Object-Oriented Glacier Boundary Extraction Based on Multi-Feature Fusion: Postprint

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Abstract

Given that pixel-level classification struggles to accurately identify glacier changes when spectral features are similar, particularly as the spectral characteristics of debris-covered areas exhibit high similarity with surrounding mountains and rocks, leading to low extraction accuracy. To address this issue, this study takes the Yinsugaiti Glacier and Yanong Glacier as research areas, based on the Google Earth Engine platform, combines spectral indices, microwave textures, and topographic features, employs an object-based (OB) machine learning algorithm for automated glacier extraction, and compares it with pixel-based (PB) classification methods. The results demonstrate that: (1) The OB classification method based on multi-feature fusion contributes to improved glacier extraction accuracy. Specifically, the OB_{RF} classification achieves overall accuracy, Kappa coefficient, and F1 score of 98.1%, 0.97, and 98.67%, respectively, outperforming the OB_{CART} and OB_{GTB} methods. Compared with PB_{RF} classification, the overall accuracy, Kappa coefficient, and F1 score are enhanced by 1.7%, 0.024, and 5.57%, respectively. (2) From 2001 to 2022, the average annual retreat rates of Yinsugaiti Glacier and Yanong Glacier are 0.08% and 0.13%, respectively. (3) The debris-covered areas of Yinsugaiti Glacier are primarily distributed below 5000 m in elevation, whereas those of Yanong Glacier are mainly distributed below 4800 m; during 2001–2022, the debris-covered areas of both glaciers exhibited an upward expansion trend.

Full Text

Object-Based Glacier Boundary Extraction Utilizing Multi-Feature Fusion

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Abstract

Pixel-based classification struggles to accurately identify glacier changes when spectral characteristics are similar, particularly in debris-covered areas where spectral features closely resemble surrounding mountains and rocks, resulting in low extraction accuracy. To address this limitation, this study examines the Yinsugaiti and Yalong Glaciers using the Google Earth Engine platform, integrating spectral indices, microwave texture features, and topographic data. An object-based (OB) machine learning algorithm is employed for automated glacier extraction and compared with pixel-based (PB) classification methods. The results demonstrate that: (1) The OB classification approach with multi-feature fusion significantly improves glacier extraction accuracy. The OB_{RF} classifier achieved an overall accuracy of 98.1%, a Kappa coefficient of 0.97, and an F1 score of 98.67%, outperforming both OB_{CART} and OB_{GTB} classifiers. Compared to PB_{RF}, the overall accuracy, Kappa coefficient, and F1 score increased by 1.7%, 0.024, and 5.57%, respectively. (2) Between 2001 and 2022, the Yinsugaiti and Yalong Glaciers retreated at average annual rates of 0.08% and 0.13%, respectively. (3) Supraglacial debris was primarily distributed below 5000 m on the Yinsugaiti Glacier and below 4800 m on the Yalong Glacier. During this period, debris-covered areas on both glaciers exhibited an upward expansion trend.

Keywords: glacier boundary extraction; object-based; pixel-based; machine learning; multi-feature fusion

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1. Introduction

Glacier change serves as a crucial indicator of climate change. Glacier formation involves processes of snow accumulation, compaction, and refreezing, while debris-covered glaciers form when glacier ablation, movement, rock weathering, and collapse cause the glacier surface to become covered with debris. As important freshwater resources, glacier meltwater profoundly impacts regional hydrology and ecological environments. Therefore, rapidly and accurately obtaining glacier boundary change information not only reveals dynamic changes in glacier area but also provides support for estimating ice volume and monitoring glacier mass changes, which is of significant scientific importance and practical value for understanding glacier change mechanisms and developing response strategies.

Currently, the Global Land Ice Measurements from Space (GLIMS) system only provides single-class vector data without distinguishing different glacier categories, which limits research on dynamic changes of different glacier types and their environmental impacts. With the development of satellite remote sensing technology, the increasing number of satellites and sensors provides richer data support for glacier dynamic change research. Automated and semi-automated methods based on multispectral satellite imagery can be used to extract dynamic changes in glacier area, including the Normalized Difference Snow Index (NDSI), band ratio methods, interferometric synthetic aperture radar technology, and object-based approaches. Although these methods perform excellently in bare ice area extraction, they face difficulties in debris-covered areas where spectral characteristics are extremely similar to surrounding mountains and rocks, making glacier boundary extraction challenging.

