Postprint: A Multi-scale Comprehensive Classification Method for Landform Morphology

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Abstract

Geomorphological objects often exhibit significant size disparities, spanning specific spatial scales. Existing automatic classification methods for geomorphological forms have not adequately accounted for this characteristic, thereby constraining classification accuracy. By employing the size of geomorphological forms as a scaling criterion, we propose a multi-scale integrated classification method that addresses the scale-spanning nature of geomorphological objects. This method comprises three steps: multi-scale segmentation, scale-sequential screening, and multi-scale merging. Specifically, scale-sequential screening constitutes an iterative confirmation process for objects to be classified, grounded in multi-scale feature extraction and supervised classification, and governed by the principles of small-scale (small-size) priority and probability maximization. Experimental results from the Loess Plateau demonstrate that the proposed method is both straightforward and reliable (achieving an overall accuracy of 75.16% and a Kappa coefficient of 0.71), and is suitable for refined classification of geomorphological forms.

Full Text

A Multi-Scale Integrated Classification Method for Landforms

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Abstract

Landform objects often exhibit vastly different sizes, spanning specific spatial scales. Existing automatic landform classification methods have not fully accounted for this characteristic, which constrains classification accuracy. This study proposes a multi-scale integrated classification method for landforms that addresses scale-spanning characteristics. The method consists of three steps: multi-scale segmentation, screening according to scale order, and multi-scale merging. The screening step is an iterative confirmation process for classified objects based on multi-scale feature extraction and supervised classification, guided by the principles of small-scale (small-size) priority and probability maximization. Experimental results from the Loess Plateau demonstrate that the method is simple and reliable, achieving an overall accuracy of 75.16% and a Kappa coefficient of 0.71, making it suitable for detailed landform classification.

Keywords: landforms; classification; multi-scale; Loess Plateau

1 Introduction

Landforms refer to the objective geometric characteristics of the Earth' s surface and represent boundary conditions for the formation and evolution of numerous natural and anthropogenic processes. Landform classification is a subjective process of dividing different types of landforms according to specific criteria, widely applied in ecological modeling and landslide prevention. Landform classification typically utilizes digital elevation models (DEM) or other data sources and includes both manual and automatic implementation approaches. Manual classification offers high accuracy but suffers from slow speed, high cost, and poor repeatability. Automatic classification can be further divided into pixel-based and object-based approaches. The latter, which uses image segmentation units as classification objects, better aligns with human spatial cognition processes and demonstrates superior classification effectiveness.

Landforms are complex and diverse, with common types exhibiting significant variety, which creates numerous difficulties for classification. To date, the accuracy of object-based landform classification remains unsatisfactory. A key reason is that landforms of interest to humans often exhibit multi-scale or scale-spanning characteristics. On one hand, different types of landforms may have overall scale differences. For example, in a large topographic relief area, valley plains are generally narrower than other landforms but become objects of interest due to their convenience for production and life. Existing studies have addressed this through hierarchical recognition strategies, extracting different landform types at various segmentation scales. However, selecting optimal segmentation scales requires multiple trials and visual judgment, a process that is cumbersome and highly subjective. On the other hand, different objects of the same landform type also frequently exhibit scale differences. For instance, the areas of loess tablelands (yuan) and loess ridges (liang) can vary enormously, reaching several times or even greater differences. Any single-scale segmentation and classification result is always suboptimal for such cases, a consideration rarely addressed in existing research.

Therefore, developing landform classification methods that fully consider cross-scale characteristics is essential. This paper proposes a multi-scale integrated classification method for landforms that addresses scale-spanning characteristics (hereinafter referred to as MSIC), aiming to avoid the subjectivity of selecting optimal segmentation scales for different landform types in previous studies while enabling extraction of the same landform type objects at different scales. This approach expands research perspectives on landform classification methods, achieves detailed landform classification, and provides technical support for compiling refined landform maps, with positive implications for rational land use, effective soil erosion prevention, and natural disaster reduction.

2 Methodology

2.1 MSIC Procedure and Principles

The MSIC method comprises three components: multi-scale segmentation, screening according to scale order, and multi-scale merging (Figure 1). Multi-scale segmentation utilizes existing multi-scale segmentation algorithms to obtain objects at various scales. Screening according to scale order is an iterative confirmation process for classified objects based on multi-scale feature extraction and supervised classification, guided by the principles of small-scale (small-size) priority and probability maximization. Probability maximization is a general principle in image classification, while small-scale priority ensures that small-scale objects with spatial containment relationships can be excluded when extracting and classifying large-scale objects. Multi-scale merging combines the landforms screened at each scale to produce the final classification result.

The specific procedure is described as follows:

Step 1: Multi-scale segmentation. Determine a series of scales manually and use existing multi-scale segmentation algorithms to obtain multi-scale objects.

