

Research on an Object-Oriented Intelligent Extraction Method For Landslide

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ABSTRACT

Landslides are the most important type of geological disaster development in China. Heavy rainfall and earthquakes often cause mass landslides. Rapid extraction of postdisaster landslide information is an important method for realizing scientific and efficient emergency investigations and can provide a key basis for disaster assessment and emergency response decision-making. Rapid extraction of postdisaster landslide information is an important method for realizing scientific and efficient emergency investigations and can provide a key basis for disaster assessment and emergency response decision-making. Using Fujian as an example, based on basic topography, geology and other data, the multiscale segmentation method is used for image segmentation, and different features are selected. The applicability of the rule-based extraction method and support vector machine, random forest and other machine learning methods. The applicability of the rule-based extraction method and support vector machine, random forest and other machine learning methods in small-scale landslide extraction in the study area is compared. The results showed that the extraction accuracy of the rule-based extraction method was 90.86%, the extraction accuracy of the support vector machine was 65.95%, and the extraction accuracy of the random forest was 93.43%. A comparison of the three methods revealed that the random forest method was most suitable for landslide extraction in the study area.

KEYWORDS

High-Scoring Data; Multiscale Segmentation; Rule-Based; Machine Learning; Landslide Extraction; "5.27" Landslide In Wuping County

1. INTRODUCTION

The use of remote sensing technology for landslide identification has gone through two major stages: visual interpretation and computer interpretation[1-4]. In the stage of visual interpretation, it has the advantages of low cost, direct and convenient nature, a low rate of omission and misjudgment, and generally high accuracy; however, it is more dependent on the knowledge and experience of experts, which is time-consuming and laborious, and it is difficult to meet the demand for rapid interpretation of landslides from a wide range of remotely sensed images[5-8] Computerized interpretation methods include image element-based, object-oriented and deep learning methods.

Most landslide extraction methods based on image elements process all feature information at the same resolution; however, these methods cannot fully utilize the rich structural and textural information in images, resulting in wasted information, and the extraction results exhibit the "pretzel phenomenon" and spatial discontinuity.[9] Object-Oriented Information Extraction (OOIE) The object-oriented information extraction method takes a single object as the processing unit; this method can simulate the cognitive process of the human brain to a certain extent and classifies objects with

the same characteristics into the same category by taking into account the spectral, textural, shape and contextual information of the features so that the "salt and pepper phenomenon" can be effectively avoided and the recognition accuracy can be improved.[8] Many scholars at home and abroad have conducted research on this method. Many scholars at home and abroad have explored this method; for example, Martha et al. used object-oriented analysis technology and proposed a landslide identification method based on multiple feature combinations according to the spectral and topographic features of segmented objects. Similarly, Han et al. used object-oriented analysis technology and proposed a landslide identification method based on multiple feature combinations.[10] Han et al. used the object-oriented classification method to extract landslide information from Gaofen-1 and Sentinel-2 data and determined the destructiveness of landslides by comparing the results of object-oriented classification before and after landslides[11]. Wang and Ping et al. used an object-oriented approach to extract landslide information from the earthquake-affected area of Lushan County city, Ya'an city, in the 2013-04-20 earthquake and analyzed the extracted results by comparing them with the results of manual interpretation[12]. Chenhui Li et al. used GF-6 remote sensing images as a data source and adopted an object-oriented classification method to identify landslides in the Panda Sea area of Jiuzhaigou[13]. Among the object-oriented classification methods, rule-based classification methods are widely used because of their simplicity, convenience and strong interpretability, and commonly used rule-based classification methods include threshold classification and fuzzy classification; machine learning classification methods are fast and easy to use because of their high speed and high accuracy.[14] Machine learning classification methods are widely used because of their fast speed and strong fit, and commonly used machine learning classification methods include support vector machines, random forests, and neural networks.[15] The commonly used machine learning classification methods include support vector machines, random forests, neural networks, etc. When scholars adopt object-oriented methods for landslide extraction, they mostly use a single classification method without considering whether the selected method is applicable to the geological profile of the study area.

