Automated Extraction of Landslides Using Deep Learning and Multiple Environmental Factors

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Abstract: As a common geological hazard, landslides pose a threat to human life and property safety. This study employs the ResNet34 method, a deep learning approach, while also considering environmental factors that influence landslides in landslide susceptibility assessment methods. The study focuses on Taiwan Island, selecting optical satellite images and 10 environmental factors to establish training and validation samples. Deep learning models can automatically extract features from sample data, a process referred to in this paper as extraction.The study utilizes optical satellite images from the entire Taiwan Island for the years 2015 and 2016, along with corresponding environmental factors such as NDVI, geology, soil, precipitation, land use, DEM, slope, aspect, planar curvature, and profile curvature. These datasets are overlaid in a band fusion manner and then input into the ResNet34 model. The experiment investigates the impact of different datasets on landslide feature extraction. Ultimately, it is found that land use data brings the most significant gain, while DEM data results in a negative impact.

Keywords: Landslide, Deep learning, Taiwan, RestNet34.

1 Introduction

Taiwan is located at the convergence of the Eurasian Plate and the Philippine Sea Plate. Due to intense orogeny, approximately 70% of the land is characterized by steep mountains. Disasters such as landslides and debris flows triggered by rainfall frequently occur[1]. Consequently, Taiwan has been the focus of numerous landslide studies. Among these, the detection and mapping of landslides are crucial components of landslide research. Field surveys are the most traditional method for detecting and mapping landslides under current conditions. However, field surveys have limitations such as high costs and lengthy time requirements. Therefore, the application of remote sensing technology for landslide detection and mapping has become a cost-effective method.

Traditional methods for landslide identification include visual interpretation, deformation detection, specific thresholds, machine learning, and deep learning[2]. This study opts for the more effective deep learning approach. In landslide research, susceptibility analysis is one of the most common research objectives. It involves evaluating

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the factors that may contribute to landslide events within a study area using various methods, including statistical analysis, machine learning, and deep learning. However, this paper does not focus on predicting landslide occurrences but emphasizes the identification of landslides that have already happened. In terms of landslide identification, the effectiveness of deep learning does not automatically surpass traditional machine learning; it depends on the design, including network depth, sliding window, and training strategies[3]. ResNet is a key breakthrough in the field of image recognition, and this paper uses it as a representative deep learning model for landslide identification experiments.

2 Materials and Methods

2.1 Study Area

The study area includes the entire island of Taiwan. Taiwan is located at the convergence of the Eurasian Plate and the Philippine Sea Plate, and due to orogenic movements, its terrain is characterized by significant undulations. With an average elevation of 660 meters, an average slope of 14 degrees and 14 minutes, and an average relative height of 312 meters per square kilometer, approximately 30% of the land is mountainous, 40% is hilly, and 30% is flat. Influenced by the monsoon climate, Taiwan experiences an average annual rainfall of about 2500 millimeters. Due to the combined effects of topography and rainfall, landslides are more prone to occur. The occurrence of landslides, in turn, impacts people's lives and development.

