物理探査データを用いた機械学習による都市域における三次元浅部S波速度構造の推定

Estimating 3D shallow S-wave velocity models from geophysical data based on machine learning in urban areas

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S-wave velocity (Vs) is directly related to small strain shear modulus and the one of the most important physical properties in various geotechnical issues, such as the local site amplification of ground motion from earthquakes, liquefaction, and slope stability. Time averaged Vs to 30 m depth (VS30) is one of the most important proxies to estimate the site amplification in earthquake engineering.
To estimate regional 3D Vs models, we developed a method that estimates regional shallow three-dimensional (3D) S-wave velocity (Vs) models based on deep neural network. The method uses dispersion curves obtained by active and passive surface wave measurements, and horizontal-to-vertical spectral ratio (H/V) obtained by single station three-component microtremor measurements. Since the number of sites with dispersion curves is smaller than those with H/V measurements, the deep neural network consists of two stages. The first stage (A) predicts Vs profiles from H/V using training data of Vs profiles obtained from dispersion curves, and the second stage (B) predicts Vs profiles from surface topography and geomorphological classification etc. using training data of Vs profiles obtained from the first stage.
Estimation procedure for a 3D regional shallow Vs model can be summarized as four steps and two stage deep learnings (Figure 1). At the first step, we estimated 1D Vs profiles by the inversion of dispersion curves at sites where both dispersion curve and H/V were observed. At the second step, the first stage deep learning (A) predicts 1D Vs profiles from H/V spectra based on the first stage network trained by H/V spectrum-1D velocity profiles together with other regional information including coordinate, surface elevation, geomorphology, and bedrock depths in community velocity model. The first stage (A) training predicted 1D Vs profiles from H/V spectra measured at sites without surface wave methods. At the third step, we used 1D Vs profiles predicted in the second step as initial profiles, and applied non-linear inversion using H/V to finalize 1D Vs profiles. At the last step, the second stage deep learning (B) predicts 1D Vs profiles in the investigation area from geological and other regional information, based on the second stage network trained by the geological information-1D Vs profile pairs.
We applied the proposed method to the Eastern part of Tokyo Metropolitan area to Southeastern part of Saitama prefecture, Japan, using dispersion curves, H/V and Vs profiles open to public as digital data, and predicted Vs profiles to 90 m deep with 200 m grid intervals. The number of sites with dispersion curves obtained from active and passive surface wave methods was approximately 500. The number of sites with H/V was approximately 3200. Figure 2 shows a geomorphological map (left) used as training data and VS30 (right) calculated from Vs profiles predicted by the second stage deep neural network (B) in Tokyo downtown area. K~K’, Sha~Sha’, and Shi~Shi’ indicate Kanda River, Shakujii River, and Shirako River

respectively. These small rivers flowing on Pleistocene terrace covered with volcanic ash. The VS30 is relatively high along the rivers. Figure 3 shows a west-east Vs cross section crossing Nakano and Okachi-machi stations at latitude of N 35.705 degree. Depth to the engineering bedrock (Vs > 350 m/sec) is relatively shallow at the Kanda-river and it results in higher VS30 along the river. The engineering bedrock is deep between Okachi-machi and Shinozaki stations and it corresponds to a buried channel. The predicted Vs model was reasonably consistent with surface topography, surface geology and geomorphological classification and clearly delineated geological features along with small rives on Pleistocene terrace covered with volcanic ash and a buried channel below Holocene Alluvium.

キーワード：S波速度、機械学習、三次元、都市域、表面波探査、常時微動
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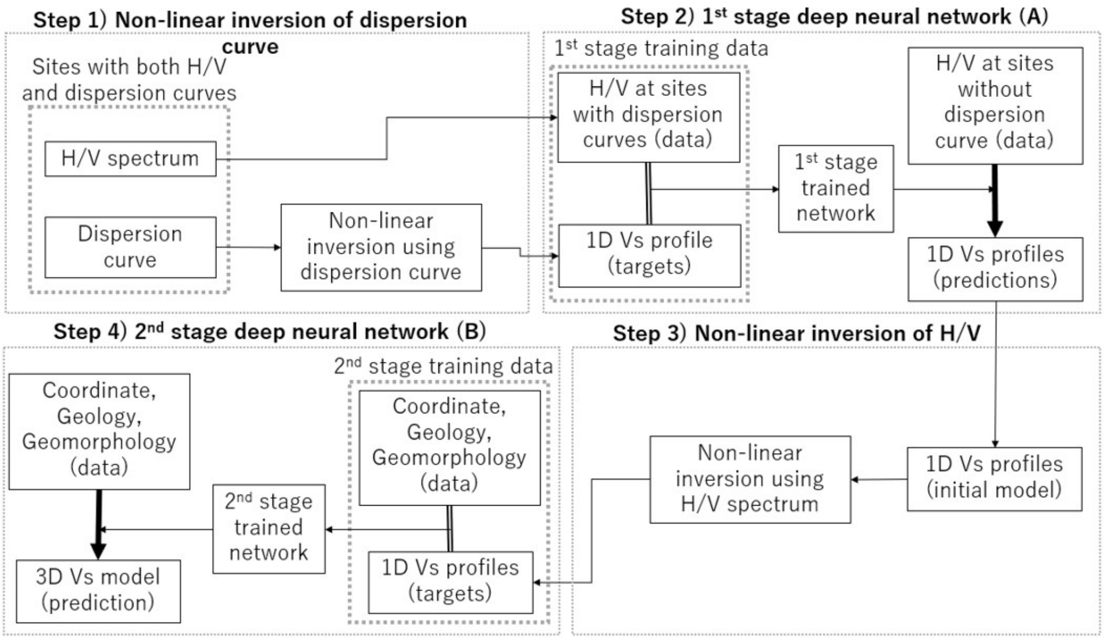

Figure 1. Four processing steps with two deep neural networks (A and B) to predict three-dimensional S-wave velocity (Vs) model.