In this paper, on the basis of in-depth analysis of landslide disaster characteristics and feature correlation, different object-oriented classification methods are used to extract the information of group-emergent granite landslides in the study area, and the objects are generated by a multiscale segmentation algorithm. The extraction accuracy of rule-based classification methods is compared with that of support vector machine (SVM) and random forest methods in machine learning classification methods, and the applicability of the three methods in the extraction of landslides in the study area is explored.

2. OVERVIEW OF THE STUDY AREA AND DATA SOURCES

In this paper, the natural villages of Zhonghe and Zhongdi in Shifang Township, Wuping County, Longyan city, Fujian Province, and along the highway were selected as the study area; the geographic coordinates ranged from 25°0'N to 25°1'N and 116°8'E to 116°12'E; the area of approximately 15.5 km²; the elevation ranged from 258 to 533 m; and the slope ranged from 0 to 43°. As shown in the figure, the topography of the area is dominated by mainly low mountainous and hilly landforms, with natural slopes on both sides of the valleys having slopes of approximately 15-53°. The mountains and valley basins are oriented in a northeast direction, and the overall terrain is in the form of two high sides and a low center. In addition to the subtropical oceanic monsoon climate, rain and heat, rainfall is relatively concentrated, the average annual temperature is 19.6°C, and the average annual precipitation is 1800 mm. In the area exposed by the Yanshan period granite strata, the surface layer is covered with varying thicknesses of weathering residual material and a loose structure. The development of landslides in this area is influenced by the thickness of the residual sediment and root soil layer. The scale is mostly less than 10,000 m³, and the thickness is less than 2 m. Rainfall seepage damage is the main triggering factor. 2022, from May 26th to 27th, under the influence of sustained heavy rainfall, a mass geologic disaster occurred in the Wuping County area, and a superficial

landslide occurred in Zhonghe village of Shifang town, the surface area of which reached 1,992,596 m², while the total volume of landslides reached 993,305 m³, with a total volume of 1,993,305 m³. 993305 m³, mainly small landslides with thicknesses between 1~2 m. The material composition of the landslide is mainly powdery clay, containing gravel and rounded gravel.

