

A Heterogeneous Ensemble Learning Method Combining Spectral, Terrain, and Texture Features for Landslide Mapping

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I. INTRODUCTION

Abstract—The existing landslide recognition methods mainly focus on the use of spectral bands of optical remote sensing and machine learning base classifiers, which are insufficient in landslide characterization in complex scenes, resulting in a high missed and false detection of landslides. In this article, we develop a landslide recognition framework, which combines the multidimensional feature advantages of spectral, terrain, and texture of optical satellite images, and constructs a heterogeneous ensemble learning method for landslide mapping. First, we construct a landslide multidimensional feature dataset using Sentinel-2A and Advanced Land Observing Satellite digital elevation model data. Then, we construct a heterogeneous ensemble learning landslide recognition method, which combines the advantages of fully convolutional network, U-Net, and attention U-Net base classifiers to fully learn the multidimensional features of landslides. Finally, we evaluate the performance of the landslide recognition framework in the Bailongjiang River Basin complex scenes. The experimental results show that integrating the multidimensional features of spectral, terrain, and texture and using the heterogeneous ensemble learning method can reduce the missed and false detection of landslides in complex scenes. Specifically, compared with using only spectral bands, integrating spectral bands, spectral indexes, terrain factors, and texture indexes achieves the highest Recall, Kappa, F1-score, and MIoU in testing areas, and missed alarm (MA) is reduced by 15.56%. Compared with deep learning base classifiers, the constructed heterogeneous ensemble learning demonstrates improvements in Recall ranging from 41.67% to 69.89%, and MA is reduced from 52.17% to 30.11%. This study provides a new idea for high-precision landslide recognition in complex environments.

Index Terms—Ensemble learning, landslide detection, spectral index, texture index, U-Net.

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A landslide is a frequent geological disaster in nature. Landslides have caused huge losses to the ecological environment, communication systems, transport services, and human life and property [1], [2]. China is a country with frequent geological disasters, among which the landslide disaster occurs most frequently [3]. A total of 3 668 geological disasters occurred in China in 2023, of which 925 were landslides, accounting for 25.21% of the total annual geological disasters. Therefore, it is very important to obtain landslide information quickly and accurately for formulating disaster relief plans and emergency measures [4]. Using geological data and information technology to quickly detect and warn landslides in a large area is of great significance for speeding up disaster reduction and prevention and winning the battle of disaster prevention and control [5], [6].

Landslide recognition methods mainly include visual interpretation, object-oriented [7], traditional machine learning [8], [9], and deep learning [10], [11]. Among them, the deep learning method can obtain the optimal parameters of the construction model [12], [13]. Deep learning has been widely used in landslide recognition; for example, fully convolutional network (FCN) [14], [15], U-Net [16], [17], region-based convolutional neural network (R-CNN) [18], and YOLO [19], [20]. FCN and U-Net models are simple and have a strong ability to learn features, so they are widely applied for landslide recognition [15], [17]. However, most of the existing studies mainly use the spectral bands of optical remote sensing. In the face of complex geographical and geological environments, landslide colors in remote sensing images of different regions are diverse spectral and textural characteristics of different background environments [21], such as soil type, water content, solar incidence angle, and vegetation. For example, in some areas with sparse vegetation, landslide colors in remote sensing images are very similar to those of bare lands. The existing landslide recognition methods based on deep learning using spectral bands have high missed and false detection rates in complex environments [11].

Some studies have tried to increase spectral index [22], terrain factor [16], [23], [24], and texture index [25] to extract information, respectively, and these studies have achieved excellent results. However, the existing studies do not integrate the multidimensional features of spectral band, spectral index, terrain index, and texture index for landslide detection, which leads to

many uncertainties in landslide detection results. In addition, for multidimensional feature learning, it is difficult for existing deep learning base classifiers to make full use of spectral, terrain, and texture multidimensional features of landslides. Ensemble learning techniques build multiple base classifiers and allow them to independently predict the input data and then combine the prediction results of each base classifier in a certain way to produce a final prediction result [26], [27], [28]. Each base classifier can learn in different feature subsets or different model spaces, thereby reducing the generalization error of the model [29]. The heterogeneous ensemble learning techniques have been widely used in image recognition, text classification, and susceptibility assessment, and have achieved excellent research results [30], [31], [32]. There were few studies on landslide identification using ensemble learning. Wang et al. [33] employed an ensemble strategy in landslide identification, which integrated the advantages of different machine learning-based classifiers, further improving the accuracy of recognition. However, there is no report on the heterogeneous ensemble learning method based on multidimensional features for landslide mapping.

Therefore, we construct the multidimensional feature dataset of remote sensing images, which fills the gap of the landslide dataset containing landslide multidimensional features. We develop a heterogeneous ensemble learning landslide recognition model based on FCN, U-Net, and attention U-Net base classifiers, and comprehensively utilize multidimensional features of remote sensing images to effectively supplement the context information of landslide objects in complex environments, to improve the accuracy of landslide recognition and reduce the missed and false detection of landslides. The main contributions of this study are as follows.

- 1) Multidimensional feature datasets that contain the spectral, terrain, and texture of optical satellite images are constructed. The datasets enrich the characteristics of landslides, and the missed and false detection of landslides is effectively reduced in complex scenarios.
- 2) A heterogeneous ensemble learning landslide recognition model is developed. The model can make full use of multidimensional features and effectively improves the predictive ability of the FCN, U-Net, and attention U-Net base classifiers.
- 3) A developed landslide recognition framework is evaluated by the Bailongjiang River Basin. The developed landslide recognition framework reduces the missed detection and false detection of landslides in complex scenes.

II. DATA SOURCES

A. Experimental Scene

Bailongjiang River Basin is situated at the transition zone between the second and third tiers of mainland China (see Fig. 1). The Bailong River Basin is one of the four areas with high incidences of landslide and debris flow disasters. The Bailong River Basin has a complex geographical environment, spatial heterogeneity, and discrete landslide distribution. The Wenchuan earthquake on May 12, 2008, aggravated the damage of mountain and geotechnical structures, induced a series of new

geological disasters of landslide and debris flow, and caused many geological hazards. The geomorphology is complex, with mountain gorges and loess landforms alternating. Meanwhile, frequent earthquakes occur, and deep river valleys are formed, providing favorable conditions for landslide disasters, resulting in frequent landslides [34].

B. Sentinel-2A Image and DEM

Sentinel-2A satellite carries a multispectral imager. Sentinel-2A covers 13 bands from visible light to near-infrared spectrum, a width of 290 km, a ground resolution of 10, 20, and 60 m, and a total of three levels, with rich band information. Sentinel-2A data are Level-1C (L1C) level data for atmospheric correction. In this article, Sen2cor, a plug-in is used for atmospheric correction of L1C data. In this article, Sentinel-2A image with cloudless is collected from April 29, 2021.

Advanced Land Observing Satellite (ALOS) digital elevation model (DEM) data are the elevation data collected by ALOS satellite. The accuracy of horizontal and vertical is up to 12.5 m. This data can be applied in several areas. This article selects the ALOS DEM data to calculate the elevation, slope, and aspect.

C. Landslide Database

Based on the historical landslide data and field investigation verification, we obtain landslide boundaries by visual interpretation using high-resolution images from the Google Earth platform. After multiple checks and revisions, 732 landslides are obtained (see Fig. 1). These landslides data completed by vectorization annotation are converted into raster data in the ArcMap 10.7, and exported into binary images in portable network graphic format to obtain real landslide samples for deep learning model training.

III. METHODOLOGY

This study evaluates the landslide identification performance of the developed landslide recognition framework. The main steps are as follows.

- 1) Construct a multidimensional feature dataset based on Sentinel-2A and ALOS DEM data.
- 2) Construct a heterogeneous ensemble learning model based on the deep learning single model for landslide identification.
- 3) Evaluate the developed landslide recognition framework by the Bailongjiang River Basin complex scene.

The flowchart is shown below (see Fig. 2).

A. Multidimensional Feature Dataset Construction

In the Bailong River Basin, the terrain is complex, and only spectral band data of optical remote sensing images are used for landslide recognition, which results in high missed and false detection of landslides. In this article, spectral bands, spectral indexes, terrain indexes, and texture indexes of remote sensing images are used for landslide recognition.

1) *Spectral Bands*: Spectral bands of Sentinel-2A optical remote sensing are rich (12 bands) with diverse resolution.

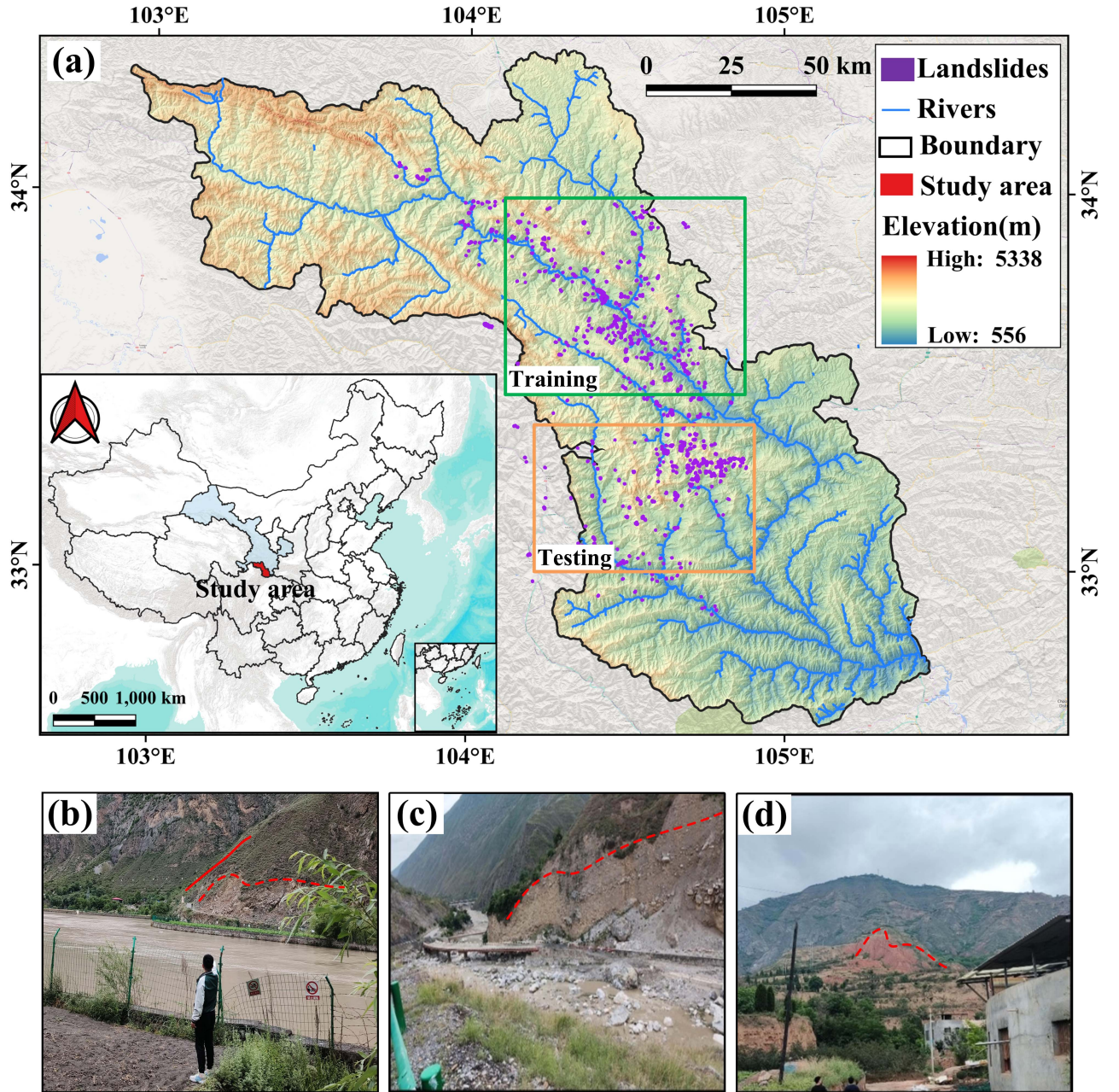


Fig. 1. The location of Bailong River Basin: (a) study area, (b)–(d) UAV images.

