

Binary and Fractional MODIS Snow Cover Mapping Boosted by Machine Learning and Big Landsat Data

Wenbo Luan^{ID}, Xueliang Zhang^{ID}, *Member, IEEE*, Pengfeng Xiao^{ID}, *Senior Member, IEEE*,
Huadong Wang^{ID}, and Siyong Chen^{ID}

Abstract—It is promising to improve Moderate Resolution Imaging Spectroradiometer (MODIS) snow cover mapping by training effective machine learning models. However, considering the strong spatiotemporal heterogeneity of snow cover, the representativeness of training samples becomes a critical issue to ensure the model effectiveness over large areas and long terms. To deal with this issue, we propose the m -day dynamic training strategy. The core of this strategy is to divide a long-term snow cover mapping task into multiple short-term tasks with consecutive m days (m is greater or equal to the number of days that higher resolution remote sensing images used as equivalent ground references cover the study area once). It can ensure the spatial representativeness of training samples by utilizing all available equivalent ground references data, and reduce the issue caused by snow cover changing over time. We apply this strategy to random forest (RF) for both binary snow cover mapping (BSC) and fractional snow cover mapping (FSC) using Landsat-8 data as equivalent ground reference and validate its effect on the Tibetan Plateau. Results show that this strategy achieves higher accuracies than other training strategies, with $F1$ of 0.9596 for BSC mapping, R and mean square error (MSE) of 0.9037 and 0.0260 for FSC mapping, respectively. In addition, spatiotemporal analysis of results further demonstrates that this strategy holds advantages for snow cover mapping in areas of complex terrain and in periods when snow cover changes rapidly. In conclusion, this strategy can effectively ensure the representativeness of training samples generated from Landsat-8 data and thus improve MODIS snow cover mapping through machine learning.

Index Terms—Fractional snow cover, Landsat, machine learning, Moderate Resolution Imaging Spectroradiometer (MODIS), random forest (RF), snow cover mapping, Tibetan Plateau.

I. INTRODUCTION

SNOW cover plays an important role in the energy balance and atmospheric circulation due to its high albedo and low

thermal conductivity [1], [2]. As a natural reservoir of water, snow cover provides domestic water for one quarter to one sixth of the global population [3]. Snow cover extent (SCE) is a key input parameter in environmental dynamics modeling related to climatology [4] and hydrology [5], [6]. Besides, SCE is also very important in the estimation of other snow cover parameters, e.g., estimating snow depth (SD) and snow water equivalent (SWE) by assimilating SCE data [7], [8], [9], [10] or downscaling passive microwave SD data by combining high-spatial resolution SCE data [11].

In general, SCE is expressed in two ways, including binary snow cover mapping (BSC, i.e., snow/no snow) and fractional snow cover mapping (FSC, i.e., percentage of snow cover within a pixel). The optical remote sensing data in the visible and short-wave infrared bands are used for both BSC and FSC. Moderate Resolution Imaging Spectroradiometer (MODIS) is popularly employed in snow cover mapping due to its high temporal resolution [4], [12], [13]. The SNOMAP algorithm [14] and linear statistical regression analysis [15] were adopted for MODIS daily binary and fractional snow cover products (MOD10A1), respectively. In addition, the linear spectral mixture analysis algorithm was developed to produce another fractional snow cover product based on MODIS (MODSCAG) [16].

The SNOMAP algorithm adopts the normalized difference snow index (NDSI), the threshold of which is commonly set to be 0.4, to distinguish snow from others [17]. The linear statistical regression analysis establishes a linear regression dependency between the NDSI and the FSC value [15]. The linear spectral mixture analysis assumes that the reflectance of a pixel is a linear combination of the spectra of surface components within that pixel, and that the weight of each component is proportional to the area occupied by the component [16], [18], [19].

