Landslide Detection of Hyperspectral Remote Sensing Data Based on Deep Learning With Constrains

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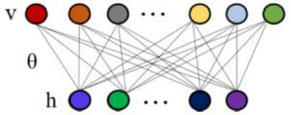
ABSTRACT

There is a growing demand for constructing a complete and accurate landslide maps and inventories in a wide range, which leading explosive growth in extraction algorithm study based on remote sensing images. To the best of our knowledge, no study focused on deep learning-based methods for landslide detection on hyperspectral images.We proposes a deep learning frameworkwith constraints to detect landslides on hyperspectral image. The framework consists of two steps. First, a deep belief network is employed to extract the spectral–spatial features of a landslide. Second, we insert the high-level features and constraints into a logistic regression classifier for verifying the landslide. Experimental results demonstrated that the framework can achieve higher overall accuracy when compared to traditional hyperspectral image classification methods. The precision of the landslide detection on the whole image, obtained by the proposed method, can reach 97.91%, whereas the precision of the linear support vector machine, spectral information divergence, and spectral angle match are 94.36%, 84.50%, and 86.44%, respectively. Also, this article reveals that the high-level feature extraction system has a significant potential for landslide detection, especially in multi-source remote sensing.

Deep learning, RBM, DBN, and landslide detection frameworks

- the first step is to transform the raw data into the input format of DBN.Therefore, the pixel value obtained from the same spatial position in a cube constitutes a one-dimensional ($1 \times N$) vector as the input data of the first layer that denotes the initial spectral features. In terms of spatial information, a neighboring region of the pixel is extracted as a sub-data cube ($H \times H \times N$) of the image and stretched into a one-dimensional vector with ($1 \times H \times H \times N$) elements.
- Second, after being normalized, the visible units of the first layer are replaced by the real-valued vector, which is added Gaussian noise. Then, following the CD method proposed by Hinton, the DBN starts training the parameters of every layer in an unsupervised manner. After this process, the output data of the top layer are regarded as a high-level feature vector that is inserted into a classifier to discriminate among different objects.
- Finally, our framework, with features extracted by the DBN, employs LR to detect landslides. In addition, the LR layer attached to the top layer of the DBN is responsible for another function: fine-tuning the whole framework with labeled pixels. To improve the accuracy of landslide detection, the framework adds some constraints to the LR layer, which include soil edibility, fault, river, road, rainfall erosivity, vegetation coverage, DEM, and slope..



$$E(v, h; \theta) = -\sum_{i=1}^{n} a_i v_i - \sum_{j=1}^{m} b_j h_j - \sum_{i=1}^{n}\sum_{j=1}^{m} w_{ij} v_i h_j \quad (1)$$

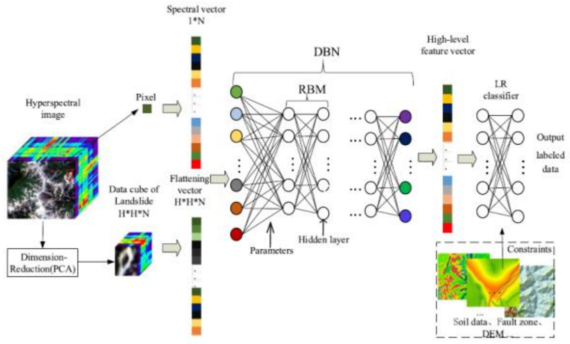


Fig. 1. Landslide detection using the DLWC framework.

Experimental Data

For the study area in our experiments, we selected a part of Yinxing country, Wenchuan County, Central Sichuan, China. On May 12, 2008, a catastrophic earthquake with Ms 8.0 struck the LMS region . The earthquake was triggered by a sudden massive crust displacement along the Yingxiu- Beichuan Fault. As of January 5, 2009, more than 15 000 geo-hazards were detected by using high-resolution color aerial photographs, satellites,and field investigation.

