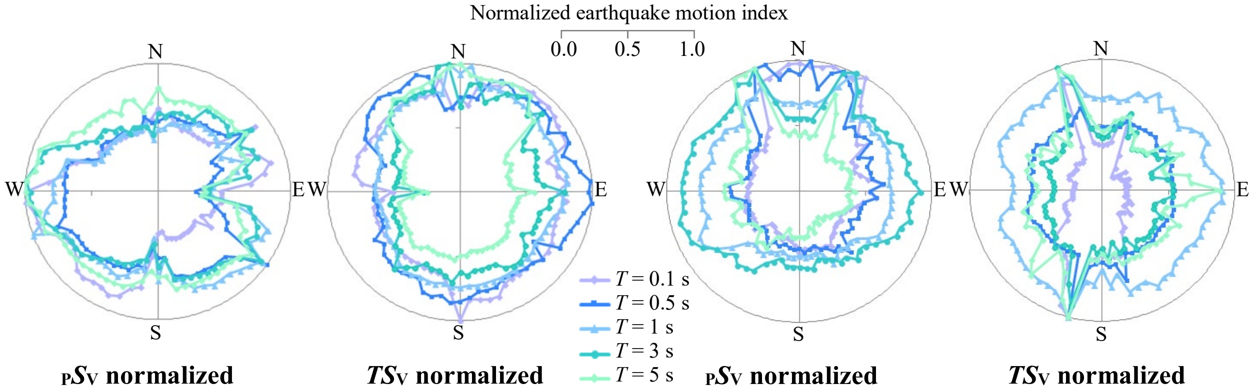
Fig. 5 – Examples of relationship between the observed target variable values and the evaluated ones ($\log_{10} PGA$, $\log_{10}\ {}_{p}S_V$, TS_V) and histograms of the ratios of the evaluated earthquake motion indexes to the observed ones (PGA, ${}_{p}S_V$, TS_V) (period T [s], damping factor 0.05)

Table 1 – Ratios of the evaluated earthquake motion indexes (PGA, ${}_{p}S_V$, TS_V) to the observed ones

Earthquake motion index	PGA	${}_{p}S_V$					TS_V				
Period [s]	—	0.1	0.5	1	3	5	0.1	0.5	1	3	5
Average μ of ratios of the evaluated to the observed											
Model S (SIT006)	1.08	1.10	1.14	1.11	1.09	1.09	1.16	1.06	1.07	1.09	1.10
Model T (TKY028)	1.15	1.15	1.16	1.14	1.13	1.13	1.09	1.07	1.06	1.09	1.09
Common logarithmic standard deviation σ of ratios of the evaluated to the observed											
Model S (SIT006)	0.19	0.22	0.25	0.22	0.21	0.21	0.19	0.12	0.13	0.15	0.16
Model T (TKY028)	0.24	0.24	0.28	0.25	0.24	0.24	0.17	0.11	0.12	0.15	0.15

Fig. 6 shows examples of the epicentral direction dependency of the evaluated earthquake motion indexes (${}_{\mathrm{P}}S_{\mathrm{V}}$, TS_{V}) which are normalized by the maximum values calculated in 72 directions changing in 5 degree increments. The resuls of Model S in the cases of M_{W}=5, H=10km and X=120km are illustrated on the left side and the ones of Model T in the case of M_{W}=6, H=10km and X=180km are illustrated on the right side. Fig. 7 shows examples of the epicentral direction dependency of the evaluated earthquake motion indexes (${}_{\mathrm{P}}S_{\mathrm{V}}$, TS_{V}), raw values, in the case of M_{W}=6, H=10km and X=180km, calculated in 72 directions changing in 5 degree increments. The resuls of ${}_{\mathrm{P}}S_{\mathrm{V}}$ are illustrated above and the ones of TS_{V} are illustrated below. These examples show epicentral direction dependencies whose characteristics are different depending on the site and the period, and also different between ${}_{\mathrm{P}}S_{\mathrm{V}}$ and TS_{V}. For example, in the cases of events in the north-northwest direction, especially in long periods, both ${}_{\mathrm{P}}S_{\mathrm{V}}$ and TS_{V} show large values. These may reflect the seismic wave propagation characteristics caused by the deep underground structure from Niigata prefecture to the Tokyo metropolitan area. In most cases, the absolute values of ${}_{\mathrm{P}}S_{\mathrm{V}}$ and TS_{V} are both larger in the results of Model T than in Model S. At least under the conditions of these examples, it can be said that TKY028 has larger site characteristics than SIT006 due to its deep bedrock and soft surface ground.

