Multi-modal deep learning detection of deep-seated gravitational slope deformation by Typhoon Talas in Kii Peninsula in 2011

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1. Introduction
When predicting landslides, it is important to understand past landslide cases and prepare for similar case scenarios. The gravitational deformation topography is useful in understanding the deformation process. This has been applied to landslide prediction in an increasing number of heavy rainfall disasters. However, it is difficult to collect several disaster cases in the same area, i.e., with the same geological distribution and similar topography, because of the probability of a landslide of the same area is low. A method using deep learning-the collapse is objective, as opposed to the conventional method of topographic map reading by skilled engineers. In this study, we conducted deep learning using 35 landslides with mountain gravity deformation and their surrounding non-landslide areas that occurred in 2011.

2. Method
Deep learning is an analytical method that uses a neural network, which is a multi-layer structure modeled after the neural circuits of the human brain. We conducted an analysis using a CNN, which is highly effective for image recognition. A CNN is a machine learning method that contains multiple convolutional layers within the structure of the neural net that convolve and generate the feature values for each layer and pooling layers that compress these values. The convolutional layer of the CNN has a good perception of the local characteristics of the image and can sense the relationship between the pixel of interest and the surrounding pixels.

3. Data setting
In this study, instead of creating learning data from topographic features based on human interpretation, we created learning data with objective features from multiple types of numerical analyses. Applying multiple analysis techniques to learning data is a basic procedure in machine learning. These parameters had eight types: slope angle, Eigenvalue ratio, curvature, overground openness, underground openness, topographic wetness index (TWI), wavelet, and elevation. The area subjected to numerical analysis was approximately twice the range of the slide area. The DEM dataset was a 1-m mesh. The procedures for converting the data for the numerical methods are summarized in the Appendix. The resolution of the initial data is 1 m DEM. The raster data obtained through the numerical analyses were divided into squares by 50×50 pixels. To classify the tiles, the objective variables were labeled as y0 when the image contained over 80% slide area, y1 when the image contained over 80% non-slide area and y2 for all others.

4. Result
The results of the analysis using an unknown non-slide site had an accuracy rate of 0.856. An important aspect of DLs prediction is the automatic recognition of DGSDs specific to the DL. Finding the same terrain as the collapse site with high probability can predict landslides. For the results comparing evaluation and training, the recall of slide (y'0) was 95.7%. The recall for non-slide (y'2) was from 51.9%. The results indicate that the learning was implemented efficiently for slide (y'0) and non-slide (y'1) areas. The significance of deep learning here is judged by examining whether the topographic features specific

to slide areas can be identified automatically. Evaluation as "Unknown data" using the trained model was conducted for three of the 38 slide sites (IDs 8, 20, and 23) and non-slide areas that were not used for training and validation(Fig-1). This study targeted points where DGSDs manifested and shows that it is possible to estimate the locations of DLs by utilizing image analysis and CNN methods.

Keywords: Deep-seated landslide, Deep-seated gravitational slope deformations, Convolutional neural network, Multi-modal deep learning

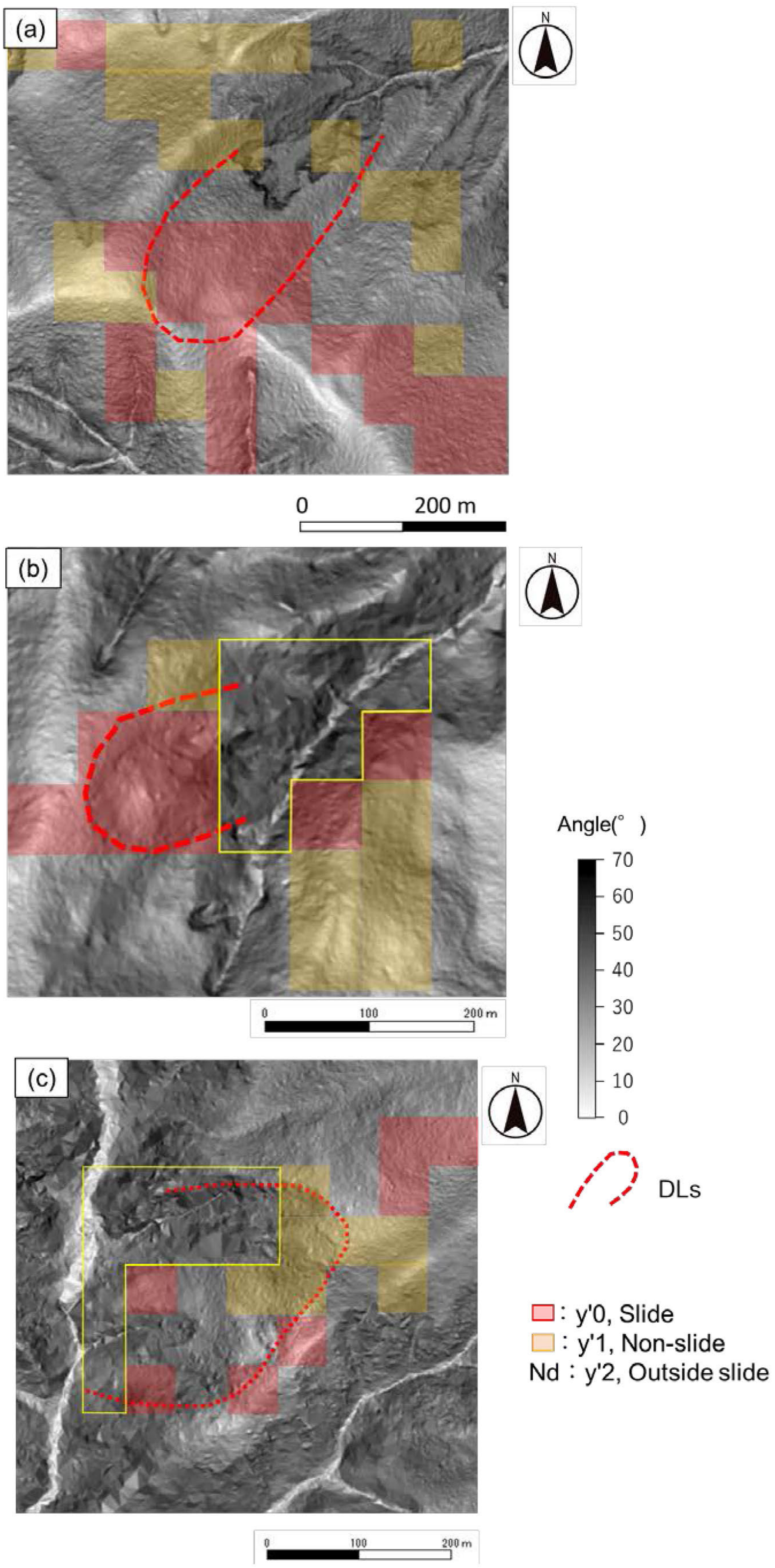

Fig. 1 Results of learning data test on ID 8,20 and 23.
Before the slide, red dotted line indicates the slide area. Yellow line indicates the large TIN area that was low-density LiDAR data