Therefore, cloudless Sentinel-2A remote images on April 29, 2021, are selected as the spectral band data source in this article. To more accurately identify landslide characteristics and boundary information and reduce data processing complexity and computing cost, we choose bands 2, 3, 4, and 8 of Sentinel-2A as spectral bands [see Fig. 3(a)–(d)]. The spatial resolution of these bands is 10 m.

2) *Spectral Bands*: Spectral index is a mathematical tool used to describe spectral features, which can enhance the features of different ground objects. The spectral index is calculated from the optical image bands. After a landslide occurs, soil leakage, vegetation loss, and soil moisture change are usually caused around it, and its spectral index will change, which is

conductive to landslide identification. Therefore, the spectral index is selected as the data source for landslide recognition. Normalized Red Band (NR), Normalized Green Band (NG), Normalized Blue Band (NB), and Normalized Green-Red Difference Index (NGRDI) [22], [25], [35] are used for landslide recognition. The four spectral indexes are calculated from the bands of Sentinel-2A remote sensing images [see Fig. 3(e)–(h)]. The specific calculation formula is as follows:

$$NR = \frac{R}{B + G + R} \quad (1)$$

$$NG = \frac{G}{B + G + R} \quad (2)$$

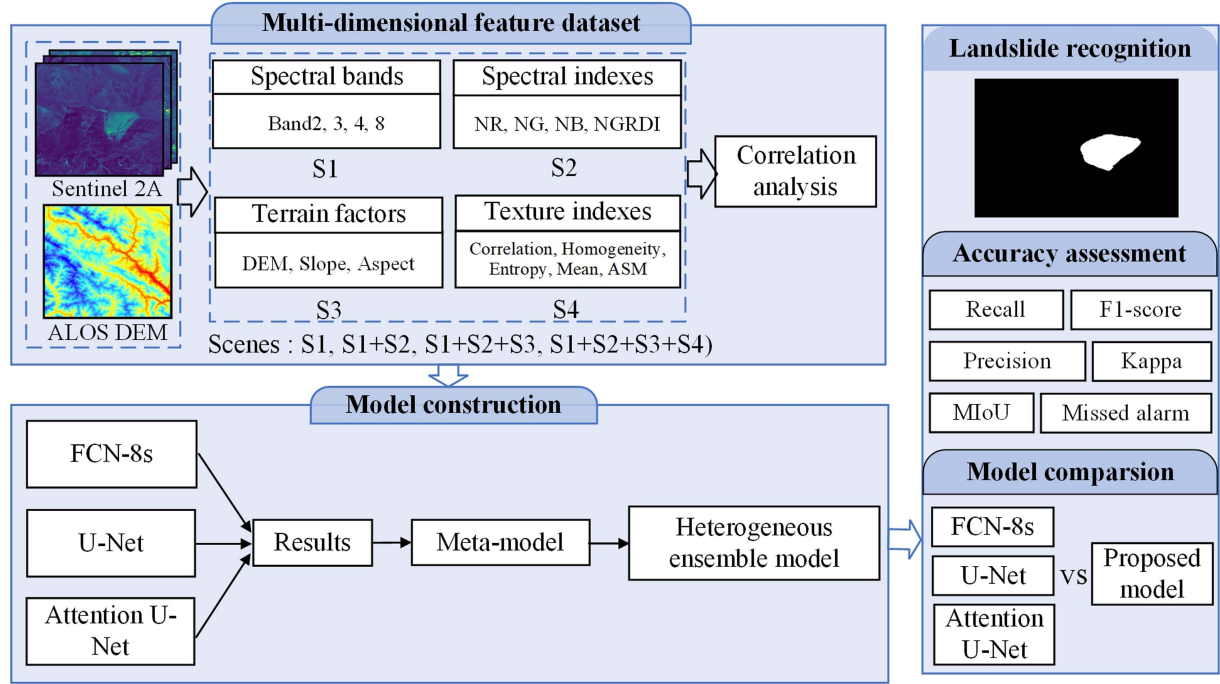


Fig. 2. Flow diagram of this study.

$$NB = \frac{B}{B + G + R} \quad (3)$$

$$NGRDI = \frac{G \times R}{G + R}. \quad (4)$$

Among them, R, G, and B represent the red, green, and blue wave segments of remote sensing images, respectively.

3) *Terrain Factors*: Terrain factors are important parameters to characterize surface topography, which has an important influence on the formation and distribution of landslides and can be used as auxiliary data for landslide identification. For example, areas with higher slopes may be more prone to landslides, and the aspect also affects the distribution of landslides. Terrain factors include DEM, slope, and aspect data. DEM are derived from ALOS 12.5 m DEM data, and slope and aspect are calculated based on DEM data [see Fig. 3(i)–(k)].

4) *Texture Indexes*: Texture index can provide texture information of surface objects and reflect the texture and spatial changes of surface objects in remote sensing images [25]. The damage and movement of the surface caused by landslides will cause significant changes in the texture characteristics. For example, the movement and mixing of soil, rock, and other materials on the surface caused by landslides make different texture characteristics appear in the originally similar surface areas. These changes can be used as one of the important indicators to identify landslides, and the texture index image can be used to better describe the characteristics of the landslide area. The texture indexes selected in this article are Correlation, Entropy, Homogeneity, Mean, and Angular Second Moment [22], [36]. Sentinel-2A data are used to calculate texture indexes based on the gray level co-occurrence matrix (GLCM) [37] in ENVI 5.6 software [see Fig. 3(i) and (m)–(p)].

The Correlation is used to measure the similarity of the image's gray level in the direction of rows or columns, and its magnitude reflects the local gray level correlation.

$$\text{Correlation} = \sum_{i,j=0}^{N-1} P_{i,j} \left[\frac{(i - \mu_i)(j - \mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}} \right] \quad (5)$$

where $P_{i,j}$ is the probability that the values i and j appear in adjacent pixels in the original image inside the window that defines the neighborhood, and i and j are the column and row labels of GLCM, respectively.

$$\sigma_i^2 = \sum_{i,j=0}^{N-1} P_{i,j}(i - \mu_i)^2, \sigma_j^2 = \sum_{i,j=0}^{N-1} P_{i,j}(j - \mu_j)^2. \quad (6)$$

The Entropy is a measure of the amount of information in an image, and also a measure of the degree of nonuniformity or complexity of the texture, representing the complexity of the image.

$$\text{Entropy} = \sum_{i,j=0}^{N-1} P_{i,j}(-\ln P_{i,j}). \quad (7)$$

The Homogeneity reflects the local variation of image texture. If different regions of image texture are uniform and change slowly, Homogeneity will be larger, and vice versa.

$$\text{Homogeneity} = \sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1 + (i - j)^2}. \quad (8)$$

The Mean reflects how regular the texture is. If the texture is chaotic and difficult to describe, the mean value is small. If the

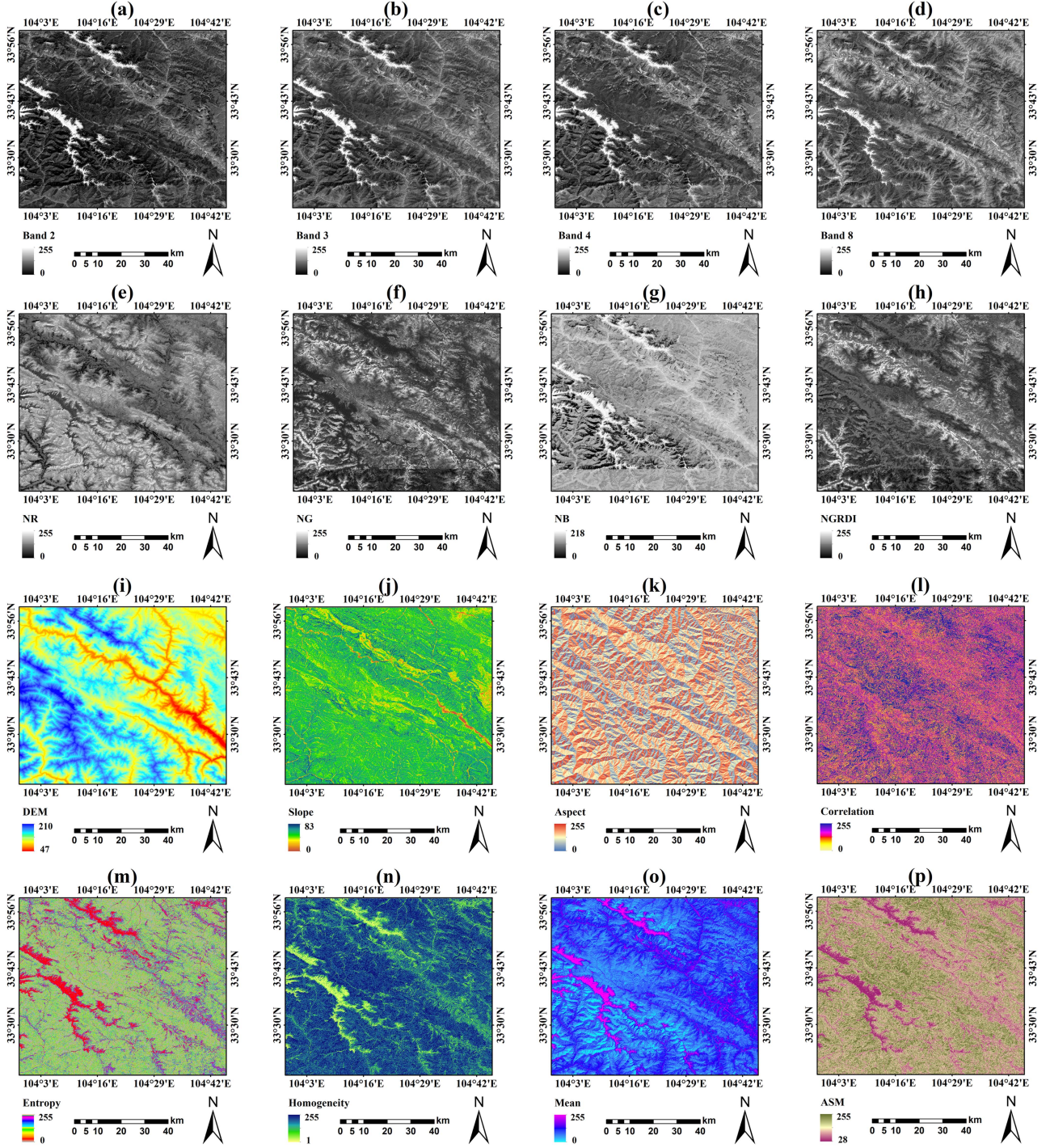


Fig. 3. Spatial distribution of spectral bands, spectral indexes, terrain factors, and texture indexes: (a) Band2, (b) Band3, (c) Band4, (d) Band8, (e) NR, (f) NG, (g) NB, (h) NGRDI, (i) DEM, (j) Slope, (k) Aspect, (l) Correlation, (m) Entropy, (n) Homogeneity, (o) Mean, (p) ASM.