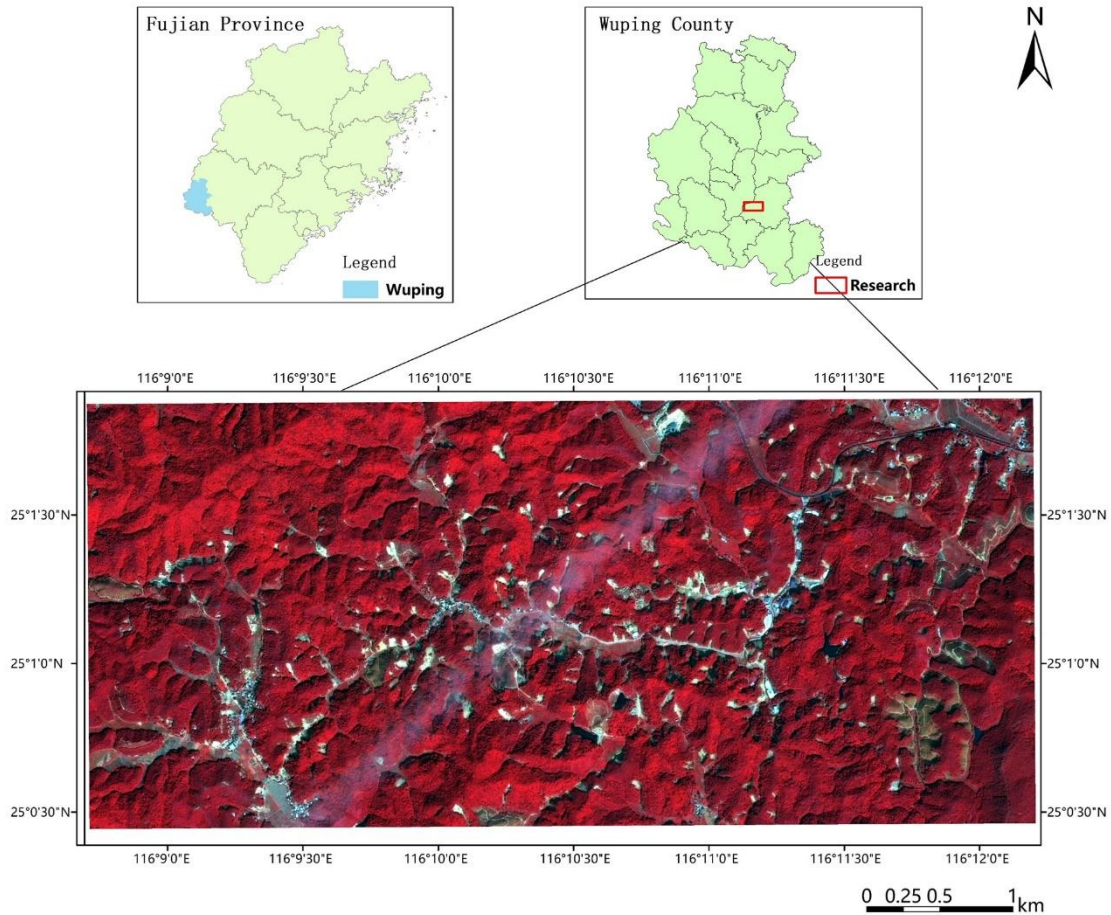


Fig. 1 Overview of the study area

In this paper, GF-1 data were obtained on October 25, 2022, with a spatial resolution of 8 m and a spectral range of 0.45~0.89 μm in the multispectral band and a spatial resolution of 2 m and a spectral range of 0.45~0.9 μm in the panchromatic band. The digital elevation model (DEM) data are derived from 1:10,000 scale topographic maps vectorized to raster.

Tab. 1 GF-1 band information

Band name	Spectral range/ μm	Spatial resolution/m
Band 1 Blue	0.45~0.52	8
Band2 Green	0.52~0.59	8
Band3 Red	0.63~0.69	8
Band4 NIR	0.77~0.89	8
Band Pan	0.45~0.9	2

3. RESEARCH METHODOLOGY

3.1. Technical routes

In this paper, we use GF-1 data as the data source and carry out preprocessing steps, such as radiometric calibration, atmospheric correction, ortho-correction and image fusion in ENVI software; vectorize the topographic map in ArcGIS software; convert it to a DEM; and overlay the preprocessed

high-resolution image with the DEM data. Then, based on the eCognition platform, we carry out multiscale segmentation of the overlaid image; construct a recognition rule set containing spectral, textural, geometric and topographic features; and use the rule-based classification method to recognize landslides to obtain result 1. We establish different categories, select feature samples, use the support vector machine in the cart classifier to train samples; use the trained samples for landslide recognition to obtain result 2; use the above samples; use the random forest in the cart classifier to train samples; use the trained samples for landslide recognition to obtain result 2; use the above samples; use the random forest in the cart classifier to train samples; and use the trained samples to obtain result 2. The trained samples are used for landslide identification to obtain result 3. Finally, the results are compared with the visual interpretation results for accuracy evaluation. The main method flow is shown in Figure 2.