These snow cover mapping approaches achieved high overall accuracies in relatively simple geographical conditions. Under the clear sky, the overall accuracy of SNOMAP is mostly between 85% and 99% around the world, and the mean square error (MSE) of linear statistical regression analysis is 0.0529 [14], [15], [17], [20]. Nevertheless, due to the strong spatial and temporal heterogeneity of snow, the optimal threshold of NDSI, the linear relationship between NDSI and FSC and the spectral reflectance curve of snow vary in different underlying surface types, elevations, and snow cover periods. Hence, the global NDSI threshold, unified linear

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The authors are with the Jiangsu Provincial Key Laboratory of Geographic Information Science and Technology, Key Laboratory for Land Satellite Remote Sensing Applications of Ministry of Natural Resources, School of Geography and Ocean Science, Nanjing University, Nanjing 210023, China (e-mail: mg20270083@mail.nju.edu.cn; zxl@nju.edu.cn; xiaopf@nju.edu.cn; huadongw098@gmail.com; dg21270004@mail.nju.edu.cn).

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equation, and linear spectral mixture analysis may have defects in the local snow cover mapping, especially in complex terrain and surface coverage areas and transitional periods of snow cover accumulation and melting [20], [21], [22], [23].

Aiming at dealing with the problem caused by the strong spatial and temporal heterogeneity of snow cover, the higher resolution data, e.g., Landsat, were used as ground equivalent reference data for MODIS to explore snow cover mapping methods with higher accuracy [24]. These methods can be generally classified into two categories: 1) taking the strong spatial and temporal heterogeneity of snow cover into account for improving SNOMAP algorithm and linear spectral mixture analysis and 2) using machine learning algorithm for snow cover mapping.

In terms of improving SNOMAP algorithm, to alleviate the local inapplicability of NDSI threshold value of 0.4, the automatic thresholding methods such as unsupervised Bayesian thresholding algorithm [25] and Otsu algorithm [26] were adopted to achieve automatic selection of local optimal thresholds. Utilizing the optimal threshold of NDSI that varies under different land cover types based on Landsat and MODIS image pairs could effectively improve the accuracy of snow cover in the Tibetan Plateau especially in grassland areas [27]. To deal with the influence from temporal change of snow cover, Härer *et al.* [26] developed calibrated quadratic polynomial model of optimal threshold accounting for seasonal threshold dynamics.

In terms of improving spectral mixture analysis, MODSCAG allows the snow's spectral reflectance to vary pixel-by-pixel to deal with spatial heterogeneity of snow cover [16]. The proposed spectral mixture analysis can achieve better results than linear statistical regression analysis, but it needs to traverse the spectral combination in the spectral library when calculating the FSC of each pixel, resulting in longer computation time [20], [28]. Bair *et al.* [29] proposed to cluster similar spectra and interpolate them to reduce computation time.

In terms of applying machine learning methods to snow cover mapping, Yin *et al.* [30] compared support vector machine (SVM) with nine automatic threshold methods and demonstrated the better performance of SVM for BSC mapping. Dobrev and Klein adopted an artificial neural network (ANN) to estimate FSC from MODIS surface reflectance, NDSI, normalized difference vegetation index (NDVI), and land cover types with Landsat FSC data as [31]. Then, Moosavi *et al.* [32] used wavelet analysis to preprocess the original data for improving the performance of ANN on estimating FSC. One step further, Czyzowska-Wisniewski *et al.* [33] tried to use ANN to estimate FSC by combining terrain and reflectance data. Furthermore, Hou *et al.* [34] improved ANN for estimating FSC by considering elevation and land surface temperature. Compared with MODIS FSC product, the ANN-estimated FSC achieved lower MSE. Liu *et al.* [35] applied random forest (RF), SVM, and ANN to snow cover mapping with unmanned aerial vehicles (UAV) reference data, showing that the RF achieves the best accuracy among the three machine learning models. Besides, Kuter *et al.* [36] and Kuter [37] applied four commonly used

machine learning algorithms to snow cover mapping, including RF, SVM, ANN, and multivariate adaptive regression splines (MARS), and found that their accuracy and effect were similar, but RF and MARS algorithms outperformed ANN and SVM methods in computational efficiency.