texture is regular and easy to describe, the mean value is larger.

$$\mu_i = \sum_{i,j=0}^{N-1} i(P_{i,j}), \mu_j = \sum_{i,j=0}^{N-1} j(P_{i,j}). \quad (9)$$

ASM is the sum of the squares of all the row values in the GLCM, which reflects the uniformity of the texture. In addition, the second-order angular distance also represents the energy information of the image, and it can be considered that the coarse

texture contains more energy.

$$ASM = \sum_{i,j=0}^{N-1} (P_{i,j})^2. \quad (10)$$

B. Dataset Making

To train the model, the original data is cut, and the real landslide sample image is combined to make the dataset. Considering the image resolution and landslide scale comprehensively, the

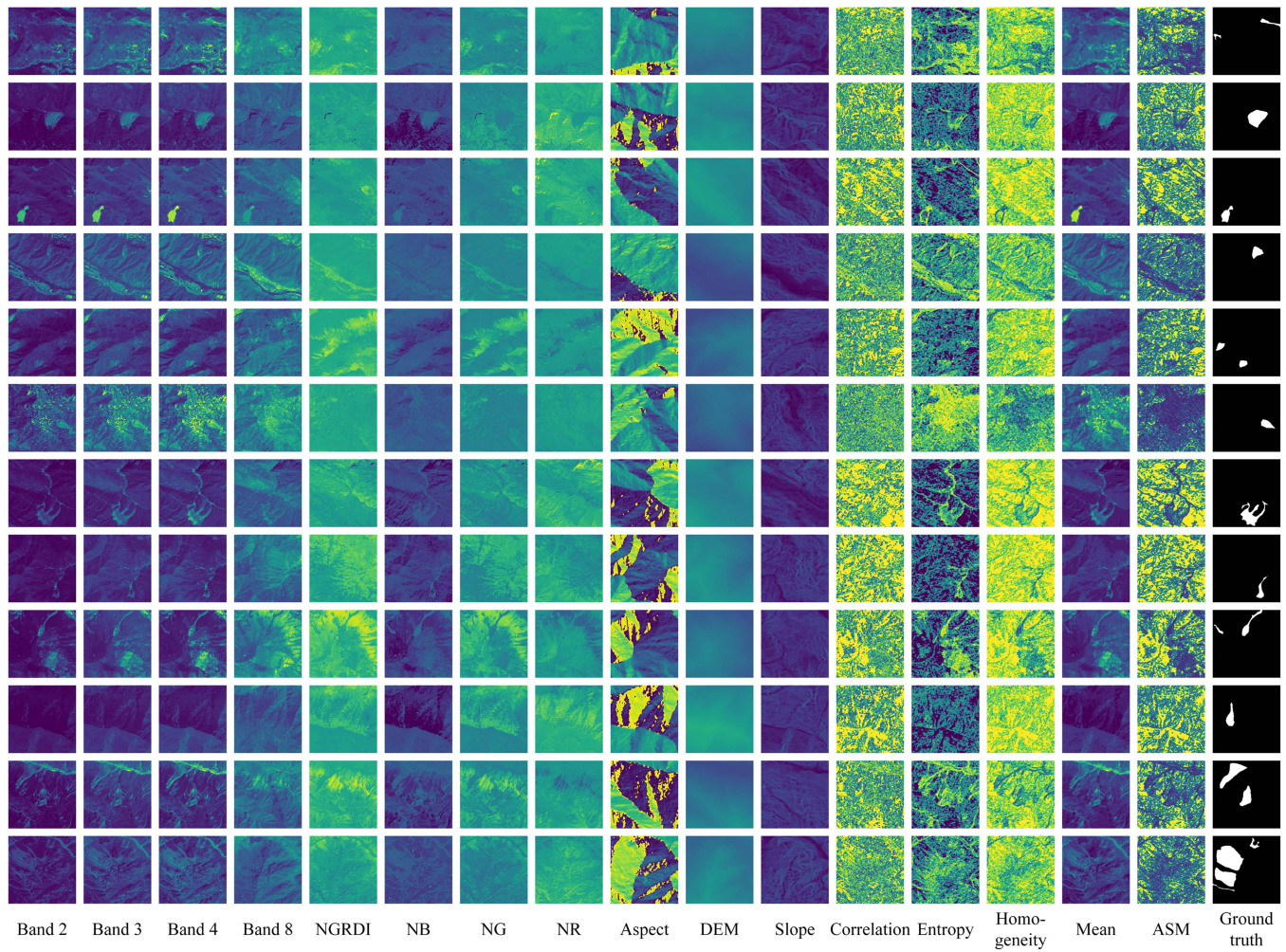


Fig. 4. Visualization of some datasets.

image cutting size is set to 256×256 pixels. The step size is set to 128. The images of the spectral band, spectral index, terrain factor, texture index, and real landslide samples are cut into several sub-images. We adopt the mirroring and rotation to enhance the dataset to increase the number of samples. To simplify the training dataset, images without landslide areas are removed from the dataset. The label image contains two pixel types: 1 represents the landslide area and 0 represents the nonlandslide area. Subsequently, the datasets are randomly divided at 8:2 for training and verification, and the training sets and verification sets are mutually exclusive (see Fig. 4).

C. Development of Landslide Identification Method

1) *FCN Network Model for Landslide Identification*: FCN proposed by Shelhamer et al. [38] is an end-to-end image semantic segmentation network model. FCN network structure is mainly divided into three parts: full convolutional structure, deconvolution structure, and skip connection structure. FCN processes images through operations such as convolution, pooling, and upsampling to achieve pixel-level semantic segmentation, avoiding the full connection layer, thus reducing the number

of parameters and making the network easier to train. The full convolutional structure usually uses a typical CNN network to extract the features of the input image. The deconvolution structure gradually restores the resolution of the feature map through an up-sampling operation and converts it into pixel-level classification results. The skip connection structure is usually added to the decoder part to fuse low-level and high-level feature maps to provide richer semantic information and improve segmentation accuracy. FCN can be divided into different versions according to its internal structure and skip connection mode, among which the common ones are FCN-32s, FCN-16s, and FCN-8s. In this article, FCN-8s is selected as one of the base classifiers for landslide identification (see Fig. 5).

2) *U-Net Network Model for Landslide Identification*: U-Net is an image semantic segmentation network based on an improved FCN structure proposed by Ronneberger et al. [39]. U-net is a U-shaped structure consisting of an encoder, a decoder, and a skip connection structure. It is a typical encoder-decoder structure. This method can retain more detailed information and can better capture the local information in the image, and better locate and segment the target, which helps to improve the accuracy of segmentation. The encoder part like visual geometry

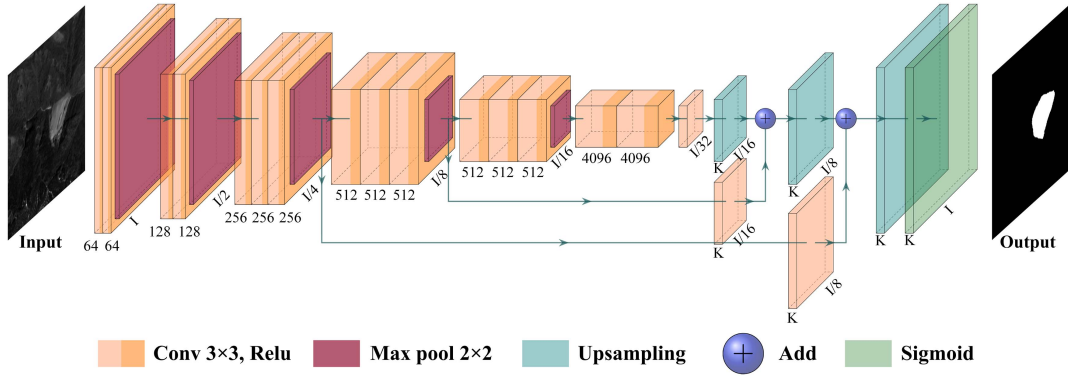


Fig. 5. FCN-8s model for landslide identification.

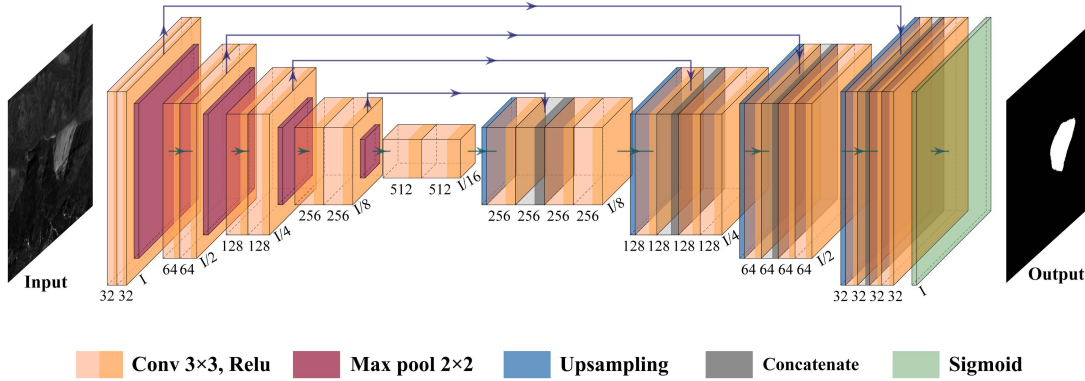


Fig. 6. U-Net model for landslide identification.

group (VGG) architecture, consists of a sequence of convolution and pooling layer stack. The convolution layer was used to extract the local spatial features of the input image. The pooling layer by reducing the size of the feature mapping reduces the amount of calculation and can extract the main information of the feature map. The decoder part usually includes a series of convolutional layers, upsampling (deconvolution or transposed convolution) layers, and join operations that are used to up-sampling the feature map extracted by the encoder so that it is consistent with the size of the input image. The input image can be predicted at pixel level. The skip connection is the key part of the U-Net network, which realizes the feature fusion between the encoder and decoder. Through the skip connection, the decoder can obtain the feature information extracted by the encoder at different levels, to better recover the spatial information and details of the images. This method of feature fusion helps improve the accuracy of the image segmentation. In this article, U-Net is used as one of the base classifiers for landslide identification. The number of network channels used starts from 32 and becomes 512 after four downsampling times (see Fig. 6).