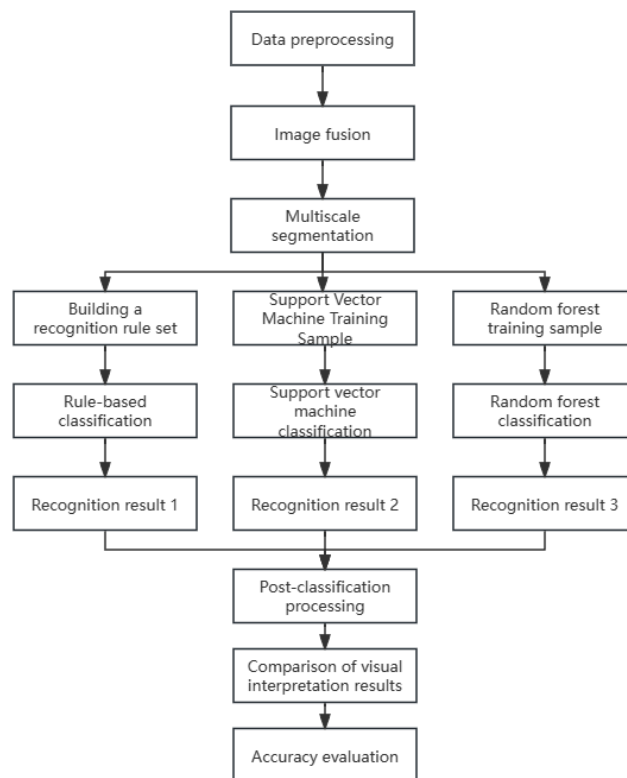


Fig. 2 Technical flowchart

3.2. Multiscale segmentation

Multiscale segmentation is a region merging technique in the bottom-up approach. This approach takes a single image object as the starting point and calculates the heterogeneity index by its neighboring image objects, which include spectral and shape features. In addition, if the minimum growth of heterogeneity is met, the object needs to be merged; the merged "new object" is used as the basis for repeating the above process (i.e., the iterative method) until the set segmentation parameters are met. If the minimum growth requirement of heterogeneity is met, then the data need to be merged; based on the merged "new object", the above process (i.e., iterative method) is repeated until the set segmentation parameters are met, and finally, the irregular image object is obtained.[19] The final result is an irregular image object.

3.3. Rule-based classification methods

Rule-based methods specify the class to which a feature belongs by specifying threshold values for different features. The rule-based classification methods used in this paper include threshold

classification, affiliation classification, and threshold classification. The latter is a hard classifier algorithm whose purpose is to obtain the threshold value according to the distribution of various features, which is a kind of "true" or "false" logical decision. This is a kind of "true" and "false" logical decision, and the object that meets the conditions of this threshold is completely categorized into a certain class; otherwise, it is the other class.[19] An object that meets this threshold is completely categorized into a certain class; otherwise, it is classified into another class.

The affiliation classification, also known as fuzzy logic classification (fuzzy logic classification), expresses the relative degree to which an element belongs to a set, i.e., any element x in a set U has a number $A(x) \in [0, 1]$ corresponding to it, and $A(x)$ is called the degree of x 's affiliation with A . The closer the degree of affiliation $A(x)$ is to 1, the higher the degree to which x 's belongs to A is, and the closer $A(x)$ is to A to a lesser extent[19]. Similarly, the closer $A(x)$ is to 1, the greater the degree to which x belongs to A is.

3.4. Machine Learning Classification Methods

The machine learning method is a data-driven approach in which various types of relevant features are extracted from the data used for training and the trained classifier is used to recognize landslides. This article uses two methods: support vector machine (SVM) and random forest (RF) methods.

A support vector machine (SVM), a new type of machine learning algorithm based on statistical theory, is a type of supervised learning classification method that classifies data in a Binary classification form. A generalized linear classifier divides the samples by finding the optimal hyperplane to maximize the spacing of the samples, with Decision Boundary being the maximum margin hyperplane for solving the learned samples[21]. The decision boundary is the maximum margin hyperplane solved for the learned samples.

The random forest (RF) algorithm is an integrated learning algorithm. The core idea is to integrate multiple weak classifiers to obtain an integrated classifier with better prediction. The random forest algorithm uses the bagging algorithm, i.e., each time there is a put back to take out n training samples from the training set, to form a new training set. The new training set is used to train the M submodels. For the classification problem, a voting method is used, and the classification category of the submodel with the most votes is the final category; for the regression problem, a simple averaging method is used to obtain the predicted values[22].

4. LANDSLIDE CHARACTERIZATION

On the high-resolution remote sensing image, the difference in color between the newly occurring landslide and surrounding features is large, the landslide features are represented by a bright-toned plate, and the vegetation and water bodies and other features are represented by a dark-toned plate; however, in the study area, in addition to the landslide, there are also roads, vegetation, and buildings as well as bare ground; relying on only a single spectral information cannot accurately distinguish between the landslide area and the other features of the same hue, and it is difficult to obtain a higher-precision classification result. Additionally, the recognition accuracy can be improved by adding more landslide features or excluding the interference of the remaining features.

4.1. Spectral characterization

The spectrum of fresh landslides has strong reflectivity, and the surface is exposed to loose rock and soil bodies, which are generally light and grayish-white in tone and have high brightness values compared to those of the surrounding features. The vegetation in the landslide occurrence area is completely destroyed and has a low vegetation index, which is reflected by the ratio vegetation index

(RVI), which strengthens the distinction between vegetated and nonvegetated areas and can be removed by spectral features.

$$RVI = \frac{NIR}{R} \quad (4-1)$$

where NIR is the reflectance in the near-infrared band and R is the reflectance in the red band.