Machine learning methods can effectively use auxiliary information and thus serve as a promising way to improve the accuracy of snow cover mapping. However, considering the strong spatial and temporal heterogeneity of snow cover, the representativeness of training samples becomes a key issue to ensure the machine learning models' effect, which indicates that a model trained at a certain time in one scene is not sure to be applicable to other times and scenes [38], [39]. It was found that the best strategy to develop machine learning models is using higher resolution images recorded on the same date and at the same location as MODIS images, which is difficult to implement because higher resolution images are not as complete in time and space as MODIS images due to the trade-off between spatial resolution and sensor strip width [34]. Therefore, the previous machine learning-based snow cover mapping were often limited to a small geographic area and a short and discrete time range, which cannot meet the urgent requirement of more accurate large-scale and long-term snow cover data for climate and hydrology studies [40]. How to ensure the temporal and spatial representation of training samples in data-absent area becomes a major problem that restricts machine learning models for large-scale and long-term snow cover mapping.

Hou *et al.* discussed how to select the optimal MODIS and Landsat-8 image pairs from the aspects of date selection, location selection, priority of date and location, etc. They formulated the strategy of initially determining a reasonable location and subsequently selecting the acquisition date of the image pairs to guarantee that the training dataset represents the entire study area well, under the comprehensive consideration of computing power limitation and estimation effect [34]. With the development of remote sensing cloud computing technology, we can obtain a large number of training samples from Landsat and MODIS image pairs in recent decades around the world, and have enough computing power to utilize this large data.

It is also noted that the number of training samples is not the more the better. The problem that needs to be solved is how to use these data to improve the accuracy of snow cover mapping in a simple and efficient way. Accordingly, we propose an m -day dynamic strategy for machine learning-based snow cover mapping based on the spatial and temporal laws of Landsat and MODIS imaging. A large number of validation experiments on the Tibetan Plateau demonstrate that: 1) the m -day dynamic strategy provides a practical way to effectively use the existing large amount of Landsat data to improve MODIS snow cover mapping; 2) the m -day dynamic strategy is spatiotemporal adaptive, which can effectively cope with snow cover mapping issues caused by the spatiotemporal heterogeneity and the rapid changes of snow cover on the Tibetan Plateau; 3) applying the m -day dynamic strategy to RF model is demonstrated to be effective to overcome the difficulties caused by complicated terrains and land covers,

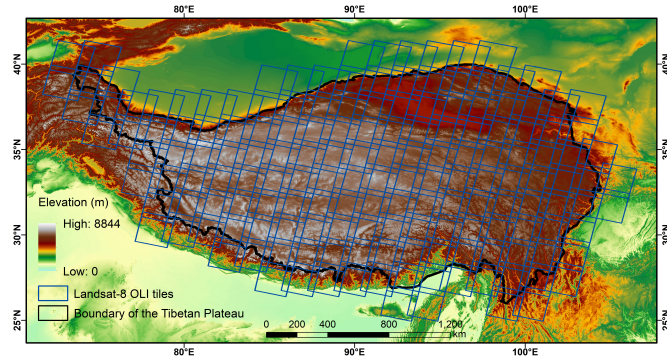


Fig. 1. Location of the study area and distribution of Landsat-8 OLI tiles.

and thus improves the BSC and FSC mapping accuracies in different snow periods, terrains, and land cover types; and 4) the m -day dynamic strategy achieves a balance of accuracy and efficiency, and has the application potential of accurate large-scale and long-term snow information extraction.

The rest of this article is organized as follows. The study area and the used data, including MODIS data, Landsat-8 data and other auxiliary data, are described in Section II. The details of the proposed m -day dynamic strategy, adopted machine learning model, and experimental design are presented in Section III. Experimental results are presented in Section IV, followed by discussions in Section V. Finally, the conclusions are drawn in Section VI along with prospects for future work.