Step 2: Feature extraction. Extract object unit features scale by scale, including terrain attributes, texture features, and other potential terrain features that may improve classification effectiveness.

Step 3: Supervised classification. Select training samples through field surveys or high-resolution remote sensing imagery, perform supervised classification to obtain multi-scale pre-classification information.

Step 4: Screening of classified objects at the minimum scale. Using the principles of small-scale priority and probability maximization, screen and confirm classified objects at the minimum scale.

Step 5: Multi-scale object updating. Remove the current minimum scale from the multi-scale objects and clip the confirmed classified objects from all other scale objects.

Step 6: Iteration. Starting from the next scale above the current minimum scale, repeat Steps 2 through 5 until all scales have been processed.

Step 7: Multi-scale merging. Combine the confirmed objects screened at each scale to obtain a complete landform type map.

2.2 Accuracy Assessment

Classification accuracy assessment examines the degree of correspondence between classification results and real ground features. It is an essential component of image classification for information extraction or land use/land cover classification and is indispensable for landform recognition. Selected evaluation metrics include overall accuracy (OA), producer's accuracy (PA), user's accuracy (UA), and Kappa coefficient.

Overall accuracy is the ratio of the sum of diagonal elements in the confusion matrix to the total number of samples. This parameter reflects the overall accuracy of all landform categories in the automated classification but does not indicate the accuracy of each individual category. Producer' s accuracy, also known as PA, represents the proportion of samples actually belonging to class i that are correctly classified as class i, serving as a measure of the producer' s classification accuracy. User' s accuracy reflects the correctness of extracted samples for a particular class. The Kappa coefficient can accurately reflect overall landform classification accuracy and consistency with validation data, providing an objective evaluation of classification results.

$$\text{Kappa} = \frac{N\sum_{i=1}^{k} m_{ii} - \sum_{i=1}^{k}(m_{i+} \times m_{+i})}{N^2 - \sum_{i=1}^{k}(m_{i+} \times m_{+i})}$$

where i and j are sample category numbers; N is the total number of samples; m is the number of corresponding categories; and k is the number of landform categories.

3 Study Area and Data

3.1 Study Area and Data

The study area is located in the western Loess Plateau of China (106.10°-106.76°E, 35.71°-36.27°N), with elevations ranging from 1,132 to 2,932 m. The terrain is higher in the northwest and lower in the southeast, containing typical loess landforms including tablelands (yuan), ridges (liang), mounds (mao), and valley plains (Figure 3). The DEM data with 30 m spatial resolution was downloaded from the Geospatial Data Cloud (http://www.gscloud.cn/). Traditional landform classification primarily uses typical terrain factors as classification features, while some studies have also considered terrain texture features. Recently, scholars have proposed the concept of landform elements and their extraction methods, suggesting that spatial structure information of landform elements is valuable for classification. Therefore, this study employs three categories of features for landform classification: terrain factors, terrain texture, and landform element structure information.

3.2 Multi-Scale Segmentation and Sample Collection

The eCognition Developer 9.0.3 multi-scale segmentation algorithm was used to segment the DEM. Scale sizes were determined based on landform dimensions, with all other parameters set to default values. After repeated experiments, the segmentation scale series was determined to be {10, 20, 40, 80, 160, 320}. The "Geomorphic Types of Loess Plateau in China"edited by Zhang Zonghu was manually digitized as a reference for the study area portion, including 12 landform types: bedrock mountains, flat-beam valleys, gentle-beam valleys, wide-beam valleys, narrow-beam valleys, low-hill gentle valleys, gentle-mao valleys, river terraces, residual-yuan valleys, wide-yuan valleys, basins, and yuan. Among these, 60% of the polygons were used as training samples and 40% as validation samples.

3.3 Feature Extraction

Terrain factors: Various terrain factors exist with certain correlations and information redundancy. The Shannon entropy method was used to identify low-correlation terrain factors, which were then quantitatively screened, ultimately selecting elevation, slope, hillshade, surface curvature, slope rate, terrain relief, and elevation variation coefficient as classification factors.

Terrain texture: The gray-level co-occurrence matrix (GLCM) proposed by Haralick has been widely applied in image texture analysis. Considering workload and correlation between features, and based on previous experience, 11 texture features were selected: elevation variation, slope mean, slope entropy, hillshade mean, hillshade variance, hillshade entropy, hillshade correlation, hillshade angular second moment, hillshade dissimilarity, hillshade homogeneity, and hillshade contrast.

Landform element structure information: First, the geomorphons method proposed by Jasiewicz was used to extract element layers. Then, the GeoPAT histogram tool was used to extract spatial structure information for each unit at each scale. Finally, principal component analysis was applied to obtain the first three principal components.