Fig. 8 shows studies on modeling methods of epicentral directions for machine learning (Model T, period T [s], damping factor 0.05, M_{W}=6, H=10km, X=180km). The examples of studies on the contribution of sine and cosine functions of epicentral directions to Model T are illustrated above and the examples of studies on on the effect of the origin direction of epicentral directions on Model T are illustrated below. The origin direction is due north for $\mathit{\Lambda}_{\mathrm{S}}$ which is the same as $\mathit{\Lambda}$, and due south for $\mathit{\Lambda}_{\mathrm{N}}$. The results using only sin $\mathit{\Lambda}$ are north-south symmetric (EW axis symmetric) and the results using only cos $\mathit{\Lambda}$ are east-west symmetric (NS axis symmetric). If the epicentral direction itself, $\mathit{\Lambda}_{\mathrm{S}}$ or $\mathit{\Lambda}_{\mathrm{N}}$, is used as a feature, the result will be discontinuous in the zero-degree direction, which is due north for $\mathit{\Lambda}_{\mathrm{S}}$ or due south for $\mathit{\Lambda}_{\mathrm{N}}$. The results with a period of 3 seconds are more variable than those with a period of 1 second. Among the results of TS_{V} with a period of 3 seconds, the absolute values by the model using $\mathit{\Lambda}_{\mathrm{S}}$ are larger than those by the others, which are about double in many directions. In the north-northwest, south-southwest, and northeast directions where the source data for machine learning (training data) exist, the results of these models are almost the same. However, in those directions or areas where there is no source data, it may be possible that a model trained successfully in accordance with the data has not been created.



Model S
(SIT006, M_{W}=5, H=10km, X=120km)

Model T
(TKY028, M_{W}=6, H=10km, X=180km)

Fig. 6 – Examples of the epicentral direction dependency of the evaluated earthquake motion indexes (${}_{\mathrm{P}}S_{\mathrm{V}}$, TS_{V}) normalized by the maximum values calculated in 72 directions changing in 5 degree increments (period T [s], damping factor 0.05)