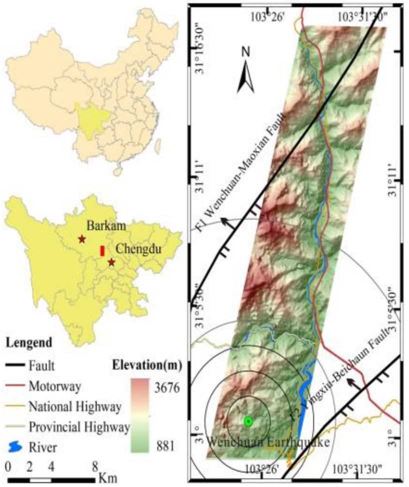


TABLE I
LAND-COVER CLASSES AND NUMBERS OF LABELED PIXELS IN HYPERION

Class code	Name	NO. of training samples	NO. of testing samples
1	Landslide	304	1218
2	Vegetation	222	889
3	River	26	102
4	Bare land	376	1504
Total		928	3713

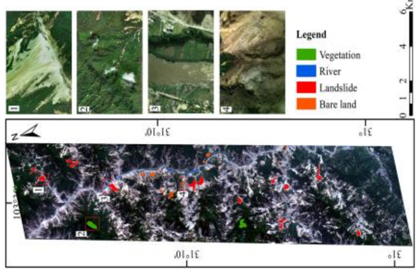


Fig. 2. general regional location and landslide samples.

Experiments and analyses

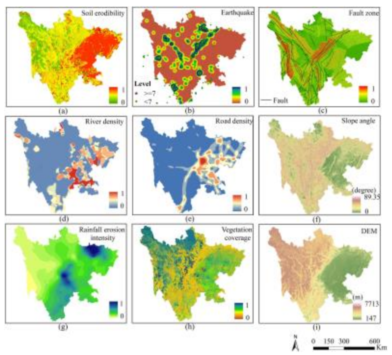


Fig. 3. Landslide-predisposing factors (Constrains)

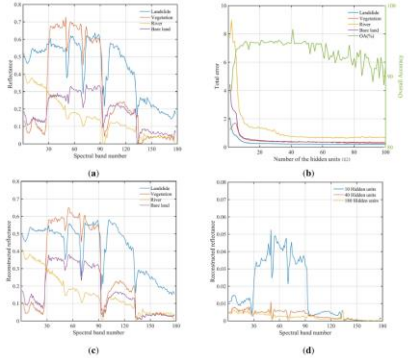


Fig. 4. Reconstruction and error of RBM.

Result and discussion

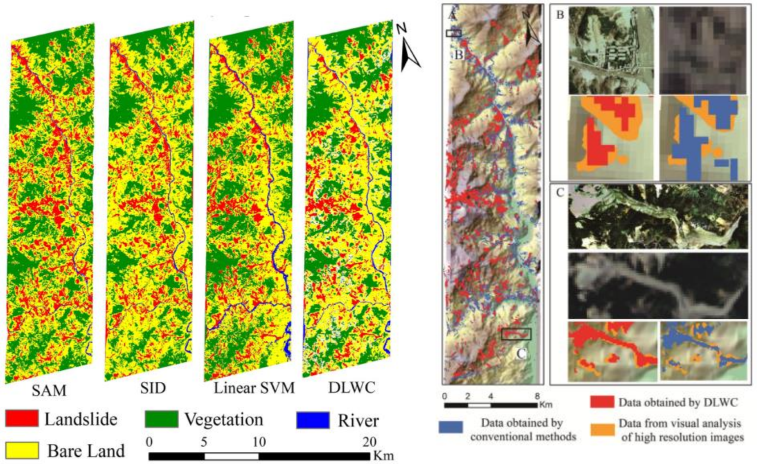


Fig. 5. Comparison of landslide mapping

Result and discussion

- the DLWC has the ability to retain morphological information of landslide on the resulting map, especially for giant landslides
- We set three hidden layers to guarantee the best accuracy of landslide detection.
- In the future, using other multi-source remote sensing (including high-resolution, SAR, and LiDAR), we will explore more effective deep architectures to detect landslides.