II. STUDY AREA AND DATA

A. Study Area

The Tibetan Plateau is in the central Eurasian continent (26°00' 12"N–39°46' 50"N, 73°18' 52"E–104°46' 59"E), approximately covering an area of 2.57×10^6 km² (see Fig. 1). It is the highest plateau in the world with an average altitude of approximately 4000 m called “Third Pole” and “Asian Water Tower,” which greatly affects the regional environment in Asia and even the entire northern hemisphere [41], [42], [43]. Changes in snow cover on the Tibetan Plateau will affect the atmosphere–land interaction [44], the East Asian monsoons [45], vegetation growth dynamics [13], and global warming [42]. The seasonal snow melt on the Tibetan Plateau is an important surface water source for southwest China and neighboring countries, affecting the production and life of these countries [46]. Therefore, the accurate snow cover map of the Tibetan Plateau is vitally important to the study of climate models and water cycle. However, the Tibetan Plateau has a complex topography, with mountains and rivers distributed alternately, with various types of underlying surface. In addition, the snow cover is thin and discontinuous in space, and the snow characteristics show dramatic spatial and temporal changes that are difficult to track [47], [48]. We focus on how to use a large number of Landsat images reasonably and efficiently for improving the accuracy of MODIS snow mapping on the Tibetan Plateau, which will provide more accurate snow information for climate and hydrological research on the Tibetan Plateau, and will also

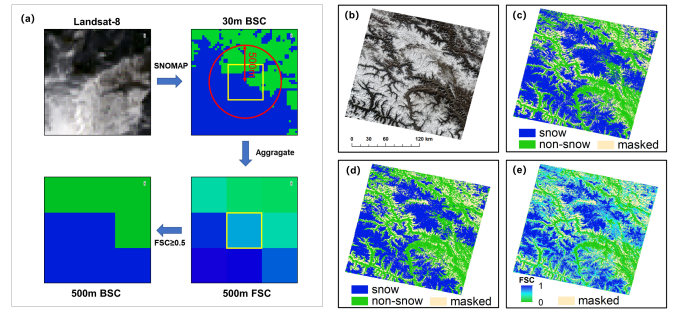


Fig. 2. (a) Schematic of producing MODIS reference data with Landsat-8 OLI images, (b) Landsat-8 OLI real color composite of scene 134/039/20191102 (path/row/date) with 30-m resolution, (c) binary snow cover map with 30-m resolution, (d) reference BSC map with 500 m resolution, and (e) reference FSC map with 500-m resolution.

provide reference for improving the accuracy of snow cover mapping in other regions of the world.

B. Data

1) *Landsat-8 Operational Land Imager (OLI) Data:* Landsat-8 has similar orbital parameters and overpass time to Terra MODIS, so that the Landsat-8 OLI data are often used as equivalent ground reference for MODIS to develop snow mapping algorithms [34], [35], [38]. Landsat-8 OLI images have a relatively high-spatial resolution of approximately 30 m but a relatively long revisit time of 16 days. To cope with the strong spatial and temporal heterogeneity of snow cover and to ensure the integrity of Landsat data in time and space as much as possible, we collect 3288 Landsat-8 OLI Level 1T images from July 1, 2019 to June 30, 2020 (containing a complete snow season) without restricting the cloudiness on the Tibetan Plateau. These images have been atmospherically corrected and with masks of cloud [49], [50]. To ensure the quality of the data, the cloud pixels are masked out using cloud masks of MODIS and Landsat-8 data. The BSC maps with 30-m resolution are generated by SNOMAP algorithm [17], [51]: a pixel will be mapped as snow, if $\text{NDSI} \geq 0.4$, and the reflectance is ≥ 0.1 in band 3 and the reflectance is > 0.11 in band 5. The reference FSC maps with 500-m resolution are obtained by taking the proportion of Landsat-8 snow pixels in a 500-m radius circle placed at the center of each MODIS pixel to reduce the impact of MODIS geolocation uncertainty [31], [37]. Based on the reference FSC maps with 500-m resolution, the reference BSC maps with 500-m resolution are produced using “ $\text{FSC} \geq 0.5$,” as shown in Fig. 2. The generated 500 m reference data are partitioned for model training and validation by simple random sampling, in which 70% of the data are used for training and 30% of the data are used for validation, as shown in Table I.