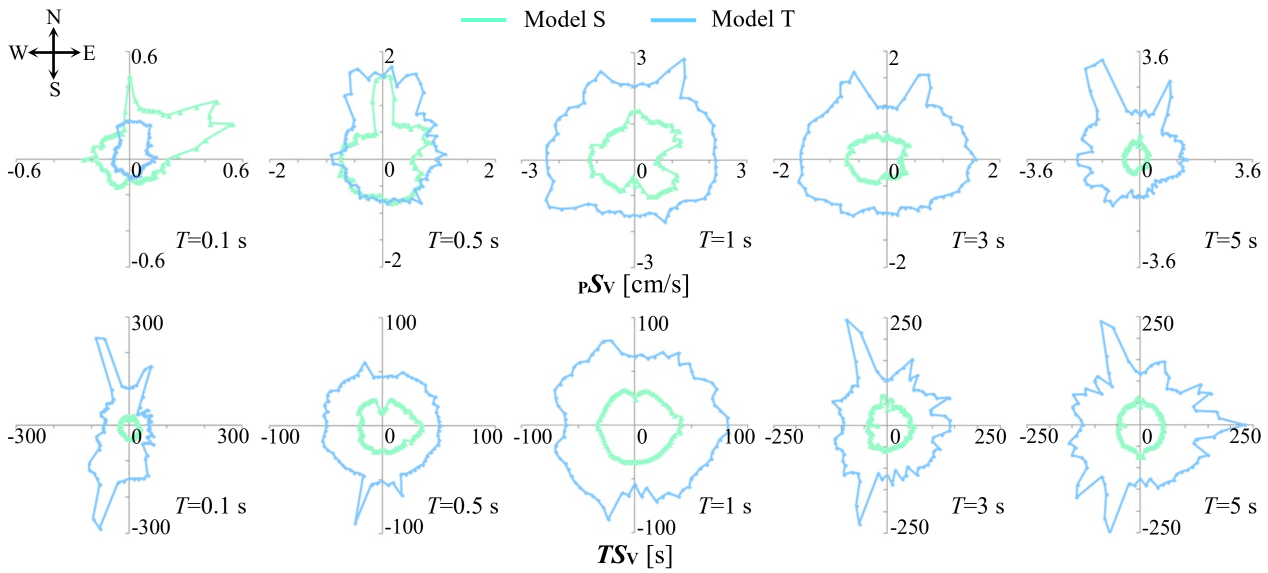
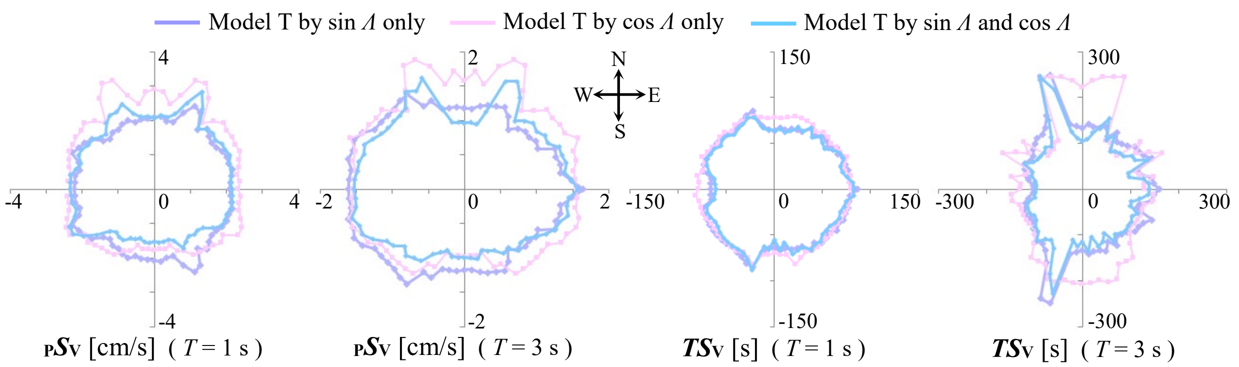
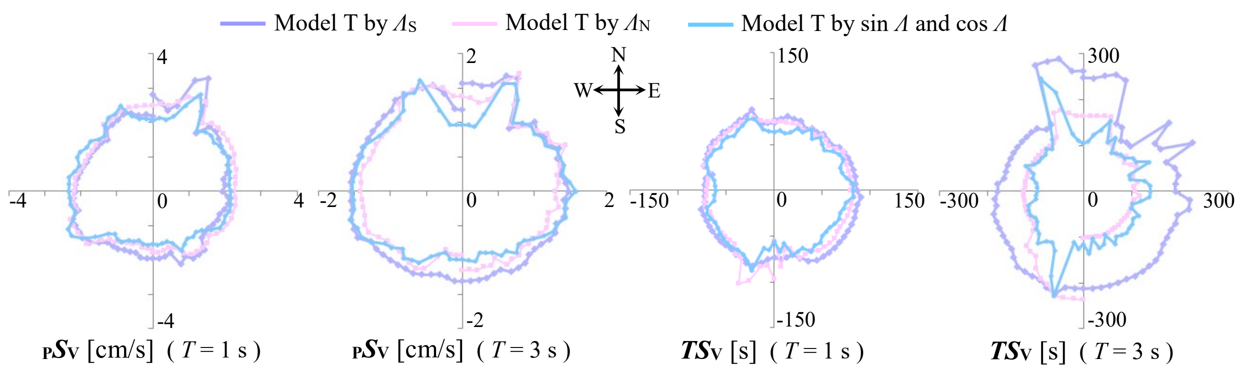


Fig. 7 – Examples of the epicentral direction dependency of the evaluated earthquake motion indexes (${}_{p}S_{V}$, TS_{V}) calculated in 72 directions changing in 5 degree increments (period T [s], damping factor 0.05, M_{W}=6, H=10km, X=180km)