3) *Attention U-Net Model for Landslide Identification:* In this article, we introduce the attention mechanism into U-Net and construct an attention U-Net model to adjust the weights of the feature maps received by the decoder from the encoder, focusing on extracting landslide-related features, improving the recognition ability of target boundaries and details, and using them as one of the base models for landslide recognition [11].

Its structure is shown in Fig. 7. The specific process includes the following steps: First, the feature maps processed by the encoder and decoder at the same level are input into the attention module and concatenated in the channel dimension to achieve feature fusion. Then, the fused feature map is processed using convolution operation combined with the Sigmoid activation function to calculate the weight matrix. At the same time, the calculated weight matrix is applied to the feature map of the encoder using Hadamard product operation to obtain the spatially weighted feature map. Finally, the feature map weighted by the attention module is passed to the decoder at the corresponding level for further processing, fusing multiscale features, and gradually restoring the feature map to the same resolution as the input image. Attention U-Net can better focus on important (landslide) feature areas through feature weighting and feature fusion.

Feature weight extraction:

$$W_{\text{concat}}(x, g) = \frac{1}{H \times W} \sum_{i=1}^H \sum_{j=1}^W f(i, j). \quad (11)$$

Feature weight update:

$$q_{\text{att}} = \text{ReLU}(W_{\text{concat}}(x, g)) \quad (12)$$

$$\alpha = \text{Sigmoid}(q_{\text{att}}(W_{\text{concat}}(x, g), \Theta_{\text{att}})). \quad (13)$$

4) *Ensemble Learning Model for Landslide Identification:* The basic idea of ensemble learning is to combine the prediction results of many single models to reduce the generalization errors of a single model and improve the prediction accuracy

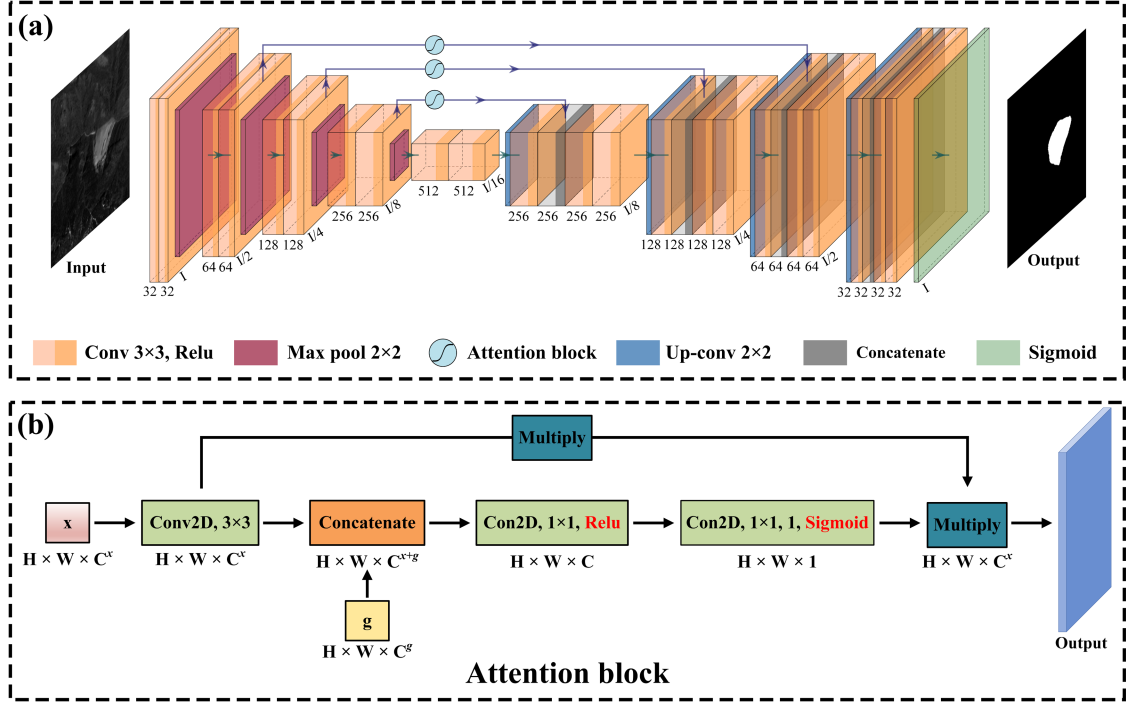


Fig. 7. Attention U-Net model for landslide identification: (a) attention U-Net model, (b) attention block.

[32]. In this article, based on the traditional stacking ensemble learning framework, we construct a new heterogeneous ensemble learning framework for landslide identification. FCN, U-Net, and attention U-Net are selected as the base classifiers. Different from the traditional stacking ensemble learning, this article is oriented towards image semantic segmentation tasks. CNN's unique design principles and network structure can better consider and effectively process image features. Therefore, this article uses the CNN model as a metaclassifier to integrate the stacking model (see Fig. 8).

The prediction results of multiple base models (FCN, U-Net, and attention U-Net) are used as new features to construct a feature matrix as follows:

$$X_{\text{stacking}} = \begin{bmatrix} \hat{y}_1^{(1)} & \hat{y}_2^{(1)} & \dots & \hat{y}_m^{(1)} \\ \hat{y}_1^{(2)} & \hat{y}_2^{(2)} & \dots & \hat{y}_m^{(2)} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{y}_1^{(n)} & \hat{y}_2^{(n)} & \dots & \hat{y}_m^{(n)} \end{bmatrix} \quad (14)$$

where n is the number of training samples, m is the number of base models, and $\hat{y}_m^{(n)}$ represents the prediction result of the m th sample on the n th base model.

After the segmentation results of each base model are obtained, the CNN metaclassifier is trained with the input features combined with the corresponding real labels, and the final landslide segmentation results are generated by learning the relationship between these features. In this way, the integrated stacking model comprehensively considers the prediction results of FCN, U-Net, and attention U-Net models. It can more effectively utilize the complementarity and correlation between the

models, make full use of the advantages of each base model, and improve the overall segmentation performance.

Train the metaclassifier (CNN) using the new feature matrix X stacking and the real label y

$$\hat{y} = f(X_{\text{stacking}}). \quad (15)$$

In the process of the stacking ensemble learning method, we use the K (K takes 4) folding cross-validation strategy to train the model. During the training of each fold, the parameters of each base classifier are set as follows: the epoch is set to 128, the batch size is set to 4, the learning rate is set to 0.0001, the weight decay factor is set to 0.5, optimizer selects Adam, and loss function selects binary cross-entropy (BCE).

When training the CNN metaclassifier, the input samples are the prediction results of each base classifier, and the real landslide samples are taken as label data. The binary classification task is still involved. Therefore, the epoch is set to 256, the batch size is set to 8, the learning rate is set to 0.0001, and the optimizer selects Adam. The loss function is BCE.

D. Model Evaluation

In this study, Recall, Kappa, MIoU, and F1-score are selected as the evaluation indicators of the models. These indicators are calculated based on the confusion matrix. The details are presented in Table I.

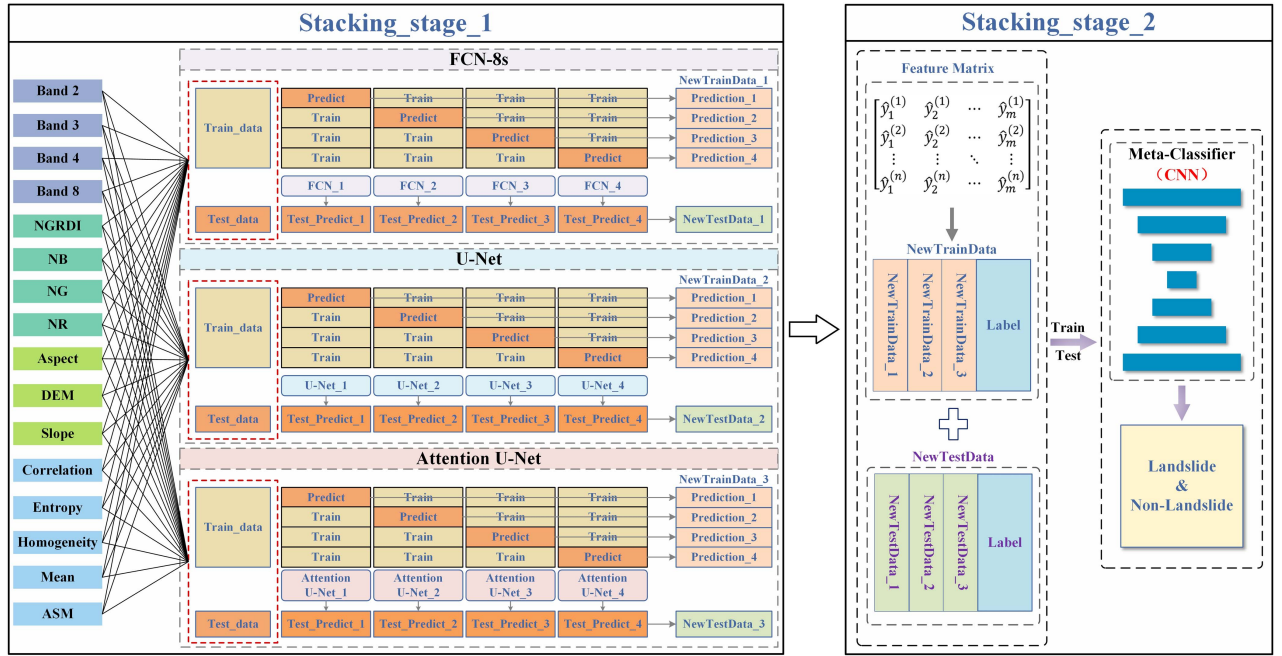


Fig. 8. Heterogeneous ensemble learning model for landslide identification.