2) *Terra MODIS Data:* The Terra MODIS data used in this study include the MODIS daily 500 m surface reflectance product (MOD09GA) and MODIS snow cover daily L3 global 500 m SIN grid (MOD10A1 V6) from July 1, 2019 to June 30, 2020. MOD09GA contains surface reflectance values of MODIS bands 1–7 (the first seven bands with 500-m resolution in the visible and short-wave infrared portion) and is the main input for machine learning algorithm. In addition, the

TABLE I
STATISTICAL DESCRIPTION OF THE DATA USED IN THE STUDY

Month	Number of MODIS - Landsat 8 image pairs	Number of available pixels	Number of pixels for training	Number of pixels for validation
2019.07	234	9,199,936	6,439,733	2,760,203
2019.08	258	10,421,904	7,295,733	3,126,171
2019.09	231	11,865,491	8,305,332	3,560,159
2019.10	290	14,184,392	9,928,925	4,255,467
2019.11	298	13,210,161	9,246,756	3,963,405
2019.12	284	12,840,293	8,988,745	3,851,548
2020.01	292	8,965,328	6,276,319	2,689,009
2020.02	285	12,786,723	8,951,292	3,835,431
2020.03	302	10,431,112	7,301,345	3,129,767
2020.04	290	9,351,782	6,546,091	2,805,691
2020.05	290	8,352,198	5,846,245	2,505,953
2020.06	234	9,230,986	6,461,689	2,769,297
Total	3,288	130,840,306	91,588,205	39,252,101

NDSI designed by snow cover's spectral characteristic can effectively reflect the existence of snow cover in a pixel, and NDVI designed by vegetation's spectral characteristic has a significant relationship with the existence of snow cover in a forest pixel [17], [51]. They are also considered as inputs and calculated from the MOD09GA data using the following formula:

$$\text{NDSI} = \frac{R(\text{Band4}) - R(\text{Band6})}{R(\text{Band4}) + R(\text{Band6})} \quad (1)$$

$$\text{NDVI} = \frac{R(\text{Band2}) - R(\text{Band1})}{R(\text{Band2}) + R(\text{Band1})} \quad (2)$$

We use the MOD10A1 V6 for comparison with the results of machine learning algorithm. It contains NDSI values in the range 0.1–1, since values less than 0.1 are converted to 0, indicating non-snow. In addition, to reduce uncertainties, it excluded all NDSI pixels that did not pass the screening tests of the product due to low visible reflectance, high surface temperature, high short-wave infrared reflectance, or low illumination conditions [52]. Using Landsat-8 data as the ground reference, we obtain the optimal threshold of NDSI for MODIS BSC mapping and the best linear regression equation between NDSI and FSC for MODIS FSC mapping.

3) *Auxiliary Data*: The auxiliary data we used include topographic data (NASADEM) and land cover type data (MCD12Q1), which are used for both model input and experimental analysis. NASADEM, a reprocessing of shuttle radar topography mission (SRTM) data, with 30 m spatial resolution, has improved accuracy and reduced void by incorporating multiple auxiliary data. We use the NASADEM data to calculate the surface roughness and then aggregate the surface roughness into 500 m. In addition, the NASADEM data are aggregated into 500-m resolution, based on which the aspect and slope are calculated. MCD12Q1 provides annual global land cover types from six different classification schemes [53]. We use the 2019 International Geosphere-Biosphere Programme (IGBP) classification scheme with 17 land cover types.