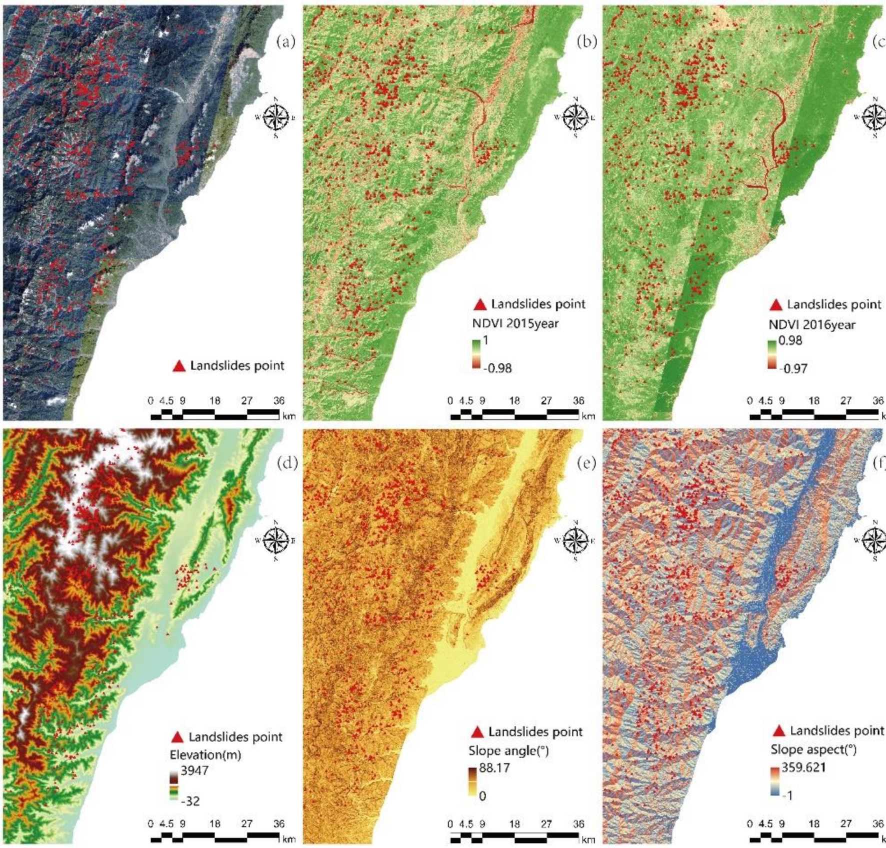
2.2 Data

The data used in this study include optical remote sensing images from the years 2015 and 2016, along with ten environmental factors, as shown in Figure 1. The landslide point data for this research are based on satellite recognition data for landslides in 2015 and 2016, further refined through manual screening, resulting in a total of 3000 landslide points. The Residual Network (ResNet) model requires both positive and negative samples as input, with landslide points as positive samples. Negative samples are randomly generated around the landslide points. However, the quantity of negative samples far exceeds that of positive samples. Considering the balance of sample quantities, this study further categorizes negative samples into types such as farmland, buildings, rivers, roads, and forests.

Landslide occurrences are associated with both environmental and human factors. To consider the impact of various factors on landslide extraction, this study selected 10 environmental factors based on considerations from recent years of susceptibility research on landslides. These 10 environmental factors are divided into three categories: natural factors, human factors, and terrain factors. Natural factors include the Normalized Difference Vegetation Index (NDVI), geology, soil, and precipitation. Human factors involve land use. Terrain factors include DEM (Digital Elevation Model), as well as slope, aspect, plan curvature, and profile curvature derived from DEM.

NDVI represents the degree of vegetation coverage, which can be used to infer the looseness of rocks and soil, thereby estimating the likelihood of landslides. Similarly, geological and soil characteristics vary with different rock and soil types, forming the fundamental material conditions influencing landslide occurrence. DEM, slope, aspect, plan curvature, and profile curvature, on the other hand, reflect the topographic relief and roughness of the region, correlating with the movement and deposition of landslides. Land use reflects the impact of human activities on the natural environment and, of course, the land cover.

The table records the data sources, data formats, and years of all collected environmental factors. Different environmental factors have different data formats and spatial resolutions, including vector and raster data formats, and spatial resolutions of 1 meter, 2 meters, and 20 meters. This study standardizes all survey factor data to a grid with a precision of 2 meters through methods such as vector-to-raster conversion and resampling.



