Prediction and Analysis of Glaciers on the Tibetan Plateau Using Random Forest Models: A Postprint

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Abstract

Glaciers constitute one of the primary targets for natural resource survey and monitoring on the Tibetan Plateau, and their investigation and research hold significant importance for understanding climate change in this region. This study focuses on Tibetan Plateau glaciers, integrating multi-source data to construct a random forest model (coefficient of determination = 0.72), obtaining annual 1 km-scale glacier prediction datasets for the period 2000–2020, and analyzing the spatial distribution patterns and spatiotemporal variation characteristics of glaciers during this period. The findings reveal: (1) Spatial distribution patterns: glaciers are predominantly distributed within slope ranges of 0°–40°, accounting for 97.92%; mainly occur at elevations of 4000–7000 m, comprising 99.38%; and generally exhibit greater coverage on north-facing versus south-facing slopes, and on west-facing versus east-facing slopes. (2) Spatiotemporal variation characteristics: temporally, glaciers on the Tibetan Plateau experienced a significant retreating trend from 2000 to 2020; spatially, marginal regions of the plateau show pronounced changing trends that gradually weaken toward the interior, where slight changes dominate. (3) Glaciers in the Himalaya and Nyenchen Thanglha ranges demonstrate significant retreating trends, those in the Karakoram exhibit slight retreating trends, while Kunlun Mountains glaciers display concurrent patterns of slight advancing and slight retreating.

Full Text

Predicting and Analyzing Glaciers in the Qinghai-Xizang Plateau Using a Random Forest Model

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Abstract

Glaciers represent a key focus of natural resource monitoring on the Qinghai-Xizang Plateau, and their investigation holds significant implications for understanding climate change in the region. This study examines glaciers across the plateau by integrating multi-source data to construct a random forest model ($R^2 = 0.72$), generating an annual-scale glacier prediction dataset at 1 km resolution for the period 2000–2020. The analysis reveals: (1) Spatial distribution characteristics: Glaciers predominantly occur on slopes of 0°–40°, accounting for 97.92% of the total, and are concentrated at elevations of 4000–7000 m, representing 99.38% of the distribution. The pattern shows a predominance of north-facing slopes over south-facing slopes, and west-facing slopes over east-facing slopes. (2) Spatiotemporal variation: Temporally, glaciers across the plateau exhibited a significant retreat trend from 2000 to 2020. Spatially, pronounced change signals appear along the plateau's margins, diminishing toward the interior where only slight changes dominate. (3) Regional variations: Glaciers in the Himalaya and Nyainqentanglha mountains show significant retreat, those in the Karakoram Mountains display slight retreat, while the Kunlun Mountains exhibit a mixed pattern of slight advancement and retreat.

Keywords: glaciers; prediction and analysis; random forest model; spatial distribution; spatiotemporal change; Qinghai-Xizang Plateau

1. Introduction

Glaciers, often termed "mountain solid reservoirs," constitute vital components of water resources. The Qinghai-Xizang Plateau ranks among the regions most sensitive to global climate change, with its towering topography driving climatic patterns across eastern China and exerting significant influence on Northern Hemisphere and global climate systems. Research demonstrates that climate change substantially impacts plateau glaciers [], which in turn affect atmospheric water cycles and radiation budgets, leading to changes in surface runoff, lake volumes, groundwater levels, and sea levels across the Northern Hemisphere with profound consequences for human survival and livelihoods. Consequently, dynamic monitoring of glacier changes is essential.

Since the 21st century, numerous scholars have investigated the spatiotemporal patterns of glacier change on the Qinghai-Xizang Plateau. Current research methodologies include numerical simulation, geodetic surveying, satellite remote sensing monitoring, and field observations. Numerical simulation employs hydrological models of glacier systems to assess glacier contributions to specific watersheds and reveals change mechanisms through physical process modeling, though typically yielding only regional total area estimates rather than detailed distribution boundaries. Geodetic methods primarily utilize modern measurement techniques to obtain surface elevation or velocity changes, such as digital elevation model differencing []. Satellite remote sensing monitoring applies remote sensing imagery and GIS technology, with glacier extraction achieved through visual interpretation or automated classification. While visual interpretation offers high accuracy, it is time-consuming, labor-intensive, and susceptible to subjective misclassification. Classical computer-assisted classification methods include ratio thresholding [], snow cover index methods [], and other index-based approaches [], along with supervised and unsupervised classification techniques []. Although effective, these methods lack universal applicability. Recent innovations include multi-scale image segmentation, neural network-based approaches, deep learning methods, and object-oriented visual interpretation techniques. However, since glacier area calculations and boundary extraction rely solely on technical approaches, all these methods lack field measurement validation. Field observations through monitoring stations are limited by sparse station distribution and insufficient measured data.