TABLE I
EVALUATION INDICATOR

Evaluation indicators	Calculation formula	Express meaning
Recall	$\frac{TP}{TP + FN}$	The ratio of predicted positive samples to the actual positive samples in the test set
Kappa	$P_o = \frac{TP + TN}{TP + TN + FP + FN}$ $P_e = \frac{(TP + FP) \times (TP + FN) + (FN + TN) \times (FP + TN)}{(TP + TN + FP + FN)^2}$ $Kappa = \frac{P_o - P_e}{1 - P_e}$	Consistency between prediction values by the model and actual labels
MIoU	$\frac{TP}{FP + FN + TP}$	The cross ratio between the predicted result and the real label
Precision	$\frac{TP}{TP + FP}$	The ratio of actual positive samples in all identified positive samples in the test set
F1-score	$2 \times \frac{Precision \times Recall}{Precision + Recall}$	Harmonic average of precision and recall
Missed Alarm (MA)	$\frac{FN}{TP + FN}$	The ratio of the negative samples which predicted to be positive samples in the total negative sample

IV. RESULTS AND ANALYSIS

A. Correlation Analysis of Multidimensional Features

In complex geological scenes, it is difficult to accurately identify landslides based on the features of spectral bands in optical remote sensing images. In this article, the multidimensional features of spectral bands, spectral indexes, terrain factors, and texture indexes are integrated to identify landslides. First, 16 data selected of spectral bands, spectral indexes, terrain factors, and texture indexes are analyzed by correlation [22] (see Fig. 9).

It can be seen from the correlation results that the correlation among the 16 data selected is generally low, indicating that 16 data selected can complement the features and be conducive to landslide identification.

B. Landslide Identification of Multidimensional Features

Different combinations of spectral band, spectral index, terrain factor, and texture index have different effects on landslide identification accuracy. In this article, four combinations S1,

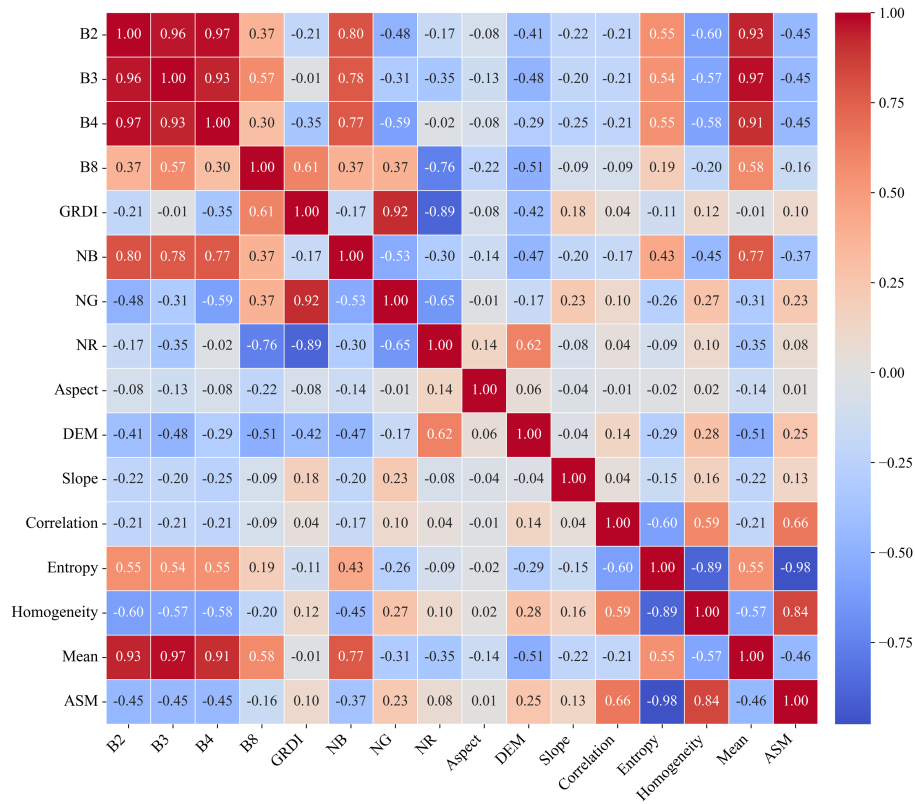


Fig. 9. Correlation among spectral bands, spectral indexes, terrain factors, and texture indexes.

TABLE II
DATA COMBINATION

Scenes	Data combination	Detailed information
S1	spectral band	Band 2, 3, 4 and 8
S2	spectral band + spectral index	Band 2, 3, 4, 8, NR, NG, NB and NGRDI
S3	spectral band + spectral index + terrain factor	Band 2, 3, 4, 8, NR, NG, NB, NGRDI, DEM, slope and aspect
S4	spectral band + spectral index + terrain factor + texture index	Band 2, 3, 4, 8, NR, NG, NB, NGRDI, DEM, slope, aspect, Correlation, Entropy, Homogeneity, Mean and Second Moment

TABLE III
EVALUATION INDICATOR VALUE

Scenes	Recall (%)	Kappa (%)	F1-score (%)	MIoU (%)	MA (%)
S1	54.33	58.16	58.28	70.44	45.67
S2	59.64	60.18	60.30	71.46	40.36
S3	69.17	62.29	62.42	72.55	30.83
S4	69.89	63.68	63.81	73.30	30.11

S2, S3, and S4 are divided, and the specific contents are shown in Table II. In addition, Recall, Kappa, F1-score, MIoU, and MA five indexes are calculated based on a confusion matrix to evaluate the accuracy of landslide identification of different combinations (see Table III).

Landslides under the four scenes are extracted based on the constructed heterogeneous ensemble learning model, landslide

identification results in the test area are compared, and some landslide identification results are randomly selected for visual display (see Fig. 10). The first, second, third, and fourth columns are landslide identification results under the combination of S1, S2, S3, and S4, respectively. The fifth column is the real landslide sample, and the sixth column is the multispectral remote sensing image. The landslide identification performance under S1 is

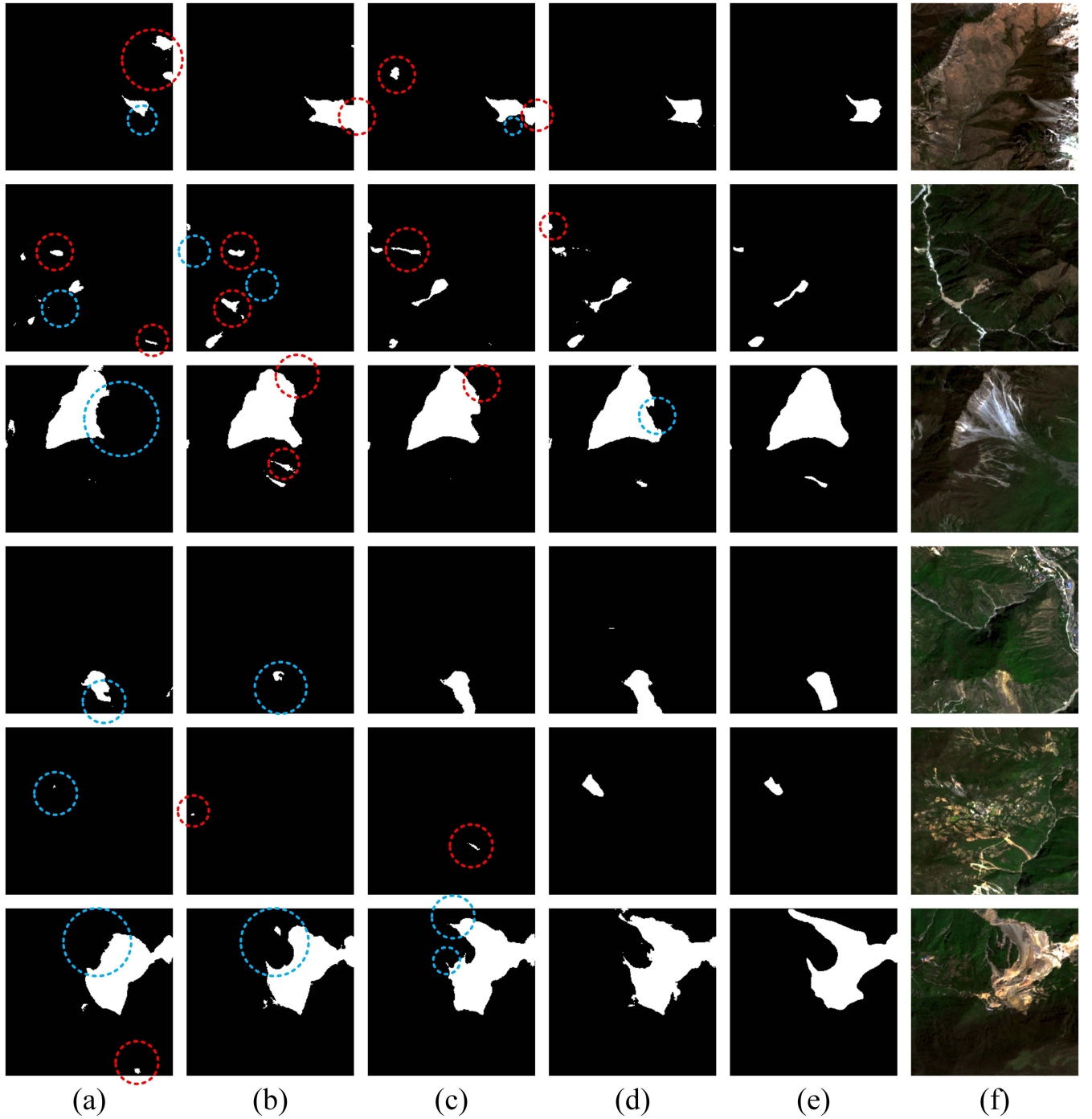


Fig. 10. Landslide recognition results of the constructed heterogeneous ensemble learning. (a) S1. (b) S2. (c) S3. (d) S4. (e) Truth value. (f) Remote sensing image. (Red represents false detection, blue represents missed detection.)

the worst, and the missed and false detection rates are high. The second is S2, the missed detection rate has decreased, but the false detection phenomenon is more. In S3, the missed and false detection rates are decreased compared with S2, but in complex areas, the false detection rate is still high. S4 has the best performance, and the overall identification results are relatively fine in terms of visual effects, and the phenomenon of missed and false detection is less, which is closer to the real situation of landslide samples. The results above reveal that the fusion

multidimensional features of spectral bands, spectral indexes, terrain factors, and texture indexes can improve the accuracy of landslide identification and reduce the missed and false detection rate of landslides in complex scenes.