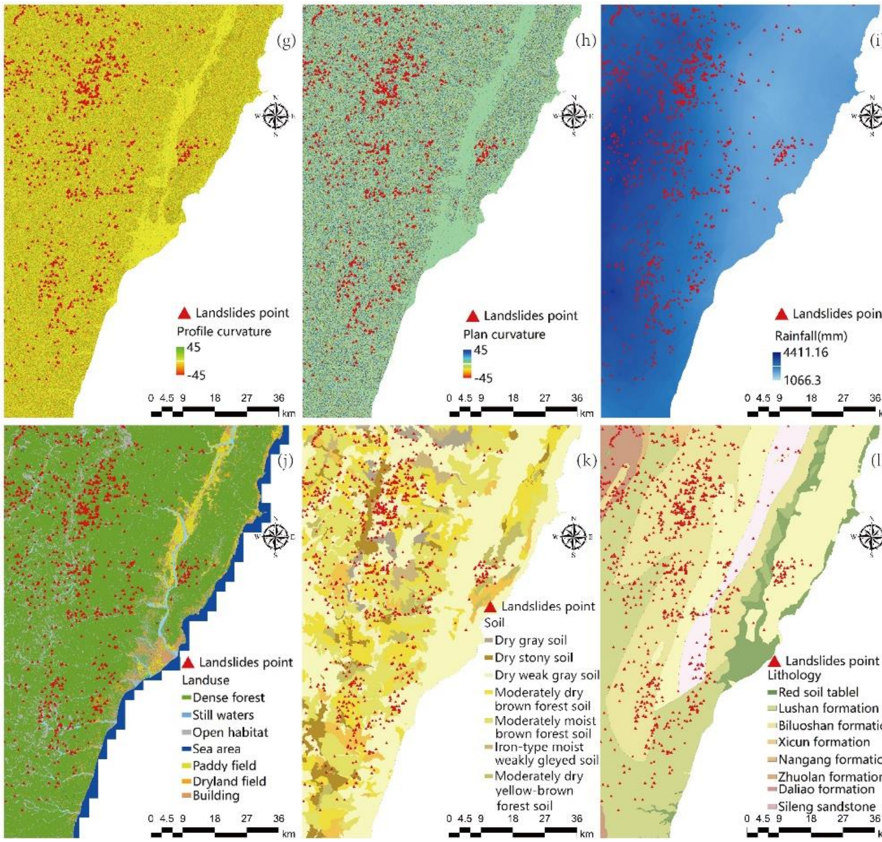


Fig. 1. Conditioning factors maps: (a) landslides point, (b) 2015year NDVI, (c) 2016year NDVI, (d) elevation, (e) slope angle, (f) slope aspect, (g) profile curvature, (h) plan curvature, (i) Rainfall, (j) land use, (k) soil, (l) lithology.

2.3 Method

Optical satellite images and various environmental factors are overlaid, and input into a Residual Network (ResNet) for data classification training, followed by a comparison of the results. The entire workflow for landslide extraction is illustrated in the diagram.

- Collect the required environmental factor data and historical landslide data. Utilize methods such as vector conversion to raster, resampling, etc., to standardize raster data to the same spatial resolution and format;
- Construct samples for model training and testing. Positive samples are selected from historical landslide data, while negative samples are randomly extracted from land use data, classified into five categories: farmland, buildings, rivers, roads, and forests;
- Evaluate the impact of different environmental factors on landslide extraction in the Residual Network through metrics such as accuracy, confusion matrix, etc.

ResNet.

The Residual Network (ResNet) structure is a type of Convolutional Neural Network (CNN), which is one of the most common deep learning methods. CNN extracts feature information from input data through convolutional layers and pooling layers. It then updates network parameters using optimization methods like gradient descent, and finally, classifies the data through fully connected layers. Unlike considering only the features at the current position, CNN considers surrounding features through convolutional filters, expanding the consideration of peripheral features by deepening the convolutional layers[4].

The Residual Network (ResNet) chosen in this study is an outstanding network structure that emerged in the development of CNNs. It possesses the following characteristics: residual modules and batch normalization layers. As the number of layers in a deep learning network increases, accuracy generally improves. However, a phenomenon known as degradation occurs, wherein accuracy, after reaching a certain level, significantly decreases as the network depth continues to increase. ResNet addresses this issue through residual modules and batch normalization, allowing the network structure to be built with thousands of layers[5]. Additionally, ResNet demonstrates faster convergence speed, higher model stability, and better generalization capability.

3 Results

This paper compares the impact of different environmental factors on landslide extraction in residual networks through metrics such as accuracy, precision, recall, specificity, and confusion matrices. The accuracy is calculated as follows:

$$accuracy = \frac{TP+TN}{\mathrm{TP+TN+FP+FN}} \tag{1}$$

The precision is calculated as follows:

$$precision = \frac{TP}{\mathrm{TP+FP}} \tag{2}$$

The recall is calculated as follows:

$$recall = \frac{TP}{\mathrm{TP+FN}} \tag{3}$$

The accuracy is calculated as follows:

$$specificity = \frac{TN}{\mathrm{TN+FP+FP}} \tag{4}$$

where TP is true positive samples, TN is true negative samples, FP is false positive samples, and FN is false negative samples.