To further improve the accuracy of debris-covered glacier extraction, various methods have been proposed, including the Normalized Difference Debris Index (NDDI), which utilizes differences in shortwave infrared and thermal infrared bands to identify debris-covered areas, and approaches that incorporate topographic parameters to further improve extraction accuracy. Some studies have also used coherence changes between SAR images, semantic segmentation, machine learning, and deep learning for debris-covered glacier extraction, achieving accuracies between 89% and 96%. However, fusing different sensor data for long-term glacier monitoring requires not only addressing inconsistencies in data format and resolution but also processing and analyzing massive amounts of remote sensing imagery, which presents significant economic and technical barriers for large-scale glacier change monitoring and analysis.

In recent years, the emergence of the Google Earth Engine (GEE) platform has enabled users to efficiently access massive remote sensing data, quickly process and analyze pixel-level data, and obtain computational results. GEE has been widely used for monitoring climate change, land use change, and snow-ice changes. Considering that pixel-based classification typically focuses on individual pixels and cannot simultaneously consider non-spectral information such as texture and topography, its performance is limited in complex terrain or areas with similar spectral characteristics. Therefore, this study proposes an object-based approach on the GEE platform that combines spectral indices, microwave texture, and topographic features, using machine learning algorithms for glacier automatic classification. This approach is compared with pixel-based classification methods to explore differences in glacier extraction accuracy between different classification methods and analyze spatiotemporal change characteristics of glaciers from 2001 to 2022, providing new ideas and technical support for large-scale, long-term glacier dynamic monitoring.

1.1 Study Area Overview

To better evaluate the effectiveness of classification methods in different debris-covered environments, two debris-covered glaciers were selected as study areas [Figure 1: see original paper]. The Yinsugaiti Glacier is located in the Karakoram Mountains (36°50 N, 76°70 E), with a total area of approximately 359 km^2, making it the largest glacier in China. The Yalong Glacier is located in the Gangrigabu Mountains, adjacent to the Gangrigabu Lake at its terminus, with a total area of approximately 179 km^2. The Yinsugaiti Glacier is concentrated between 4000-7000 m in elevation, with thick and continuous debris distribution. The Yalong Glacier is distributed between 4000–5000 m, with debris mainly concentrated at the glacier terminus, well-developed lateral moraines, and thin, ambiguous debris distribution.

1.2 Data Sources

The study utilized Landsat imagery with a spatial resolution of 30 m. Missing data for 2010 were supplemented with Landsat 7 imagery. Since cloud masking algorithms tend to misclassify high-reflectance pixels such as snow, ice, and salt lakes as cloud pixels and remove them, the imagery used in this study was manually confirmed as cloud-free after temporal and cloud screening. Microwave data were sourced from the PALSAR-2 and Sentinel-1 datasets. Elevation data were obtained from the NASADEM dataset. Glacier boundary reference data were derived from the Randolph Glacier Inventory (RGI) .

1.3 Research Methods

This study employed the Google Earth Engine platform to integrate spectral indices, microwave texture, and topographic features for glacier automatic classification using machine learning algorithms. The overall technical workflow is shown in [Figure 2: see original paper].

1.3.1 Feature Extraction Different index features suitable for glacier identification were calculated and fused with original image bands to create multi-band feature images for classification input. The Normalized Difference Snow Index (NDSI) is widely used for snow and ice identification. Snow and ice have high reflectance in the visible spectrum and very low reflectance in the shortwave infrared band. Based on the strong difference between visible and shortwave infrared band reflectance, NDSI processing is used to identify snow and ice. The Normalized Difference Vegetation Index (NDVI) does not directly identify glaciers, but snow’ s high sensitivity in the red band results in negative NDVI values, which can assist in distinguishing seasonal snow from permanent ice. The Normalized Difference Water Index (NDWI) highlights water bodies and suppresses snow and ice information, avoiding misclassification of moraine-dammed lakes at glacier termini as glaciers. Since debris-covered areas have spectral characteristics similar to surrounding bare land, using only these index features for debris-covered glacier identification remains challenging.

The cooling effect of underlying ice on supraglacial debris causes the surface temperature of debris-covered areas to be typically lower than surrounding bare land regions, providing an important basis for distinguishing debris-covered areas from non-glacier regions. Since the spatial distribution of debris is influenced by terrain and elevation, slope was calculated from DEM data and combined with elevation data to improve classification accuracy. Given that SAR can penetrate clouds and debris material to provide more internal structural information, polarization difference and polarization ratio were extracted from SAR images to highlight differences between glacier texture features and surrounding environmental features, which were then added to the original images.