III. METHODOLOGY

A. *M-Day Dynamic Strategy*

Machine learning models can effectively incorporate spectral and auxiliary data to alleviate the errors caused by the strong heterogeneity of snow cover, but the effectiveness depends largely on the representativeness of the training samples. The ideal strategy is to select samples to train the model for snow cover mapping in the same area and the same date in a small geographic area. However, since the higher resolution Landsat images are not as complete in time and space as MODIS images, it is difficult to ensure the representativeness of the samples and to achieve large-scale and long-term snow cover mapping from MODIS images by training machine learning models with samples generated from Landsat images. Moreover, we can use Landsat data to generate a large amount of training samples in large-scale and long-term snow cover mapping, but the training time of a machine learning model is often positively related to the amount of data. How to use the data with high efficiency while ensuring the effect is also a problem that must be considered.

Considering the strong spatiotemporal heterogeneity of snow cover and the MODIS & Landsat imaging laws (MODIS images can cover the study area once a day, while Landsat-8 images cover the study area once in 16 days), we design an m -day dynamic strategy for MODIS snow cover mapping where m is equal to (or greater than) 16, to ensure the spatiotemporal representation of training samples and high computational efficiency for snow cover mapping by machine learning.

The specific processes of this strategy are as follows. The first step is to divide a long-term snow cover mapping task into multiple short-term tasks with consecutive m days. The second step is to select training samples randomly from MODIS and Landsat-8 OLI image pairs that are obtained in every consecutive m days. The third step is to use selected training samples to train machine learning models, and apply them on every short-term snow cover mapping task. Fig. 3 shows the schematic of m -day dynamic strategy when m is set to 16, which is named as 16-day dynamic strategy.

The reasons why we design such a strategy are as follows.

In view of the strong spatial heterogeneity of snow cover, we can randomly select samples to train models within the entire study area every m consecutive days, if m is equal to or greater than 16 when using Landsat-8 images for producing samples. It results in the training samples being randomly distributed at different altitudes, slopes, aspect, and land cover types and thus ensures the spatial representation, so that the trained machine learning model can be effectively applied to deal with the spatial heterogeneity of snow cover.

In view of the strong temporal heterogeneity of snow cover, dynamically using training samples from every short m days to train a range of models can effectively deal with the problem brought by the change of snow cover over time. In addition, the heterogeneity of snow cover in every short m consecutive days is smaller than that in the whole year. Therefore, dividing a long-term snow cover mapping task into multiple short-term tasks with consecutive m days is also equivalent to weakening the influence of temporal heterogeneity of snow

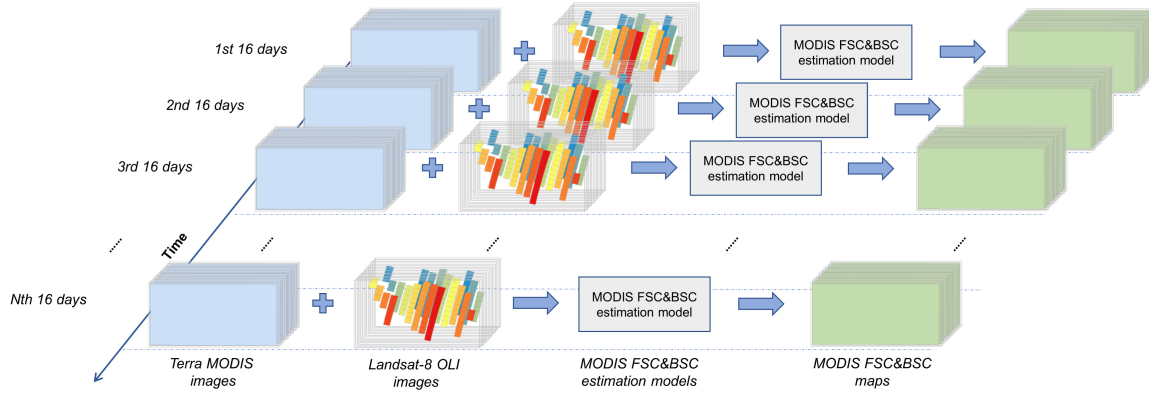


Fig. 3. Schematic of 16-day dynamic strategy for MODIS snow cover mapping.