Glacier change research typically employs remote sensing and GIS for multi-temporal image comparison of specific regions. This study explores an innovative statistical modeling approach to predict glacier distribution characteristics. Glacier changes result from combined influences of global climate change, geographic environmental factors, and human activities, making it feasible to establish probabilistic statistical relationships between environmental variables and glacier distribution. Using remote sensing, GIS, and machine learning techniques to predict glacier coverage and extract change information offers technical viability. This approach expands monitoring scope and frequency while being based on long-term equilibrium between glaciers and environmental factors such as climate and topography, without requiring consideration of dynamic coupling and response mechanisms among factors.

2. Study Area and Data

2.1 Study Area Overview

The Qinghai-Xizang Plateau, an inland plateau in Asia, represents the world's highest and largest plateau by area, covering over 2.5 million km^2 and known as the "Roof of the World." It constitutes the largest, highest-altitude, and lowest-temperature mountain glacier region at mid-low latitudes. The plateau contains glaciers in the Kunlun, Karakoram, Himalaya, Nyainqentanglha, and other mountain ranges (Figure 1). The plateau boundary data used in this study originates from the Three Poles Environmental Big Data Platform's Qinghai-Xizang Plateau boundary dataset []. The total glacier area, storage, and number of glaciers on the plateau are 50,000 km^2, 4,560 km^3, and 82,000 respectively [].

Influenced jointly by westerlies and the South Asian monsoon, plateau glaciers are classified as maritime, sub-continental, and extreme continental types, occupying important positions in national water resource budgets and ice-water cycling processes, representing invaluable resources for China.

2.2 Data Sources

This study selected multi-source data including spatiotemporal glacier distribution data [], annual normalized difference vegetation index (NDVI) data, water yield modulus data, temperature and precipitation data, land use data, and population density data (Table 1). Glacier distribution data were obtained from the National Tibetan Plateau Data Center. NDVI data were derived from MODIS products aboard Terra and Aqua satellites. Water yield modulus data came from the Chinese Academy of Sciences' Resource and Environmental Science Data Center's "China Three-Level Basin Water Yield Modulus Dataset." Temperature and precipitation data were sourced from the National Meteorological Information Center's "China Surface Meteorological Monthly Values 0.5°$\times$0.5° Gridded Dataset (V2.0)," processed through monthly and annual synthesis. Land use data were obtained from the National Basic Geographic Information Center's GlobeLand30 dataset and the European Space Agency's land use dataset at 300 m resolution. Population density data were acquired from the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, and the Center for Chinese Agricultural Policy at 1 km resolution.

The original temperature data comprised monthly maximum, minimum, and mean values at stations; precipitation data consisted of monthly station measurements. These were converted to annual temperature and precipitation values for model fitting. All covariates underwent data cleaning and were redistributed to grid cells through weighted averaging, co-Kriging interpolation, and bilinear interpolation, creating a covariate database spanning 2000–2020 with 16.99×10^{6} grid cells at 1 km resolution.

2.3 Methods

2.3.1 Variable Selection Variable relative importance serves as a crucial criterion for variable selection in random forest models. This metric evaluates each variable's contribution to predictions by calculating weight indices during regression analysis. This study collected various data potentially related to glacier spatiotemporal distribution as candidate variables (temperature, precipitation, vegetation index, grassland, permanent snow/ice, elevation, water yield modulus, bare land, population, slope/aspect, land use, other vegetation). Variables were permuted individually to quantify prediction errors, with relative importance output for each variable (Figure 2). Through iterative fitting, redundant variables with relative importance below 5% were eliminated (water yield modulus, bare land, population, land use, slope/aspect, other vegetation), ensuring remaining variables held meaningful predictive power for glacier distribution.