The quantitative evaluation indexes (Recall, Kappa, F1-score, MIOU, and MA) are further used to analyze the influence of fusion multidimensional features on the model performance. As can be seen from Table III, with the increase of data features (S1 to S4), the performance indicators of landslide recognition are

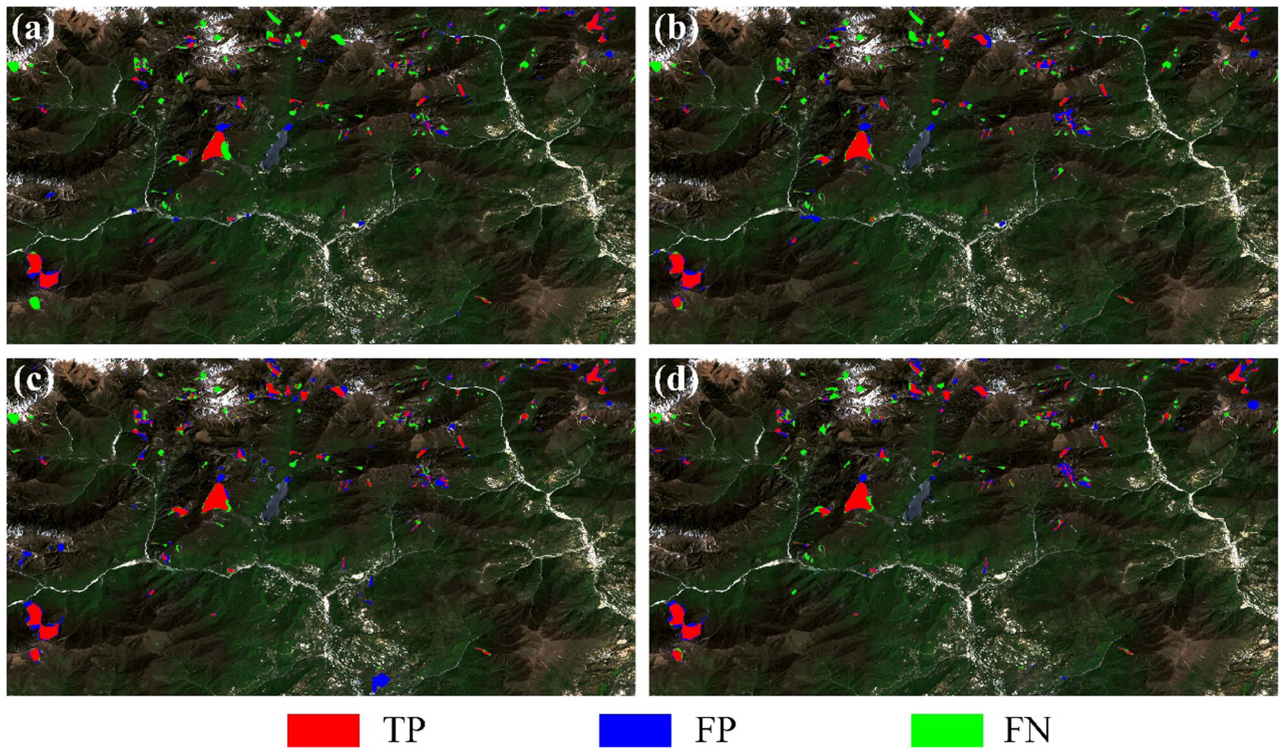


Fig. 11. Landslide identification results under various data combinations in the test area: (a) S1, (b) S2, (c) S3, (d) S4.

generally improved. Recall index reflects the model's ability to identify the real landslide. With the increase of multidimensional features data, Recall will increase successively. Compared with S1, Recall in S4 is increased by 15.56%, which means that the model's ability to identify the real landslide area will be enhanced with the increase of multidimensional data features. The higher the value of Kappa, the better the consistency of prediction. In S4, the Kappa value is the highest. F1-score is a comprehensive evaluation index, which can reveal the overall model extraction performance. With the increase of data features, the F1-score is improved overall. Compared with landslide identification results using only T1 spectral bands, the F1-score of S2, S3, and S4 increased by about 2.02%, 4.14%, and 5.53%, respectively, with the increase of data features. It is indicated that the addition of multidimensional features is helpful to improve the ability and accuracy of landslide identification. MIoU measures the overlap between the predicted landslide area by the model and the actual landslide area. MIoU increases with the increase of data features, indicating that the addition of spectral indexes, terrain factors, and texture index features improves the overlap degree of predicted value and true value, and reduces the rate of missed and false detection.

Recall is significantly improved after the addition of terrain factors (S2 to S3), while MA is significantly decreased. The possible reason is that the topographic factors (such as DEM, slope, and aspect) of the Bailong River Basin have important effects on the formation and distribution of landslides. The increase in topographic factors provides additional information related to surface morphology and geomorphology, which is important for landslide identification. Thus, Recall of the

landslide recognition model is improved, and MA is decreased. In S4, the constructed heterogeneous ensemble learning model can make comprehensive use of various data features such as spectral bands, spectral indexes, terrain factors, and texture indexes to make up for the deficiency of a single data source, so that the constructed model can better understand surface characteristics and terrain changes, and improve the comprehensive ability of landslide recognition.

In addition, the identification results of landslides are superimposed on remote sensing images for visual display (see Fig. 11). In the various combinations, compared with S1, S2, and S3, S4 has more TP pixels, and fewer FP pixels and FN pixels. This phenomenon indicates that T4 combined data can better balance Recall, indicating that more landslides can be correctly identified with multidimensional features, and the identification results are close to the real landslide samples, which proves that multidimensional features can achieve fine identification of landslides from different angles.

According to different data combinations, adding multidimensional features of spectral index, terrain factor, and texture index can learn the landslide characteristics from different angles, effectively distinguish the landslide from the similar complex ground objects around it, and reduce the missed and false detection rates of landslide identification in complex scenes.

C. Comparative Analysis of the Constructed Model

In this article, the constructed heterogeneous ensemble learning model that integrates FCN, U-Net, and attention U-Net is constructed. To verify the effectiveness and performance

superiority of the constructed heterogeneous ensemble learning model, the landslide identification results are compared with those of each base model for the test area. To display the identification results, we randomly choose some areas for visual display (see Fig. 12). In Fig. 12, the first, second, third, and fourth columns are landslide identification results of the FCN model, U-Net model, attention U-Net model, and the constructed heterogeneous ensemble learning model, respectively. The fifth column is real landslide samples, and the sixth column is multi-spectral remote sensing images.

As shown in Fig. 12, it can be seen from the first row that the base model has a high missed rate in landslide detection, while the constructed heterogeneous ensemble learning model reduces the missed rate in landslide detection. In the second and third rows, although the three base models can identify the landslide at the specified location, compared with the real landslide samples, the landslide outline extracted by the three base models is missing more. While the constructed heterogeneous ensemble learning method can accurately identify the landslide, it can also well restore the overall outline information of the landslide, and performs well in the edge details. Its visual effect is superior to any of the base models. In the fourth row, the landslide false detection rate of the base model is high, while the constructed model reduces the false detection rate of the landslide. For example, in the fifth column, most of the right side of the landslide identified by FCN is missing, but the sliver type of landslide below is identified. U-Net can recognize the whole landslide, but its performance in recognizing the boundary contour of the landslide is poor, there is a lack of recognition, and the thin landslide below is not recognized. Attention U-Net also identified most of the landslides and performed well in the boundary outline, but a small part of the landslide is missing above the landslide and the slender landslide below it is not recognized. The landslide identified by the constructed heterogeneous ensemble learning method combines the advantages of the above-mentioned landslide recognition results well, and recognizes the landslide, performs well in the boundary contour, and recognizes the slender landslide below. In row 8 of Fig. 12, most of the landslides identified by FCN are missing, and the complete landslide outline is not available. U-Net and attention U-Net recognize most of the landslide areas, but the overall contour performance is poor. The constructed heterogeneous ensemble learning model recognizes most of the landslides and performs well on the overall contour, which shows the superior performance of the constructed heterogeneous ensemble learning model.

Comparing the landslide identification results of FCN, U-Net, attention U-Net, and the constructed method with real landslide samples, we can find that the constructed model can well combine the landslide identification results and make up for the shortcomings of each base model. The constructed model can make full use of the advantages of each model, to better integrate their prediction results and obtain fine landslide recognition results.

In the test area, landslide identification results are superimposed on remote sensing images for comparison (see Fig. 13). In each scene in Fig. 13, compared with FCN, U-Net, and attention U-Net, the constructed heterogeneous ensemble learning model

has more TP pixels, while FP and FN pixels are less. This phenomenon indicates that the constructed heterogeneous ensemble learning model can realize more correct landslide identification, the identification results are close to the real landslide samples, and the performance is better than that of each base model. It is proved from different angles that the constructed heterogeneous ensemble learning model can realize effective integration and processing of the landslide identification results of each base model.

Recall values of FCN, U-Net, attention U-Net, and the constructed models are 41.67%, 42.78%, 47.83%, and 69.89%, respectively (see Table IV). Recall values of the FCN, U-Net, and attention U-Net models are low, indicating that each base model has a high miss rate when identifying landslides, that is, there are many landslide areas that have not been correctly identified. Recall of the constructed model is significantly increased to a relatively high level, indicating that the constructed heterogeneous ensemble learning model can more effectively identify landslide areas and reduce missed detection. F1-score takes Recall and Precision into consideration. F1-score values of FCN, U-Net, attention U-Net, and the constructed heterogeneous ensemble learning models are 52.60%, 53.05%, 58.83%, and 63.81%, respectively. MIOU represents the intersection ratio between the predicted landslide area by the model and the real landslide area. MIOU values of FCN, U-Net, attention U-Net, and the constructed heterogeneous ensemble learning models are 67.73%, 67.93%, 70.58%, and 73.30%, respectively. Compared with deep learning base classifiers, the constructed heterogeneous ensemble learning demonstrates improvements in MA ranging from 52.17% to 30.11%. F1-score and MIOU values of the constructed heterogeneous ensemble learning model are significantly higher than that of the base model, indicating that the constructed heterogeneous ensemble learning model can position landslide areas more accurately and identify more landslide areas better. The performance of the constructed heterogeneous ensemble learning model in different indicators is relatively stable, which indicates that the integrated multiple models can improve the robustness of the base model and have advantages in overall performance.