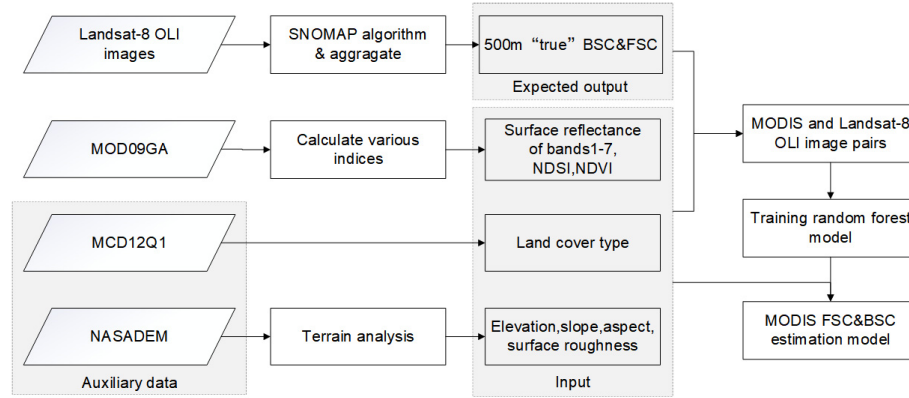


Fig. 4. Flowchart of constructing RF model for MODIS FSC and BSC estimation.

cover. At the same time, considering spatial representation of training samples described above, the m should be equal to or greater than 16 when using Landsat-8 images for producing samples.

In view of the efficiency and effectiveness issues, when a long-term snow cover mapping task is divided into multiple short-term tasks with consecutive m days, these short-term tasks are independent of each other, which can therefore be carried out in parallel for reducing the training time. In addition, the data of short-term snow cover mapping tasks have less heterogeneity, less complexity, and smaller quantities than that of long-term task, thus it is easier to be fit.

B. RF Algorithm

We use classification RF and regression RF models for BSC and FSC tasks, respectively. They are ensembles of decision/regression trees based on the bootstrap aggregation idea [54]. Specifically, the results of the trees are brought together to create the final prediction of the forest. For classification, the final prediction value is the most popular value in the decision trees. For regression, the final prediction value is the average value predicted by the component regression trees. RF algorithm is robust to outliers in predictor variables due to the fact that the algorithm handles outliers by essentially binning them. In addition, the model adjustment mainly depends on a few parameters, including the number of predictors randomly selected at each split (M_{try}), the number of trees in the forest (N_{tree}), and the max depth of trees (M_{depth}) [55].

It is noted that the proposed m -day dynamic training strategy is also suitable for other machine learning algorithms, such as SVM and ANN. The RF algorithm has been validated to be effective for snow cover mapping by comparing with other machine learning algorithms [35], [36], [37].

The 14 input components of the RF models are the MODIS surface reflectance of bands 1–7, NDSI, NDVI, elevation, slope, aspect, surface roughness, and land cover type. The reference BSC maps and reference FSC maps with 500-m resolution generated by Landsat-8 OLI images are used as the expected output values of classification RF and regression RF models for BSC and FSC, respectively. The flowchart of constructing the RF models are presented as Fig. 4.

The three key parameters of M_{try} , N_{tree} , and M_{depth} for RF are set as followed. The universally accepted values of M_{try} for classification and regression are $\sqrt[3]{p}$ and $p/3$, respectively, where p is the dimension of the input data. We randomly select 1% of the training data from the whole year, and use k -fold ($k = 5$) validation and grid search method to determine the optimal values of N_{tree} and M_{depth} . The optimal values of N_{tree} for classification and regression are 500 and 650, and the optimal values of M_{depth} are 15 and 25, respectively, which are general to different strategies, to ensure the fairness of comparison.