Temperature emerged as the dominant factor in glacier prediction, accounting for 36.46% of model weight, followed by vegetation index (27.61%), grassland (23.68%), permanent snow/ice (10.17%), and precipitation (2.08%). Temperature and vegetation index contributed most significantly to the glacier distribution prediction model, while permanent snow/ice, precipitation, and grassland collectively accounted for 36.07%, with other factors contributing less substantially.

2.3.2 Model Construction Random forest, first proposed by Breiman and Cutler [], represents a commonly used machine learning method. Based on parallel ensemble learning, it introduces random attribute selection during training to construct classifiers comprising multiple decision trees—a large-scale ensemble machine learning algorithm. Studies demonstrate that machine learning methods can effectively handle complex multi-source spatial data prediction [], making them valuable tools for large-scale glacier forecasting.

During model training, bootstrapped resampling generated training datasets for constructing regression trees, with random subsets of m predictors used for each tree. Feature variable relative importance was calculated based on out-of-bag (OOB) error, testing how each feature affected model prediction accuracy by adding noise to features and observing accuracy impacts. For a given feature X, relative importance was computed as follows: assuming N trees in the forest, for each decision tree, OOB error was calculated using corresponding OOB data and denoted as err_1; after adding random noise interference to feature X for all OOB samples, OOB error was recalculated as err_2, yielding feature importance $I = err_2 - err_1$.

The model used 2000–2019 glacier data as training samples, randomly selecting variables (temperature, precipitation, vegetation index, grassland, permanent snow/ice) and repeatedly using single nodes to construct regression trees until each terminal node contained only one data point. Initially, a single-node tree was built, then bootstrap steps were repeated until each terminal node contained only one data point, with optimal splits selected at each node of the regression tree. The final prediction represented the average of all regression trees. The training sample comprised 500.23$×10^{4}$ data points. By extracting sample data characteristics and selecting optimal splits at each regression tree node, relationships between training data and covariates were established, creating a glacier distribution prediction model based on random forest. With parallel and concurrent processing support [], using 32 parallel threads and 64 concurrent processes, single model prediction time was reduced from 232 hours to 6.70 hours through optimization, achieving near-optimal computational efficiency and predictive performance.

2.3.3 Data Prediction Following model establishment, glacier data for all years were predicted. Considering potential interference from temporary snow and river/lake ice surfaces in sample data, correction was necessary. This study identified advantageous grids within 2017–2020 predictions, designating grids with glacier dataset coverage exceeding 50% as valid training sample grids. Convolution operations were applied to valid grids through the formula:

$f[n_1, n_2] = -\infty$
$g[-n_1, -n_2] = -\infty$
$y[n_1, n_2] = \Sigma\Sigma\ f[k_1, k_2]g[n_1 - k_1, n_2 - k_2]$

where f represents the horizontal (column) and vertical (row) coordinates; g is the convolution kernel; x, y denote pixel values in image f at position (n_1, n_2); and k_1, k_2 represent displacement parameters in horizontal and vertical directions within convolution kernel g. By continuously adjusting convolution coefficients, results were made to approach true values infinitely. The same convolution operation was applied to annual glacier predictions, outputting the 2000–2020 spatiotemporal glacier distribution prediction dataset for the Qinghai-Xizang Plateau. Area errors between predicted and actual values were calculated as 5.77% and 5.23% respectively, with total predicted area error at 1.76%, ensuring data reliability.

2.3.4 Model Validation To avoid model overfitting, ten-fold cross-validation assessed model accuracy. Training samples were randomly divided into ten groups, with nine groups used for training and one group reserved for validation in each iteration. Validation data were excluded from training and used to evaluate model accuracy. Both actual and predicted glacier values were log-transformed for validation. Each iteration output prediction accuracy, with the mean accuracy across ten iterations serving as the final precision metric. Cross-validation results (Figure 3) yielded a model coefficient of determination (R^2) = 0.72. Additionally, log-transformed predicted and actual values were compared using root mean square error (RMSE = 1.52), mean fractional bias (MFB = 0.15), and mean fractional error (MFE = 0.29) to quantify prediction accuracy.