4.2. Shape characteristics

Landslides are generally composed of landslides with gentle slopes and steep landslide walls, with no fixed shape. Landslides often occur as horseshoes, skips, tongues, ox-horns, benches, crescents, ellipses, inverted pears, and so on.[23] Landslides are often horseshoe shaped, tongue shaped, cow horn shaped, bench shaped, crescent shaped, oval shaped, inverted pear shaped, etc., whereas houses and other man-made buildings are generally regular shaped, and roads are shaped like long strips. By means of morphological features, it is possible to remove the interference of regularly shaped features such as houses, roads or other artificial structures.

4.3. Terrain features

A landslide is a rock and soil body dislodged from a slope and usually occurs on a steeper slope. In general, the slope is within a certain range, the slope is between 15° and 45°, and the slope shape of the bottom of the steep, middle, slow, and upper steep region is the upper part of the ring for favorable terrain for landslide spawning.[22] This slope is favorable terrain for landslide breeding.

4.4. Texture characterization

Because of the spectral similarities between landslides and a variety of features, texture features can be utilized to eliminate the effects of spectrally similar characteristics to improve recognition accuracy. The shape of the landslide wall is represented by a curved arc in the image, which distinguishes the landslide well from neighboring features in terms of visual roughness, which can be reflected by textural information[22].

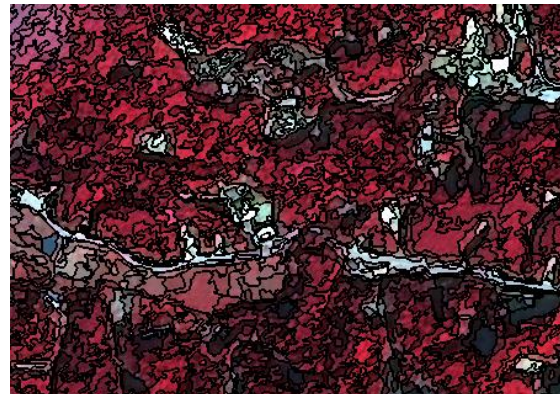
5. EXTRACTION OF LANDSLIDE INFORMATION IN THE STUDY AREA

5.1. Image segmentation

The purpose of image segmentation is to distinguish the target feature from the surrounding features and improve the target feature extraction accuracy. According to the field survey report, the landslides in the study area are mainly distributed on both sides of the road and are small in scale; therefore, when segmenting the images, the main evaluation criterion is to separate the landslides from the road. Image segmentation is carried out by the multiscale segmentation method, which greatly depends on the three parameter settings of the scale parameter, shape factor and tightness parameter. The vegetation coverage in the study area is high, and the image is displayed in standard false colors to reduce the interference of vegetation during segmentation. Based on the results of previous research, the shape factor was determined to be 0.2, the tightness parameter was determined to be 0.5, and the scale parameter was set to 80 as the starting size and 10 as the step size. A total of scale parameters were set to 80 as the starting size, 10 as the step size, and 10 as the step size. With 10 as the step size and a total of 80, 90, 100, 110, and 120, the results for the different segmentation scales are as follows:



(a) Original map



(b) Scale 80



(c) Scale 90



(d) Scale 100



(e) Scale 110



(f) Scale 120

Fig. 3 Comparison of results at different segmentation scales

When the split scale is 110, the landslide is separated from the road, the landslide integrity is better, and the split scale is finalized as 110.

5.2. Rule-based landslide extraction process

5.2.1. Removal of disturbance features

To reduce the interference of other features on landslide extraction and analyze the different features to distinguish different features from landslides, the interfering features were removed before the landslides. Compared with landslides, vegetation has low brightness, a high vegetation index, and a low mean value of vegetation in the red band; roads are mostly shaped like long strips with a large aspect ratio; and buildings are generally distributed in flat areas with regular shapes, which show special textures in the image. Combining the above features, the spectral features include the band

mean and brightness, the topographic features include the slope, the geometric features include the aspect ratio and shape index, and the texture features include the grayscale covariance matrix contrast, which ultimately results in the following feature rule set:

Tab. 2 Feature rule table

split scale	parameterization	Image Characteristics	Withdrawal Rules
110	Shape factor: 0.2 Firmness parameter: 0.5	plant cover	RVI: 2.5-3 Brightness: 850-1300 R-band average: 800-1200
		roads	Aspect ratio >3 Shape Index >4 Slope <15
		building	Grayscale covariance matrix homogeneity > 0.068

5.2.2. Landslide Extraction

After the disturbance features are removed, the landslides need to be extracted from the remaining bare ground; the landslides have fresh rock and soil bodies on the surface with larger brightness values than the bare ground; the landslides are concentrated in high and steep valleys; their topographic factor slopes are also larger; the shapes of the landslides are not unique; the texture features of the landslides are rougher than those of the bare ground; and by combining the above features, the final selection of the landslide extraction indices is the brightness, the slope, the shape index, and the grayscale covariance matrix contrast, the specific rules and thresholds are shown in the following table.

Tab. 3 Landslide feature rule table

split scale	parameterization	Image Characteristics	Withdrawal Rules
110	Shape factor: 0.2 Firmness parameter: 0.5	landslides	Brightness > 2000 Slope >20 Shape index: 1.1-2.5 Grayscale symbiotic matrix contrast >1500

After importing the corresponding data, image segmentation is carried out, different feature classes are established after segmentation. Based on the above feature rule set, the feature thresholds of the corresponding features are set, the neighboring similar features are merged after execution, and the following classification results are finally obtained:

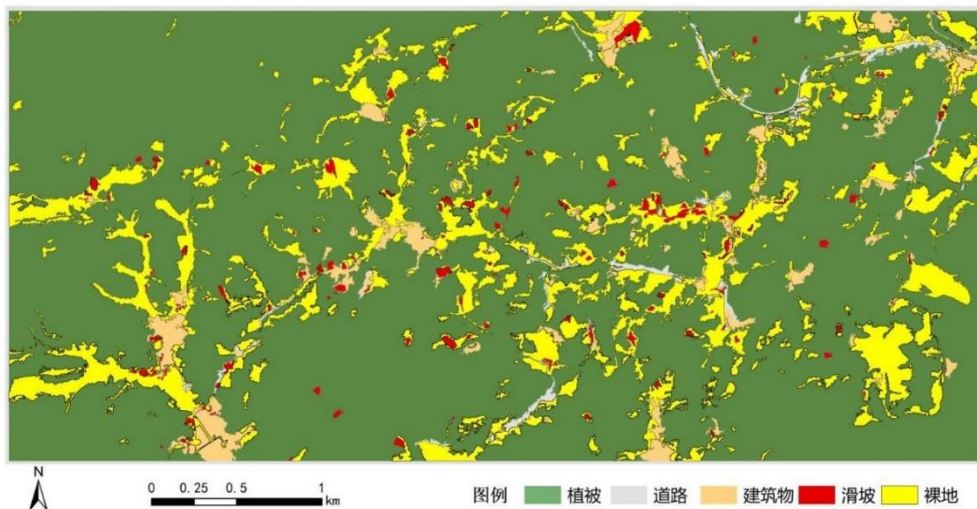


Fig. 4 Rule-based extraction results

A total of 119 landslides were extracted via rule-based landslide extraction, for a total area of 124276 m², a minimum area of 96 m², and a maximum area of 9740 m².

5.3. Machine learning-based landslide extraction process

5.3.1. Support vector machine-based landslide extraction

After the remote sensing image and terrain data are imported, the image is segmented using the multiscale segmentation algorithm, and the categories of vegetation, roads, buildings, landslides, and bare ground are established after segmentation; 100 samples of vegetation; 20 samples of roads; 30 samples of buildings; 50 samples of landslides; and 50 samples of bare ground. The features of the samples are the same as those selected in the rule set, and the spectral features are selected to be the luminance, the mean of the waveband and ratio vegetation index (RVI) for spectral features, aspect ratio and shape index for geometric features, slope for topographic features, GLCM homogeneity and contrast for texture features. After the samples and features are determined, the classifier training algorithm selects the support vector machine for training and is applied to the whole study area after training. Based on the above process used to derive the classification results, the neighboring similar features in the classification results are merged, and the final support vector machine extraction is as follows:

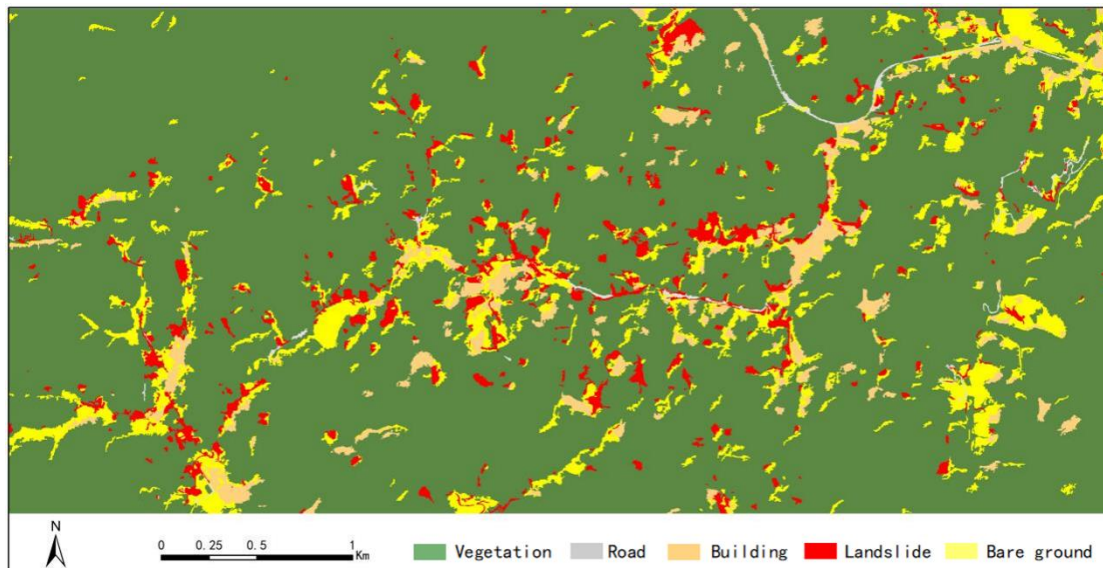


Fig. 5 Support Vector Machine Extraction Results

The support vector machine method was used to extract 436 landslides with a total area of 535, 280 m², a minimum area of 36 m², and a maximum area of 29, 968 m².

5.3.2. Random Forest-based Landslide Extraction

The sample selection of the random forest method is the same as that for feature and support vector machine use. The random forest algorithm is selected when choosing the classifier training samples, and after training, it is applied to the whole study area. After obtaining the results, the preliminary results are merged with the neighboring features of the same kind, and the final results of the random forest extraction are as follows:

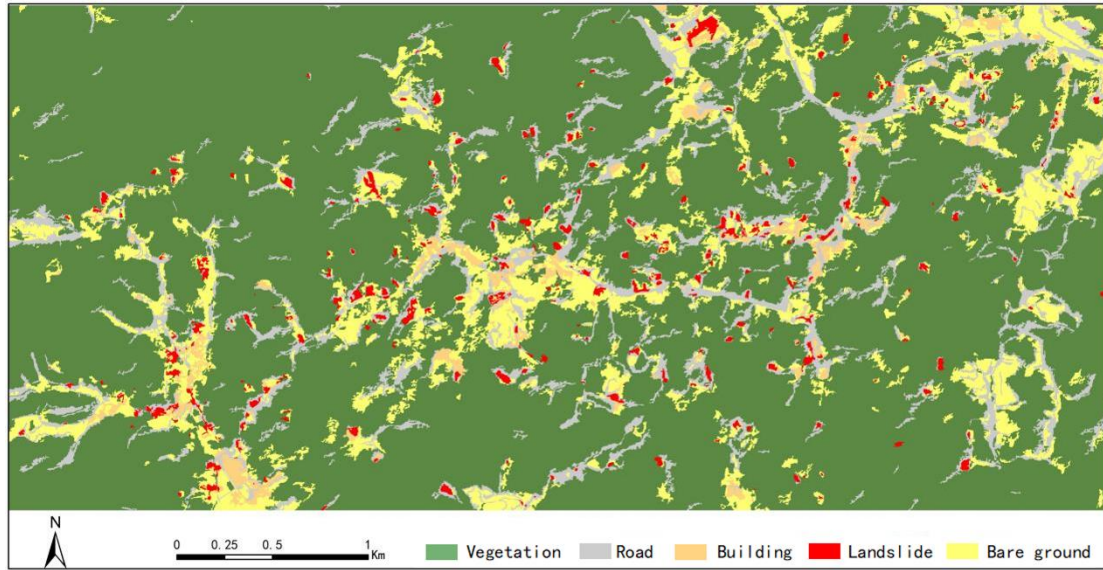


Fig. 6 Random forest extraction results

The random forest method extracted 328 landslides with an extracted area of 210044 m², a minimum area of 16 m² and a maximum area of 9852 m².

5.4. Classification accuracy evaluation

To reflect the accuracy of the classification results more intuitively, the experimental group data obtained from landslide identification were compared with the control group data obtained from visual interpretation, and three basic indices were used for comprehensive evaluation: 1) true area (TA), which refers to the area identified as a landslide based on the method in the text, and the area verified as a landslide based on visual interpretation; 2) omitted area (OA), which is the area verified as a landslide based on the method in the text but the area identified as a nonlandslide; and 3) false area (FA), which is the area identified as a nonlandslide based on the method in the text. The omitted area (OA) is visually interpreted and verified as a landslide but is recognized as a nonlandslide by the method in the text. 3) The false area (FA) is recognized as a nonlandslide based on the method in the text but is verified as a nonlandslide by visual interpretation.

The accuracy (Acc) represents the proportion of the correctly identified landslide area to the total area.

$$Acc = \frac{TA}{TA + OA + FA} \quad (5-1)$$

The precision (Pre) represents the proportion of the correctly identified landslide area to the total identified area.

$$Pre = \frac{TA}{TA + FA} \quad (5-2)$$

Recall, which indicates the proportion of correctly identified landslide areas to all correctly classified areas.

$$Recall = \frac{TA}{TA + OA} \quad (5-3)$$

The extraction results of the above three methods were exported to ArcGIS software, the area of the extracted landslides was determined using the "Statistics" function, and the area statistics and accuracy comparisons are shown in the table below:

Tab. 4 Accuracy evaluation statistics table

extraction methods	Actual extraction area/m ²	Correct extraction area/m ²	Error extraction area/m ²	Missed extraction area/m ²	correct rate	accurate	recall rate
rules-based	124276	112912	11364	47560	72.32%	90.86%	70.36%
support vector machine	305280	201320	103960	3004	65.30%	65.95%	98.53%
random forest	210044	196236	13808	12674	94.31%	93.43%	93.93%

6. CONCLUSION

The article takes Zhonghe and Zhongdi natural villages and areas along the highway in Shifang town, Wuping County, Fujian Province, as the study area and adopts an object-oriented approach to establish a feature set by utilizing the characteristics of landslides in terms of spectral, topographic, geometric, and textural features; adopts a rule-based classification method to extract landslides; selects different feature samples for training; conducts landslide extraction using support vector machines and random forest methods; and compares the results of the three methods with the visual interpretation extraction results to explore the applicability of the three methods in small-scale landslide extraction in the study area. The following main points of understanding are obtained:

- (1) Based on the analysis of landslide hazard characteristics and feature correlation, the article concludes the following: landslides have high brightness values and low vegetation indices; landslide geometry is irregular; landslides usually occur on steeper slopes; and landslides have greater visual roughness, i.e., textural features are rougher than those of the surrounding features.
- (2) The extraction accuracy of the rule-based landslide model is 90.86%, the extraction accuracy of the support vector machine method is 65.95%, and the extraction accuracy of the random forest method is 93.43%, which indicates that among the three methods, the random forest method is most suitable for the extraction of group-emergent granite landslides in the study area.
- (3) Comparing the three extraction methods, the rule-based extraction method extracts a small number of landslides due to the difficulty in accurately determining the feature thresholds; the missed landslides are mainly small landslides that do not satisfy the feature thresholds, but the accuracy of the extracted landslides is high. The support vector machine method extracts the most landslides, omits fewer landslides, and has a high recall rate; moreover, the incorrectly extracted landslides are mainly bare ground and some bright buildings.

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