Table 1 presents the accuracy, precision, recall, and specificity obtained by importing optical remote sensing images and different environmental factors into the residual neural network.

Table 1. Indicators obtained by overlaying conditioning factors.

Overlaying Conditioning Factors	Accuracy	Precision	Recall	Specificity
None	0.868	0.926	0.908	0.986
Elevation	0.863	0.914	0.923	0.984
Lithology	0.878	0.918	0.922	0.985
Land-use	0.953	0.971	0.963	0.995
NDVI	0.874	0.926	0.919	0.986
Rainfall	0.871	0.927	0.934	0.986
Soil	0.872	0.94	0.93	0.989
NDVI, Lithology, Soil, Rainfall	0.873	0.943	0.934	0.989
NDVI, Lithology, Soil, Rainfall, Land-use	0.946	0.958	0.972	0.992
NDVI, Lithology, Soil, Rainfall, Land-use, Elevation, Slope angle, Slope aspect, Profile curvature, Plan curvature	0.949	0.998	0.994	1.0

From Table 1, Figure 2, and Figure 3, it can be observed that the individual environmental factors have varying effects on landslide extraction. Among them, land use contributes the most to the extraction effectiveness, resulting in the highest values for accuracy, precision, recall, and specificity. When multiple environmental factors are combined for landslide extraction, the best results are achieved by overlaying the 10 selected environmental factors considered in this study.

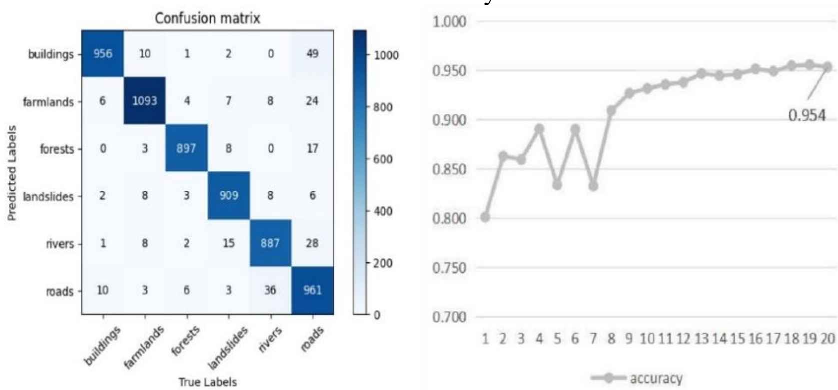


Fig. 2. The confusion matrix obtained by overlaying land use and the accuracy at each iteration of the model

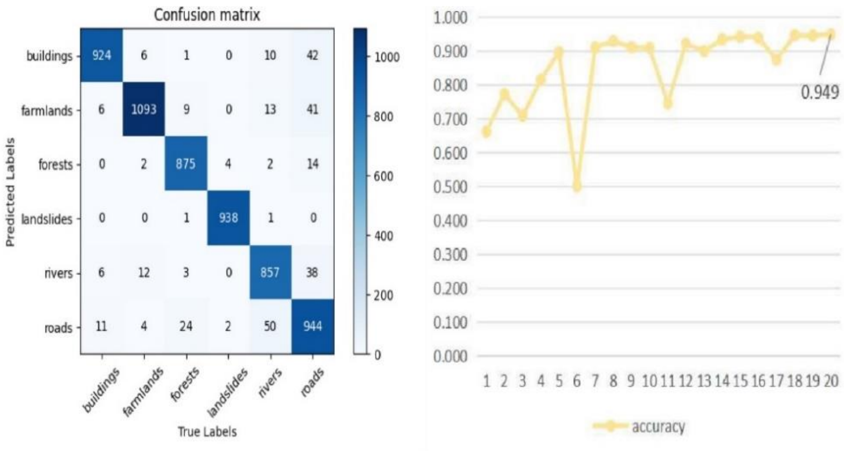


Fig. 3. The confusion matrix obtained by overlaying 10 conditioning factors and the accuracy at each iteration of the model

4 Conclusions

The land use factor yields the greatest enhancement for landslide extraction, and other environmental factors also contribute to the enhancement. Combining all factors together provides additional benefits for landslide extraction, but the gain is not as significant as when land use data is added alone. This may be related to the model structure, and future research could further explore the combined effects of different models and different environmental factors on landslide extraction.

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