Adding spectral indices, texture, and topographic features can significantly improve glacier classification accuracy. However, excessive input band data can cause redundancy and reduce computational efficiency. Therefore, after integrating spectral indices, texture features, and topographic factors, feature importance scores were calculated. Features with the lowest contribution were removed, and model overall accuracy and performance were evaluated after each iteration. Through iterative combination, the 12 most important band features were finally selected for image fusion [Figure 3: see original paper].

The formulas for the indices are:

$$NDVI = \frac{\rho_{Nir} - \rho_{Red}}{\rho_{Nir} + \rho_{Red}}$$

$$NDSI = \frac{\rho_{Green} - \rho_{Swir1}}{\rho_{Green} + \rho_{Swir1}}$$

$$NDWI = \frac{\rho_{Green} - \rho_{Nir}}{\rho_{Green} + \rho_{Nir}}$$

$$NDDI = \frac{\rho_{Swir2} - \rho_{Swir1}}{\rho_{Swir2} + \rho_{Swir1}}$$

Where ρ_{Green}, ρ_{Red}, ρ_{Nir}, and ρ_{Swir1}, ρ_{Swir2} represent the green, red, near-infrared, and shortwave infrared bands, respectively.

1.3.2 Simple Non-Iterative Clustering Superpixel Segmentation

Object-based classification uses objects as the minimum study unit, leveraging spatial relationships between objects to enhance classification coherence and reduce noise effects in optical remote sensing imagery, thereby achieving better classification results. Segmentation is a critical step in object-based classification, helping to reduce isolated misclassified pixels (i.e., "salt-and-pepper noise"). This study employed the SNIC algorithm to segment images, which clusters similar pixels into superpixels based on color, texture, brightness, and spatial location information.

Key parameters include compactness, connectivity, seed or grid size, and neighborhood size. The compactness parameter defines cluster shape, with values closer to 1 resulting in more square-like pixel shapes. The connectivity parameter defines the connectivity direction when merging neighboring superpixels, with a value of 4 indicating orthogonal adjacency and 8 including diagonal adjacency. Seed size determines the initial position or spacing of cluster centers, and its segmentation scale directly affects results. For parameter configuration, the "least squares" was selected as the loss function, with a learning rate of 0.1. Through iterative testing, model accuracy stabilized and reached optimal performance when Ntree was around 100.

1.3.3 Glacier Extraction Based on Machine Learning Three commonly used machine learning algorithms (RF, GTB, CART) were selected to automatically classify glaciers on segmented and unsegmented images. The Random Forest (RF) algorithm is a supervised machine learning method that combines outputs from multiple decision trees to produce a single result. Two key parameters affect classification performance: the number of classification trees (Ntree) and the number of referenced features. Through iterative testing and recording classification accuracy at each step, model accuracy reached its highest point and stabilized when Ntree was around 100. The Ntree parameter was set to the arithmetic square root of the total number of features in the training samples.

The Gradient Tree Boosting (GTB) algorithm enhances model predictive capability by progressively optimizing a series of weak learners. Each time a new decision tree is added, it corrects the prediction errors from the previous round, continuously improving overall model accuracy. The Classification and Regression Tree (CART) algorithm builds a single decision tree model through recursive data partitioning.

Machine learning classifiers rely on labeled data for training. In this study, samples of bare ice, debris-covered areas, and non-glacier regions were selected through visual interpretation. Based on the 2001 imagery, 1,500 sample points were selected, including 500 bare ice samples, 500 debris-covered area samples, and 500 non-glacier region samples. For the 2009 imagery, 500 bare ice, 500 debris-covered, and 500 non-glacier samples were selected. For the 2022 imagery, 500 bare ice, 500 debris-covered, and 500 non-glacier samples were selected. Samples were randomly divided 70/30 for training and validation.

1.3.4 Accuracy Assessment A confusion matrix was used to evaluate classification model performance, with primary metrics including overall accuracy, Kappa coefficient, and F1 score. Overall accuracy represents the proportion of correctly classified samples in the validation set. The Kappa coefficient measures the consistency between predicted results and actual categories, with higher values indicating greater consistency. The F1 score calculates both precision and recall, then computes their harmonic mean.