3. Results

3.1 Spatial Distribution Characteristics of Glaciers on the Qinghai-Xizang Plateau

Glacier distribution on the Qinghai-Xizang Plateau is primarily controlled by combined climatic and topographic influences, particularly favoring mountains with low temperatures, abundant precipitation, high elevations, and gentle slopes—conditions providing optimal material foundation, accumulation space, and storage environments for glacier formation. According to 2020 prediction data, glaciers are mainly distributed across the Kunlun and Karakoram mountains in western plateau, the Gangdise and Himalaya mountains in the southwest and south, the Nyainqentanglha Mountains in the south, the Hengduan Mountains in the southeast, the Tanggula Mountains in the central region, and the Qilian Mountains in the northeast, showing a general decreasing gradient from southwest to northeast. Among these, the Kunlun, Karakoram, and Himalaya mountains account for over half of glacier distribution, with other ranges hosting relatively fewer and smaller glaciers.

Topographic factors strictly constrain glacier distribution patterns and influence change trends and rates. Using 2020 prediction data as an example, terrain analysis via ArcGIS yielded glacier area proportions across slope, aspect, and elevation gradients (Table 2), validated against 2017 glacier product data for reliability.

Slope analysis (Figure 4) indicates that glaciers on 0°–10° slopes account for the largest proportion at 36.46%, similar to patterns in the Himalaya region []. The 10°–20° range follows at 27.61%, with 20°–30° at 23.68%. Slopes of 30°–40° contain relatively small proportions (10.17%), while slopes exceeding 40° host minimal glacier development at only 2.08%. Overall, slopes of 0°–40° encompass 97.92% of plateau glacier area.

Aspect analysis (Figure 5) reveals that north-facing slopes host the maximum glacier coverage at 16.00%, followed by northeast-facing slopes at 15.27%. East-, south-, and southeast-facing slopes show similar proportions at approximately 13.38%, 13.29%, and 12.82% respectively. Northwest- and southwest-facing slopes contain relatively smaller proportions at 10.73% and 9.85%, with west-facing slopes showing the minimum at 8.66%. The overall pattern demonstrates predominant distribution on north-, east-, and south-facing slopes, supplemented by west-facing slopes, characterized by more glaciers on north-facing than south-facing slopes, and more on east-facing than west-facing slopes.

Elevation analysis (Figure 6) shows that glaciers at 5000–6000 m elevation account for 69.99% of total area, followed by 4000–5000 m at 19.98% and 6000–7000 m at 11.10%. Areas above 7000 m, constrained by temperature and terrain, contain only 0.35% of total glacier area. Overall, 99.38% of plateau glaciers are distributed between 4000–7000 m. Regarding glacier terminus elevations, continental glaciers can extend to 5100 m, while maritime glaciers may reach 3000 m.

3.2 Spatiotemporal Change Trends of Glaciers

3.2.1 Overall Plateau-Wide Glacier Change Trends The Mann-Kendall test constructs standard normal distribution statistics (Z) to assess sample change trends, commonly applied in temporal change analysis []. To comprehensively understand macro-scale glacier change patterns and typical variations across the plateau, this study applied Mann-Kendall tests to analyze spatiotemporal trends.

The test defines statistic S and calculates Z values. At a given significance level α, $Z > 0$ indicates glacier advance, while $Z < 0$ indicates retreat. When $|Z| \geq 1.64$, the trend passes significance tests at 90% and 95% confidence levels respectively. P-values represent probabilities of observed trends, with $P < 0.01$ indicating significant trends and $P > 0.05$ indicating no significant trend.

Temporal analysis reveals that Qinghai-Xizang Plateau glaciers showed overall retreat from 2000–2020 (Table 3). With Z = -∞ and P < 0.01, the trend is statistically significant at 99% confidence. Spatially, Z-values were mapped to show trend distributions, classified by confidence levels to produce a spatial distribution map of glacier change trends (Figure 7).