V. DISCUSSION

A. Distribution of Multidimensional Data

Kernel density estimation (KDE) is used to estimate the distribution of data, which helps to evaluate the influence of features on the performance and generalization ability of models [40]. If the nuclear density map shows that the nuclear density curves of positive and negative samples have significant separation peaks on some eigenvalues, then these eigenvalues may have good discriminating power for distinguishing positive and negative samples. Based on landslide sample data and spectral bands, spectral indexes, terrain factors, and texture indexes data, this article calculates the landslide samples and the KDE charts of spectral bands, spectral indexes, terrain factors, and texture indexes, and the results are shown in Fig. 14. KDE curves are significantly separated from those of landslide samples, indicating that the characteristics of spectral bands, spectral indexes,

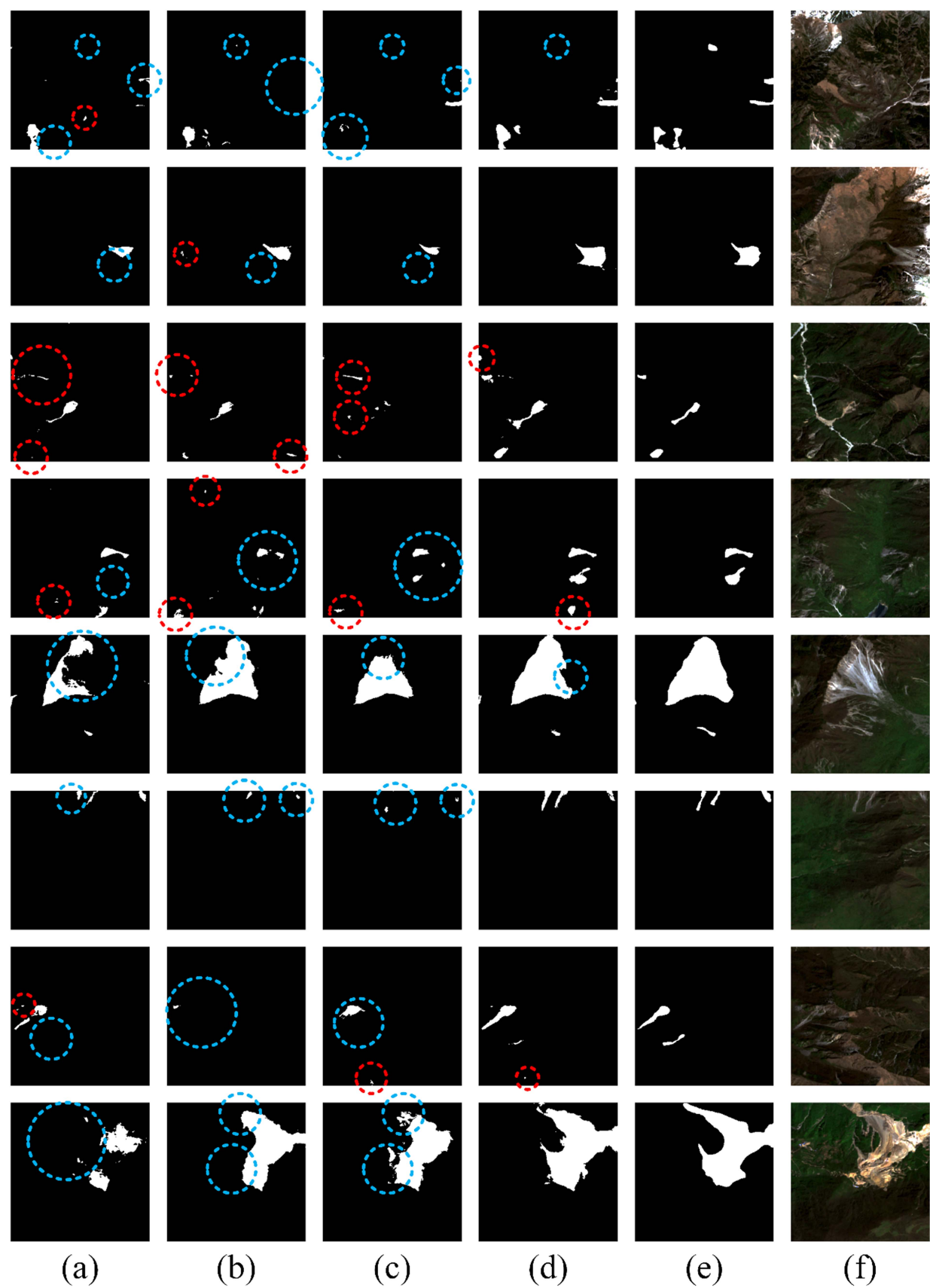


Fig. 12. Landslide identification results of different models. (a) FCN, (b) U-Net. (c) Attention U-Net. (d) Constructed heterogeneous ensemble learning model. (e) Truth value. (f) Remote sensing image. (Red represents false detection and blue represents missed detection).

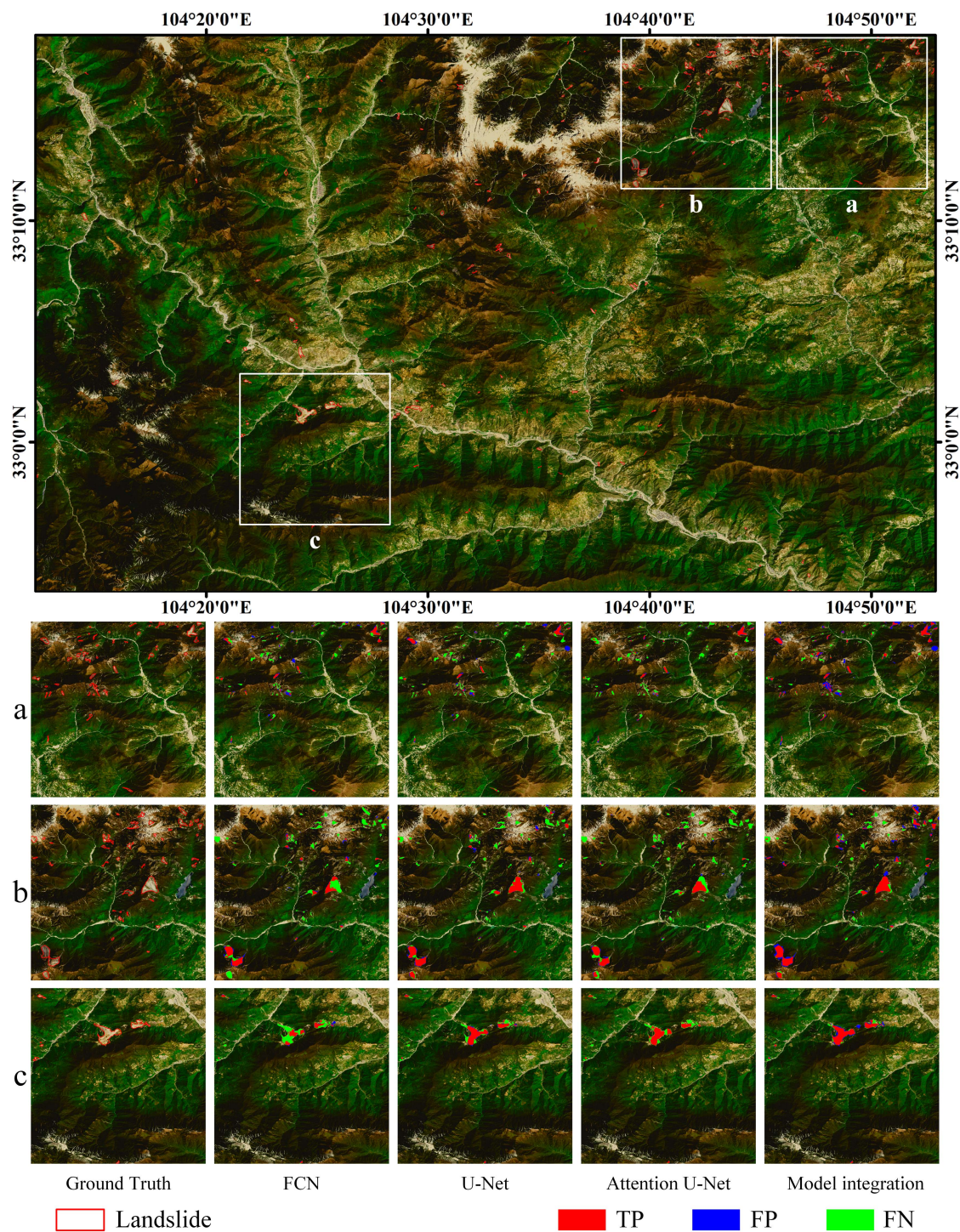


Fig. 13. TP, FN, and FP graphs of landslide identification results in the test area: (a) region a, (b) region b, (c) region c.

TABLE IV
QUANTITATIVE EVALUATION INDEXES OF LANDSLIDE IDENTIFICATION RESULTS

Models	Recall (%)	F1-score(%)	MIoU(%)	Kappa(%)	MA (%)
FCN	41.67	52.60	67.73	52.49	52.17
U-Net	42.78	53.05	67.93	52.94	58.33
Attention U-Net	47.83	58.53	70.58	58.43	57.22
Constructed model	69.89	63.81	73.30	63.64	30.11

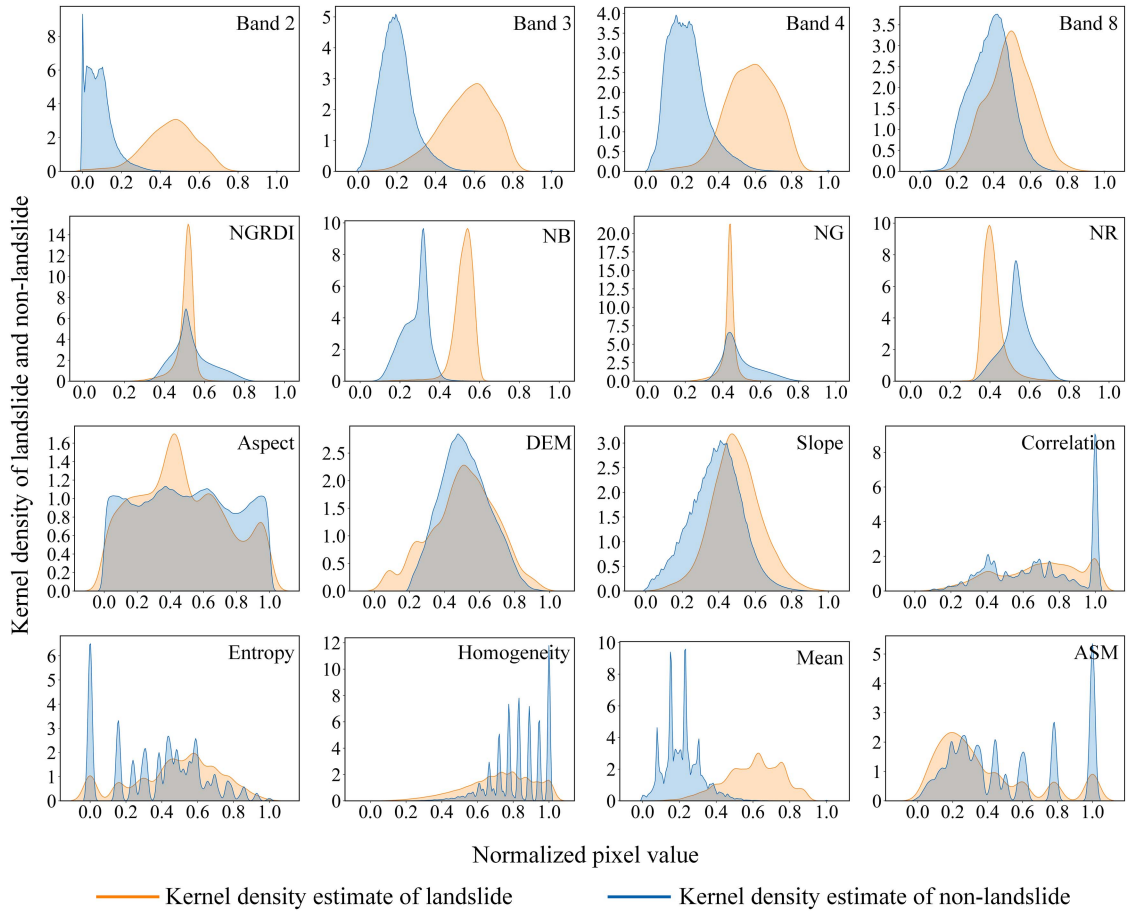


Fig. 14. Nuclear density curves of positive samples of landslide and spectral bands, spectral indexes, terrain factors, and texture indexes (horizontal coordinate is the normalized pixel value of each factor).

terrain factors and texture indexes can provide rich features for the landslide recognition, and improve the generalization ability of the model [41].