1.3.5 Area Uncertainty Assessment To quantify uncertainty in glacier boundary extraction, this study employed a buffer analysis method. This method assumes that the maximum error in area determination is within half a pixel range. The generated glacier boundaries were buffered by half a pixel to estimate error ranges. A 15 m buffer (half the pixel size of Landsat 5/7/8) was used as the buffer size for classification results from 2001 to 2022. Results showed that area calculation uncertainties for the Yinsugaiti Glacier were $±$1.09%, $±$1.04%, and $±$1.02% for 2001, 2009, and 2022, respectively. For the Yalong Glacier, uncertainties were $±$1.46%, $±$1.57%, and $±$1.47%, respectively, with an overall mean area uncertainty of $±$1.27%, which is within a reasonable range.

2. Results

2.1 Optimal Superpixel Seed Selection

In the Simple Non-Iterative Clustering (SNIC) algorithm, the most important parameter is the superpixel seed segmentation size . When the superpixel seed is too small, superpixels with the same attributes are easily segmented into different categories. However, when the segmentation scale is too large, superpixels with different attributes may be mistakenly segmented into the same category, reducing classification accuracy. In this study, a superpixel seed segmentation scale of 15 pixels yielded the best classification results.

2.2 Accuracy Comparison

The results indicate that the object-based multi-feature fusion classification accuracy is superior to pixel-based classification [Figure 4: see original paper]. In the Yinsugaiti Glacier region, the OB_{RF} model achieved overall accuracies of 96.51%, 95.24%, and 92.38% for 2001, 2009, and 2022, respectively, with Kappa coefficients of 0.94, 0.92, and 0.88. Compared to PB_{RF}, overall accuracies improved by 0.95%, 2.86%, and 1.58%, respectively. The OB_{RF} classifier demonstrated the highest classification accuracy. In the Yalong Glacier region, OB_{RF} overall accuracies and Kappa coefficients were 98.84% and 0.98, respectively, representing improvements of 3.47% and 0.05 over PB_{RF}.

To further verify model classification accuracy, F1 scores were added for supplementary validation . The OB_{RF} classification achieved the highest accuracy with an F1 score of 98.67%, confirming the reliability of the OB_{RF} classification method and representing a 5.57% improvement over PB_{RF} classification accuracy.

As shown in the glacier classification mapping results [Figure 5: see original paper], pixel-based algorithms (PB_{RF}, PB_{GTB}, PB_{CART}) exhibited numerous misclassifications and omissions. The PB algorithms produced substantial "salt-and-pepper" noise in classification results, particularly at mixed pixels between bare ice and debris. Pixel-based classification struggled to effectively distinguish these pixels, leading to confusion between bare ice and debris. In contrast, object-based classification (OB_{RF}, OB_{GTB}, OB_{CART}) 充分考虑了空间信息、纹理、光谱特征，有效改善误提取、漏提取和“椒盐”噪声情况。

The OB_{RF} classification method generated contours that better matched actual glacier boundaries, with fewer small, dispersed patches, effectively reducing post-processing manual correction time and making it more suitable for practical glacier data statistics and updates. This demonstrates that our method is feasible and can accurately and rapidly map glacier changes at regional scales [Figure 6: see original paper].

2.3 Glacier Change Characteristics

2.3.1 Glacier Area Changes from 2001 to 2022 Statistical analysis reveals that the glaciers showed overall retreat from 2001 to 2022 . For the Yinsugaiti Glacier, bare ice area decreased from 308.70 km^2 to 318.88 km^2 (a retreat of 10.18 km^2) at a retreat rate of 3.75 km^2/a. The debris-covered area expanded from 37.38 km^2 to 41.84 km^2, with an average annual expansion of 0.21 km^2. Glacier retreat magnitude varied temporally, with the largest annual area reduction (4.53 km^2/a) occurring between 2001-2009, during which bare ice area decreased by 37.38 km^2 at a retreat rate of 3.19%/a. Correspondingly, the debris-covered area expanded by 2.01 km^2 at a growth rate of 0.25%/a. Between 2009-2022, bare ice area decreased by 9.61 km^2 at an average annual retreat rate of 0.18 km^2/a. The proportion of debris-covered area to total glacier area increased from 10.79% to 11.64%.

For the Yalong Glacier, bare ice area retreated at a rate of 5.18%/a, with an average annual retreat rate of 0.15%/a. In contrast, the debris-covered area expanded by 2.01 km^2, with an average annual expansion of 0.18 km^2. Glacier changes were most pronounced at mid-low elevations of 4000-5000 m.

