D107

Spatial Interpolation of Geophysical Investigation Results Based on Deep Neural Network

〇Koichi HAYASHI, Toru SUZUKI, Tomio INAZAKI, Chisato KONISHI, Haruhiko SUZUKI, Hisanori MATSUYAMA

We developed a method that spatially interpolates one-dimensional (1D) S-wave velocity (Vs) profiles to a three-dimensional (3D) Vs model based on deep neural network to predict regional shallow 3D subsurface models.

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, the deep neural network consists of two stages. The 1st stage (A) predicts Vs profiles from H/V using training data of Vs profiles obtained from dispersion curves, and the 2^{nd} stage (B) predicts Vs profiles from surface topography and geomorphological classification etc. using training data of Vs profiles obtained from the 1^{st} stage.

Estimation procedure with four step processing includes two stage deep learnings can be summarized as follows. 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 1^{st} stage deep learning (A) predicts 1D Vs profiles from H/V spectra based on the 1^{st} 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 1^{st} 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 2^{nd} step as initial profiles, and applied non-linear inversion using H/V to finalize 1D Vs profiles. At the last step, the 2^{nd} stage deep learning (B) predicts 1D Vs profiles in the investigation area from geological and other regional information, based on the 2^{nd} 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, 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. Figure 1 shows geomorphological classification (a), surface geology (b), surface elevation (c), elevation of a layer with S-wave velocity of 350 m/sec in Vs profiles predicted by the 2^{nd} stage deep learning (d), time averaged S-wave velocity (Vs) to 30 m deep (V_{S30}) calculated from the predicted Vs profiles (e), and V_{S30} interpolated from training data of the 2^{nd} stage deep learning (f). There are Holocene valley bottom lowland along Kanda River (K~K'), Shakujii River (Sha~Sha'), and Shirako River (Shi~Shi') in the investigation area. In south Kanto region, Holocene alluvium is generally thin and Pleistocene terrace exists shallow depth in the valley bottom lowland. The V_{S30} at the valley bottom lowland is higher than one at terrace covered by volcanic ash-soil. The V_{S30} is relatively low along the Holocene valley bottom lowland in the result of deep learning (Figure 1e). We conclude that the predicted Vs model was reasonably consistent with surface topography, surface geology and geomorphological classification.

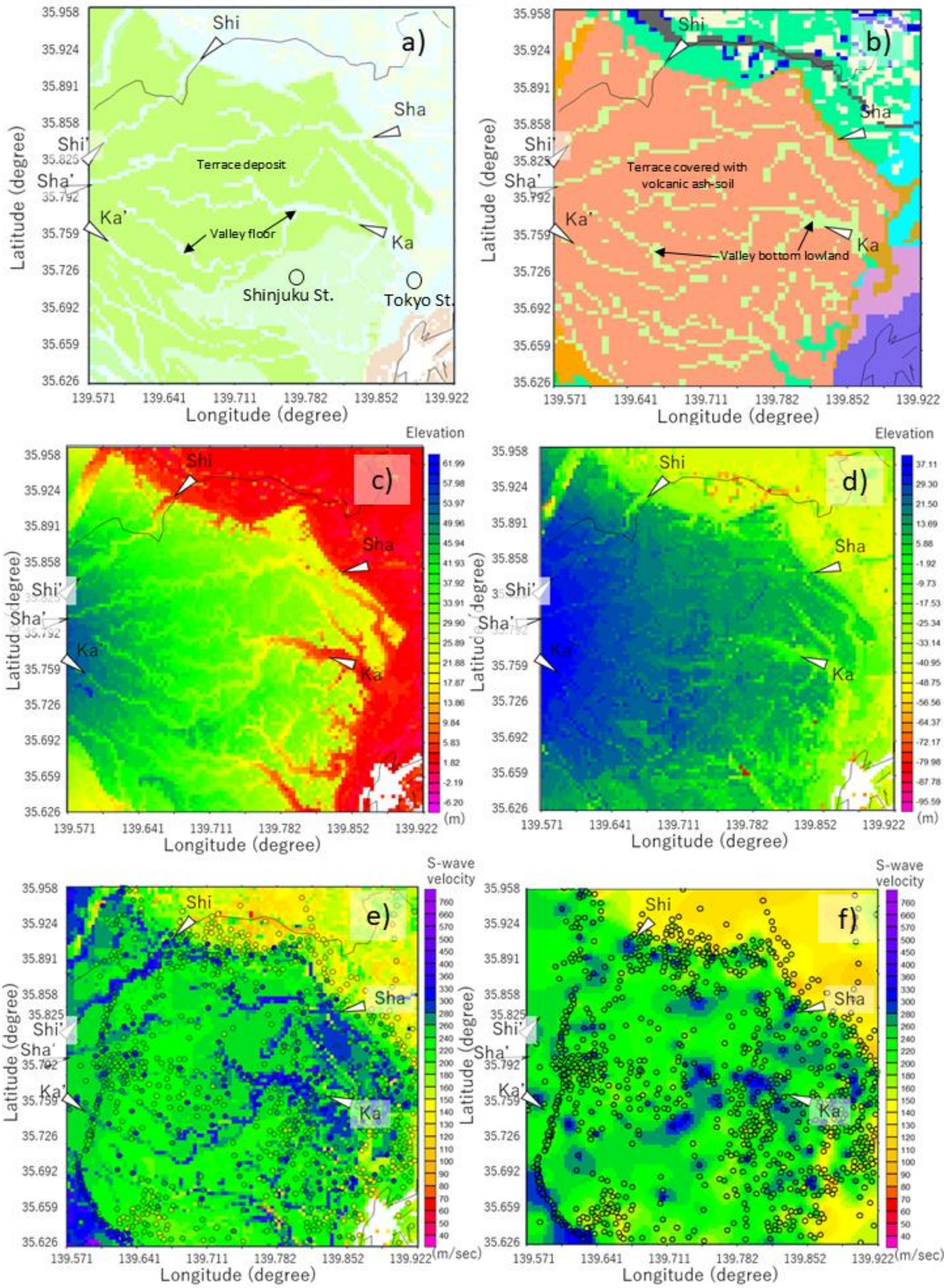

Figure 1. Geomorphological classification (a), surface geology (b), surface elevation (c), elevation of a layer with S-wave velocity of 350 m/sec in Vs profiles predicted by the 2nd stage learning (d), V_{S30} calculated from the predicted Vs profiles (e), and V_{S30} interpolated from training data of the 2nd stage learning (f), at the Tokyo downtown.