Results indicate that slight retreat dominates, uniformly distributed across the plateau and accounting for approximately 54.14%. Significant retreat areas concentrate in southeastern regions (34.07%), while slight advance areas appear in northwestern regions (21.01%). No-change areas are minimal, primarily in central regions (2.31%), and significant advance areas are sporadic (0.17%). Overall, 2000–2020 shows significant plateau-wide glacier retreat, with stronger signals along margins that diminish toward the interior, where only slight changes occur—consistent with previous research [].

3.2.2 Typical Glacier Change Trends in Major Mountain Ranges

Glaciers of different scales and types respond differently to climate change, and regional climate variations produce distinct glacial responses. Plateau-wide trends represent overall patterns, but individual glaciers show varied behaviors. To examine regional characteristics, we selected the four largest mountain ranges (Himalaya, Karakoram, Kunlun, and Nyainqentanglha) for Mann-Kendall trend analysis (Figure 8).

The Himalaya Mountains host large radiating valley glaciers. Temporally, glaciers in this range showed retreat from 2000–2020 (Table 3). With Z = -∞ and P < 0.01, the trend is significant at 99% confidence. Spatially (Figure 9), slight retreat dominates (43.84%), with significant retreat in central and eastern areas (32.67%). Slight advance areas appear locally in northern and southeastern regions (21.01%), while no-change areas are minimal (2.31%), and significant advance is nearly absent (0.17%).

The Karakoram Mountains contain the most concentrated glacier development outside polar and high-altitude regions. Temporally, glaciers showed retreat from 2000–2020, but with $|Z| < 1.64$ and $P > 0.05$, the trend is not statistically significant. Spatially (Figure 10), despite the lack of significant trend, strong slight-change signals appear, accounting for 97.55% of the region. Slight retreat dominates central and eastern areas (89.55%), while slight advance concentrates in central regions (8.00%). No-change areas are uniformly distributed (2.39%), with nearly no significant retreat (0.06%) and no significant advance.

The Kunlun Mountains, stretching across western China in eastern and western sections, host extensive glaciers in the western segment. Temporally, glaciers showed no significant trend ($|Z| < 1.64$, $P > 0.05$). Spatially (Figure 11), despite no significant overall trend, slight-change signals are strong, accounting for nearly 94.00%. Slight advance dominates western sections (59.61%), while slight retreat is uniformly distributed (33.95%). No-change areas are relatively numerous in western regions (6.26%), with minimal significant retreat (0.14%)

and nearly no significant advance (0.04%).

The Nyainqentanglha Mountains exhibit maritime characteristics in the east and continental features in the west, primarily influenced by the southwestern monsoon. Temporally, glaciers showed significant retreat from 2000–2020 ($Z = -\infty$, $P < 0.01$). Spatially (Figure 12), significant retreat dominates (90.57%), with slight retreat in eastern localities (7.42%). Significant and slight advance areas are sporadic (1.78% and 0.18% respectively), and no-change areas are minimal (0.05%).

4. Conclusions

This study innovatively integrated multi-source data to construct a glacier prediction model using random forest methodology, analyzing spatial distribution and spatiotemporal change characteristics. Key conclusions include:

1) A large-scale glacier distribution simulation method was developed, integrating remote sensing, meteorological, geographic, and environmental data to construct a glacier coverage random forest model ($R^2 = 0.72$). A covariate database spanning 2000–2020 was established, yielding a 1 km-resolution annual glacier distribution dataset.

2) Spatial distribution characteristics: Glaciers predominantly occur on 0°–40° slopes (97.92%) and at 4000–7000 m elevations (99.38%). Distribution patterns show predominance on north-, east-, and south-facing slopes, supplemented by west-facing slopes, with more glaciers on north-facing than south-facing slopes, and east-facing than west-facing slopes.

3) Spatiotemporal change characteristics: Temporally, glaciers showed significant retreat from 2000–2020. Spatially, significant changes occurred along plateau margins, diminishing toward the interior where only slight changes prevailed.

4) Regional variations: Himalaya and Nyainqentanglha glaciers showed significant retreat, Karakoram glaciers showed slight retreat, while Kunlun glaciers exhibited mixed patterns of slight advancement and retreat.

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