2.3.2 Glacier Area Variation with Elevation To further investigate glacier area changes with elevation, variations in bare ice and debris-covered areas were statistically analyzed at 200 m intervals. In the mid-low elevation region of 4600-5400 m, the Yinsugaiti Glacier was primarily distributed at 5200-5800 m, with maximum area at 5600-5800 m, while debris-covered areas were distributed at 4000-5000 m. Changes in bare ice and debris-covered areas of the Yinsugaiti Glacier were mainly concentrated at 4600-5200 m, with the greatest variation at 4800-5000 m. The Yalong Glacier was distributed at 4200-6400 m, with changes mainly concentrated at 4000-5000 m. A small expansion of bare ice area occurred at 6000-6200 m [Figure 7: see original paper].

2.3.3 Spatial Change Characteristics of Debris-Covered Areas Spatial change analysis of debris-covered areas on both glaciers shows that debris at the eastern glacier tongue terminus exhibited an upward expansion trend [Figure 8: see original paper]. At the boundary between bare ice and debris-covered areas, heat conduction from debris-covered areas releases heat to bare ice regions, raising temperatures in bare ice areas and accelerating melt. This may explain why bare ice retreat adjacent to debris-covered areas is greater than in other regions.

3. Discussion

This study confirms the significant advantages of the OB classification method for debris-covered glacier boundary extraction, a conclusion also validated in previous research. The core innovation lies in using the SNIC algorithm to cluster multi-band feature images into homogeneous regions with similar attributes, effectively overcoming the "salt-and-pepper noise" problem caused by spectral mixing effects in pixel-based classification. Particularly in debris-covered areas where glacier retreat enhances surface heterogeneity (e.g., supraglacial lake development, debris thickness gradient changes), single-band classification methods become increasingly uncertain. The OB classification enhances feature separability by fusing SAR texture features (backscatter coefficient differences) with topographic factors.

Unlike traditional methods relying on optical texture features (gray-level co-occurrence matrix), SAR backscatter coefficients have stronger penetration capability for cloud-shadow areas and mixed pixels of debris and bedrock. Compared with traditional Landsat-based methods, classification accuracy improved by 6.9%-9.2%, further validating the universality of microwave data in debris-covered glacier monitoring. Algorithmically, RF' s ability to handle high-dimensional nonlinear features and its anti-overfitting characteristics make it robust for classifying bare ice and debris-covered areas. However, GTB' s sensitivity to sample distribution leads to less stable classification than RF in regions with uneven debris coverage, a conclusion consistent with existing glacier classification studies.

The object-based classification results demonstrate that multi-source data fusion achieves information complementarity among different features, compensating for limitations of single spectral information in complex surface environments. This effectively improves the ability to resolve complex terrain and edge areas, reduces misclassification and noise interference, and achieves an overall classification accuracy of 98.1%, representing a 1%-4% improvement over pixel-based results. The F1 score improved by 4.1%-6.2%.

Analysis of Yinsugaiti and Yalong Glacier changes from 2001-2022 reveals an overall retreat trend, with cumulative retreat rates of 2.01% and 5.18% for bare ice areas, respectively, and debris expansion rates of 3.19% and 9.61%. Glacier changes mainly occurred at mid-low elevations where bare ice and debris meet. The SNIC segmentation effectively improved overall model accuracy, though classification performance was highly sensitive to superpixel seed segmentation scale. This study determined 15 pixels as the optimal segmentation scale. Vector results of glacier classification showed that boundaries based on segmented images were closer to actual glacier boundaries, greatly reducing post-processing manual correction workload.

4. Conclusion

(1) This study integrated spectral indices, texture, and topographic features for object-based glacier boundary extraction. The OB_{RF} classification method achieved the highest accuracy, with overall accuracy, Kappa coefficient, and F1 score of 98.1%, 0.97, and 98.67%, respectively. Compared with traditional pixel-based classification, overall accuracy improved by 1.7% and the F1 score improved by 5.57%.

(2) Glacier changes in the study area from 2001-2022 showed an overall retreat trend, with average annual retreat rates of 0.08% and 0.13% for Yinsugaiti and Yalong Glaciers, respectively. Debris-covered areas showed upward expansion, with debris primarily distributed below 5000 m on Yinsugaiti Glacier and below 4800 m on Yalong Glacier.

(3) Although this method achieved high accuracy in both bare ice and debris-covered areas, differences in reflectance characteristics between thin and thick debris may affect classification accuracy, and the lack of measured sample data increases classification uncertainty. Future research will focus on thick debris-covered areas and increase measured sample data to evaluate model reliability and applicability under different debris thicknesses.

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