We further count the pixel values of each index based on a single landslide slope profile, and the results are shown in Fig. 15. Fig. 15 shows that the pixel values of each index in the same landslide profile have obvious differences, which is conducive to landslide recognition. Multidimensional features can provide rich information, and thus reduce the missed and false detection rates of landslide identification.

B. Model Interpretability

Partial dependence plot (PDP) is a common machine learning interpretability tool used to analyze the relationship between features in a model and the predicted results [42]. In this article, PDP curves are used to understand the influence of features on landslide prediction and identify important features. The PDP curves of the base model are very close, and the heterogeneous ensemble model integrates the prediction results of the base model, so we only visualize the PDP curves of the U-Net base model for analysis (see Fig. 16). The change trends of PDP of spectral bands, spectral indexes, terrain factors, and texture indexes are obvious, indicating that the features of spectral bands,

spectral indexes, terrain factors, and texture indexes have a great impact on the landslide prediction results of the model, and these data features selected are very important, which further indicates that these indexes selected are reasonable and contribute greatly to the training model.

C. Analysis of the Constructed Ensemble Learning Model

FCN, U-Net, and attention U-Net have different characteristics. FCN is suitable for processing features at different scales, U-Net is suitable for classification at the pixel level, and attention U-Net introduces an attention mechanism to help focus on important feature areas. These deep learning models have different learning capabilities, and each base model may perform better in some cases and worse in others. In addition, there may be some overfitting in each base model [29], [43]. The constructed model can effectively leverage the diversity between different models by using a CNN to combine multiple base classifiers, such as FCN, U-Net, and attention U-Net. By synthesizing the prediction results of multiple models, the shortcomings of each base model can be made up [32], [44]. By combining the predictions of base models in a constructed heterogeneous ensemble learning model, the risk of error propagation can be reduced. The metaclassifier can learn

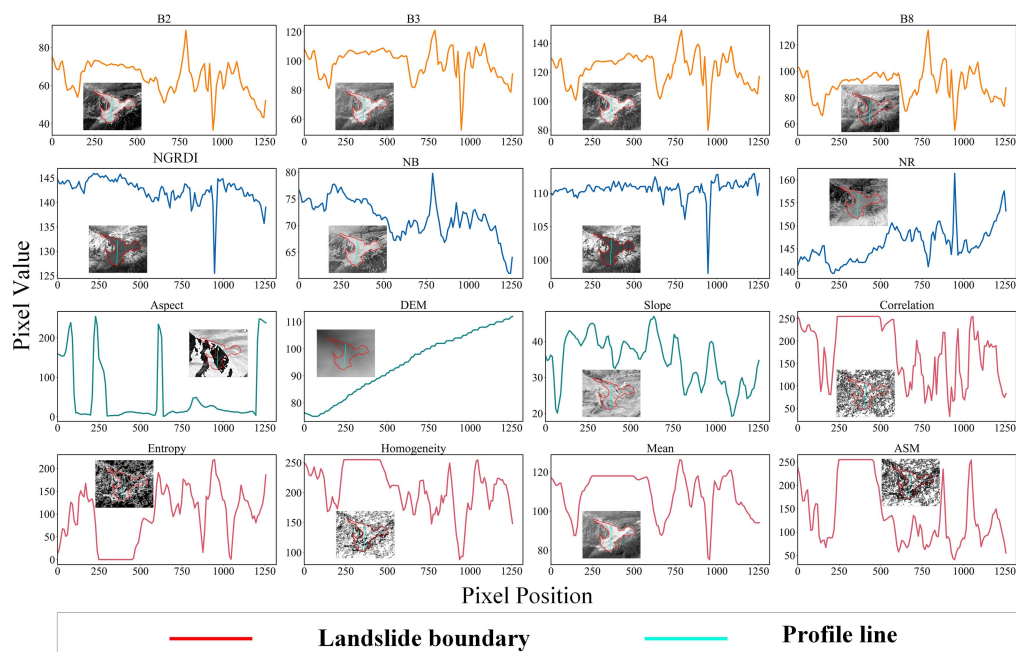


Fig. 15. Pixel value distribution of each index based on a single landslide slope profile.

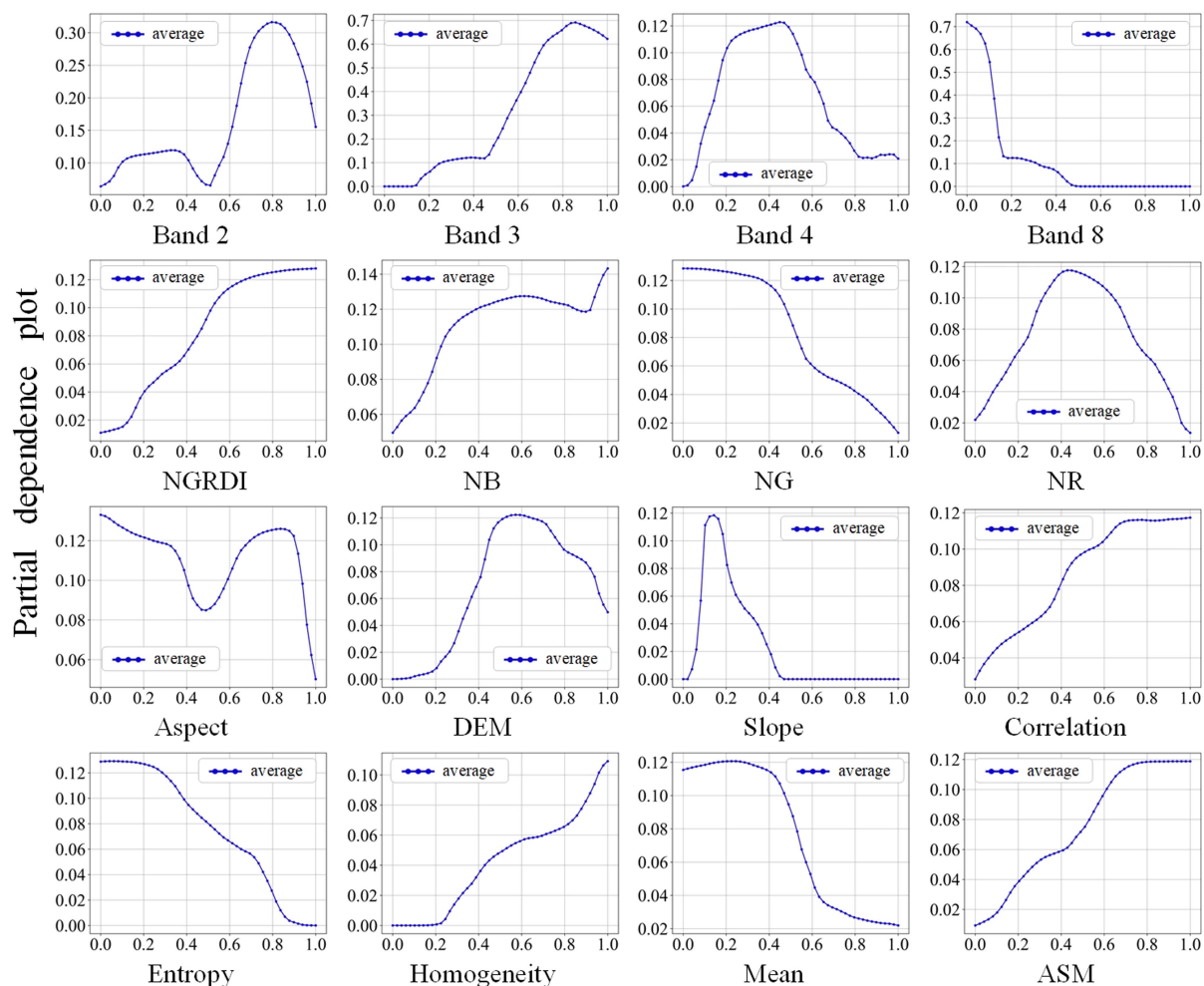


Fig. 16. PDP curves of spectral bands, spectral indexes, terrain factors, and texture indexes.

the relationship and weight between different base classifiers and combine the prediction results of each base model [22], [31]. Therefore, the constructed model can make full use of the advantages of each base model, to better integrate their prediction results, and improve the performance of the base model.

D. Limitations and Prospects

Although the proposed research framework reduces the missed and false detection rate of landslides, it still has some limitations. On the one hand, the spectral index, terrain factors, and texture index constructed in this study are only selected partly according to the existing research conclusions, without optimization selection analysis [22]. On the other hand, this article only constructs the landslide detection heterogeneous ensemble learning model based on the stacking framework and does not compare and analyze other ensemble learning model frameworks [17], [32]. Due to the length of the article, this research framework has not been extended to other scenarios for application, and the subsequent research will be extended to other complex scenarios for experimental analysis.

VI. CONCLUSION

This study integrates spectral indexes, terrain factors, and texture indexes, and develops a heterogeneous ensemble learning method based on FCN, U-Net, and attention U-Net deep learning base classifiers for landslide detection. Experimental results demonstrate that integrating spectral indexes, terrain factors and texture indexes can enhance the characteristics of landslide, MA is 15.56% higher than that of using only spectral bands. The proposed heterogeneous ensemble learning method can make full use of multidimensional features and effectively improves the predictive ability of the FCN, U-Net, and attention U-Net base classifiers, and MA is more than 20% higher than that of the base classifiers. Therefore, integrating spectral indexes, terrain factors, and texture indexes of multidimensional features, using the ensemble learning method can reduce the missed detection and false detection of landslides in complex scenes. Visual evaluation and quantitative indicators demonstrate the feasibility and advantages of the proposed new landslide detection framework.

The depth model in the proposed landslide detection framework is trained on the dataset of complex scenes, so it can be used for landslide mapping in other areas outside the study area, so it has a wide range of potential applications. However, the multidimensional feature data selected in this article is not optimized for selection and analysis, and only the ensemble learning model of landslide detection is constructed based on the stacking framework. In the future, we make full use of multimodal data and introduce more advanced depth models for landslide detection to further reduce missed and false detection of landslides.

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