Studies on the contribution of sine and cosine functions of epicentral directions to Model T



Studies on the effect of origin direction of epicentral directions in Model T (Origin direction is due north for $\Lambda = \Lambda_{S}$, due south for Λ_{N})

Fig. 8 – Studies on modeling methods of epicentral directions for machine learning (Model T, period T [s], damping factor 0.05, M_{W}=6, H=10km, X=180km)

4. Discussion

In this paper, the newly attempted site-specific earthquake motion evaluation models consider the response duration time spectra and the epicentral directions which have not been considered in the conventional prediction equations. As a result of this study, the earthquake ground motions are accurately evaluated and modeled as a whole. The ratios of the evaluated values to the observed values have a well-distribution with an average of almost 1, and most of the evaluated values are within double to half of the observed values.

In particular, the response duration time spectra could be evaluated with less variability than the amplitudes (maximum values and response spectra). It is also important to consider the differences in the earthquake motion characteristics depending on the epicentral directions. Especially, the feature impact of $\mathit{\Lambda}$ is large on TS_V. In many cases it is almost as large as the impacts of M_W, H and X, or larger, which have been considered in the conventional prediction equations. These results indicate that the epicentral direction dependency in the amplitudes and duration times of the observed earthquake ground motions can be evaluated depending on the locations of sites and the periods of earthquake ground motions. It can help the qualitative and quantitative analyses of various characteristics of earthquake ground motions which depend on site locations and periods. There is a possibility in future that the differences of three-dimensional seismic wave propagation characteristics can be reflected in such evaluation models. Interpretation of models (examination results) using individual observation records and surrounding underground structure information is necessary to be advanced in the future.

However, it is important to study using data from which adverse effects such as long-period noises have been carefully removed. Especially, it is important to carefully examine the raw data of time histories of earthquake ground motion records in order to avoid negative effects on the response duration spectra. In the future, it will be essential to develop and systematize primary processing methods such as automatic selection and automatic filtering of observed raw data.

Although the observed values seem to be evaluated well as a whole this time, the number of the training data used in this study is not necessarily enough, so a lot of careful consideration is needed in the future for quantitative evaluation. In other words, it is expected that the overall evaluation will be of even higher quality if the latest data accumulated from time to time at each site could be utilized to their fullest. Since we examined only two locations this time, it is necessary to consider and analyze more sites from now on. It is also necessary to consider the vertical ground motions.

Furthermore, in the future, it is also needed to consider carefully the deliberate measures to improve the balance of model accuracy due to the density of data. Huge training data and further ideas of interpolation and extrapolation of data are necessary for machine learning. Especially it is necessary for evaluating huge earthquakes, very strong ground motions and long duration ground motions, which are overwhelmingly little data. As a measure therefore, for example, weighting of data or utilization of simulation results by the seismic fault models or the like can be considered. It is also necessary to compare with existing earthquake motion evaluation formulas and evaluation results and to consider how much the model can explain observation records including variations.

5. Conclusion

In this paper, with the aim of acquiring new knowledge through earthquake ground motion evaluation from a new perspective, it has been attempted to create new site-specific earthquake ground motion evaluation models by machine learning using the ground motion observation records obtained in the Tokyo metropolitan area as training data. The earthquake motion evaluation models have been constructed for each earthquake observation station. The epicentral directions and the response duration time spectra of earthquake ground motions, which were not considered in the conventional attenuation relation formula, have been also examined.

In the future, it is necessary to make full use of so-called Big Data nationwide and work on studies using the Artificial Intelligence (AI). If AI and Big Data could be utilized for ground motion evaluation, there is a big advantage in constructing a site-specific ground motion model at each recording site where large amount of data and information with high quality could be obtained. When such an environment is realized, there will be a high possibility that the analyses and discussion of the source, propagation and site effects of the earthquake ground motions can be drastically advanced. By considering past earthquake motion evaluation formulas, evaluation results and their physical conditions, it is also expected to realize and improve the explanation of the examination process and results by AI which are difficult at present.

6. Acknowledgements

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