4 Results

4.1 MSIC Classification Accuracy

The MSIC classification results show that the southeastern part of the study area is primarily large-scale bedrock mountains, while the northwestern part mainly contains continuous residual-yuan valleys and gentle-beam valleys. The central region exhibits diverse landform types with interspersed large and small entities. Table 1 presents the producer' s accuracy and user' s accuracy for various landforms. Bedrock mountains achieved a producer' s accuracy of 79.70% and user' s accuracy of 51.60%, indicating low commission errors but high omission errors for yuan classification. Residual-yuan valleys achieved a producer' s accuracy of 89.47% and user' s accuracy of 45.14%, showing distinct morphological features that are not easily omitted, while yuan tends to be omitted. The overall accuracy is 75.16% and the Kappa coefficient is 0.71, indicating high classification accuracy and practical applicability.

4.2 Comparison Between MSIC and Single-Scale Classification Accuracy

Figure 5 shows classification results at single scales of 10, 40, 160, and 320. Compared with MSIC results (Figure 4), small-scale results show high similarity but excessive fragmentation with obvious over-segmentation. Large-scale results contain larger patches where smaller landforms are submerged, showing prominent under-segmentation. For example, the landform in window A should be bedrock mountains, but at scale 10 it contains narrow-beam valleys and basins, while at scale 160 it shows fewer mixed classifications. The landform in window B should be gentle-mao valleys, correctly classified at small scales but misclassified at large scales.

Table 2 compares the overall accuracy and Kappa coefficient between MSIC and single-scale classifications. Single-scale classification overall accuracies are 48.66%, 32.19%, 48.91%, 47.84%, 42.30%, and 24.98%, with Kappa coefficients of 0.38, 0.20, 0.38, 0.37, 0.31, and 0.13, respectively. The scale 40 classification achieves the highest overall accuracy and Kappa coefficient among single scales at 48.91% and 0.38, respectively. MSIC' s overall accuracy of 75.16% and Kappa coefficient of 0.71 are significantly higher than any single-scale method, exceeding the best single-scale results by 26.25% and 0.33, respectively.

To further demonstrate MSIC's advantages over single-scale methods, landforms were divided into three levels based on patch size: "large landforms," "medium landforms," and "small landforms," denoted as L, M, and S. Validation data were used to assess accuracy for merged landforms (Table 3). MSIC achieved high classification accuracy across all size levels. In contrast, single-scale methods showed low accuracy at small scales (10, 20) and large scales (160, 320), with only moderate accuracy at intermediate scales (40, 80).

5 Discussion

Xiong et al. proposed a drainage basin-based landform classification method requiring threshold determination for critical watershed size. If the threshold is too large, small watersheds are over-segmented, potentially containing multiple landform types within a single watershed. If watersheds are too small, insufficient data resolution may cause landform type errors. Wang et al. used hierarchical classification for landform mapping, but similarly relied heavily on watershed threshold selection requiring multiple trials and subjective manual screening. Although MSIC also involves multi-scale segmentation, its scale selection is less demanding than traditional methods, allowing manual specification of a scale series. Naturally, more scales yield higher classification accuracy but require greater computational effort.

MSIC has broad application potential in other remote sensing image classifications. Broadly speaking, landform classification belongs to the category of remote sensing image classification. In remote sensing classification, object-based methods primarily focus on uniform scales for the same landform type. However, the same landform type also commonly exhibits cross-scale phenomena (especially in high-resolution remote sensing imagery). Therefore, single-scale methods may not meet practical needs. MSIC can avoid the need to select optimal scales for different landforms and can handle cross-scale situations for the same landform type, making it applicable to object-based remote sensing classification to address this issue.

Future research should: (1) consider both morphological and genetic aspects of landforms, as landforms are complex combinations of form and origin; (2) optimize scale selection to achieve adaptive scale algorithms while identifying feature combinations that better reflect landform characteristics; (3) incorporate machine learning algorithms to improve classification efficiency, as conventional supervised classification is relatively inefficient.

6 Conclusion

Existing automatic landform classification methods have not adequately addressed the challenge of cross-scale classification of landform objects, constraining classification accuracy. This paper proposes a multi-scale integrated classification method that considers scale-spanning characteristics. Experiments on the Loess Plateau demonstrate that MSIC achieves an overall accuracy of 75.16% and a Kappa coefficient of 0.71, successfully identifying both small and large landforms and enabling detailed landform classification.

This study attempts to classify landforms from a morphological perspective, using landform size as a scale division unit. Although promising results were achieved, the research only considered morphological characteristics. As landforms are complex combinations of form and origin, genetic aspects were not addressed. Future research should: (1) consider both morphological characteristics and genetic origins of landforms; (2) note that experimental parameters in this study are regional and require adjustment when applied to other study areas.

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Note: Figure translations are in progress. See original paper for figures.