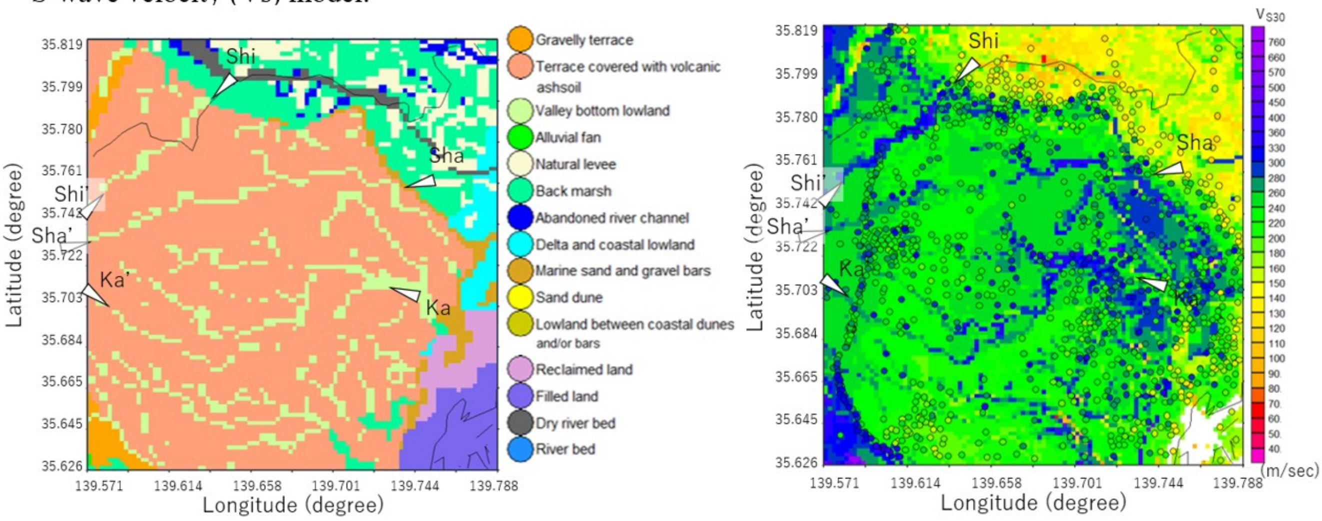

Figure 2. Geomorphological map (left) used as training data and VS30 (right) calculated from Vs profiles predicted by the second stage deep neural network (B). K~K', Sha~Sha', and Shi~Shi' indicate Kanda River, Shakujii River, and Shirako River respectively.

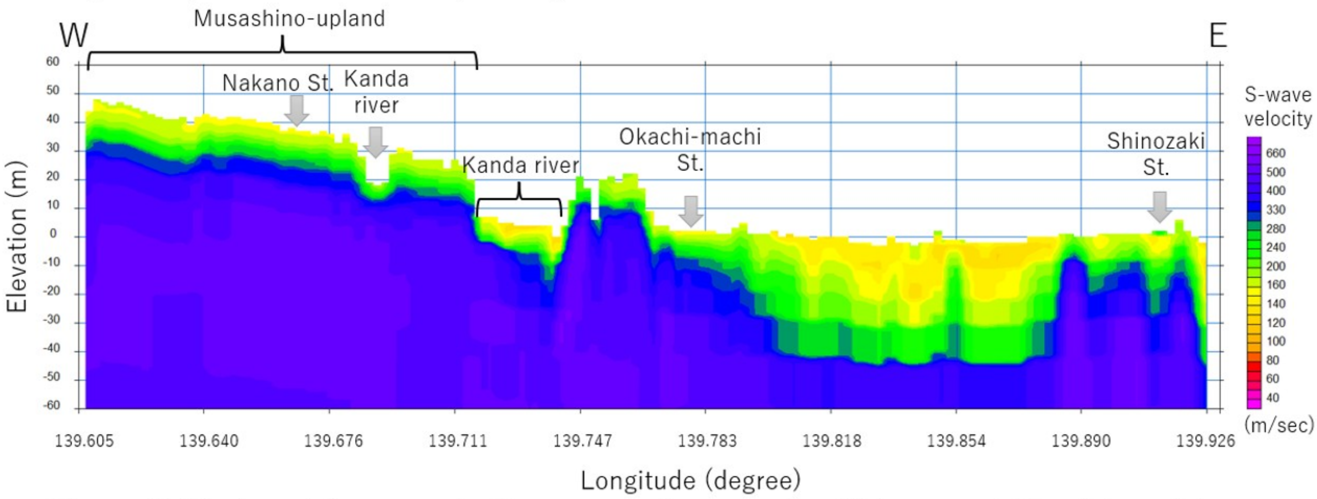

Figure 3. West-east S-wave velocity cross section crossing Nakano and Okachi-machi stations at latitude of N 35.705 degree.