C. Accuracy Evaluation

We use $F1$ -score, commission error, and omission error to assess the performance of the classification forest models for

TABLE II
PERFORMANCE METRICS EMPLOYED IN THE ASSESSMENT OF THE BSC MAPPING

Abbreviation	Measure	Explanation	Formula
<i>F1</i>	F1-score	The harmonic mean of precision and recall indicating the overall accuracy.	$F1 = \frac{2 \times TP}{2 \times TP + FP + FN}$
<i>CE</i>	Commission errors	The proportion of fake snow samples in the samples predicted as snow.	$CE = \frac{FP}{TP + FP}$
<i>OE</i>	Omission errors	The proportion of real snow samples predicted as non-snow in all real snow samples.	$OE = \frac{FN}{TP + FN}$

Note: *TP*, number of real snow samples predicted as snow; *FP*, number of non-snow samples predicted as snow; and *FN*, number of real snow samples predicted as non-snow.

TABLE III
PERFORMANCE METRICS EMPLOYED IN THE ASSESSMENT OF THE FSC MAPPING

Abbreviation	Measure	Explanation	Formula
<i>MSE</i>	Mean square error	Average squared difference between reference and predicted values.	$MSE = \frac{1}{n} \sum_{k=1}^n (y_k - \hat{y}_k)^2$
<i>R</i>	Correlation coefficient	Linear relation between reference and predicted values.	$R = \frac{\sum_{k=1}^n (y_k - \bar{y})(\hat{y}_k - \bar{\hat{y}})/(n-1)}{\sqrt{s(y)^2 s(\hat{y})^2}}$

Note: *n*, number of samples; y_k , *k*th reference value; $\hat{y}_k$, *k*th predicted value; $\bar{y}$, mean of reference values; $\bar{\hat{y}}$, mean of predicted values; $s(y)$, standard deviation of reference values; and $s(\hat{y})$, standard deviation of predicted values.

BSC. They can alleviate the problem caused by imbalanced sample size and are summarized in Table II. To assess the performance of FSC mapping, MSE and Pearson's correlation coefficient (*R*) are used and summarized in Table III.

D. Experimental Design

To validate the effectiveness of the proposed 16-day dynamic strategy, we apply monthly static, yearly static, and 16-day dynamic strategies to train the RF algorithm, resulting in six methods for comparison of BSC and FSC mapping, which are named as RFC_ December, RFC_ Static, RFC_ Dynamic, RFR_ December, RFR_ Static, and RFR_ Dynamic (see Table IV). We also apply these three training strategies on SNOMAP and linear regression algorithm to achieve local optimization, resulting in six methods for comparison, which are named as SNOMAP_ December, SNOMAP_ Static, SNOMAP_ Dynamic, LR_ December, LR_ Static, and LR_ Dynamic (see Table IV). The SNOMAP, LR, RFC, and RFR indicate SNOMAP algorithm, linear regression algorithm, classification, and regression RF model, respectively. "December" indicates monthly static strategy, in which only the data from December 2019 are used to train a single model and applied to the whole year. The reason why we chose December data for our experiment is that it has less cloud cover in this month and thus provides more data for training; "Static" indicates yearly static strategy, in which a single model is trained with data from the whole year and applied to the whole year; "Dynamic" indicates the 16-day dynamic strategy, in which multiple models are trained with data from each 16 days across the whole year and applied to each corresponding 16 days.

In the case of snow cover mapping for the whole year, training data only from December cannot cover all

characteristics, and data from the whole year is too coarse for training. Hence, the comparison of RFC_ December and RFR_ December with RFC_ Dynamic and RFR_ Dynamic is to explore the effect of the temporal representation of samples on the machine learning model for large-scale and long-time snow cover mapping and demonstrate the advantages of 16-day dynamic strategy in dealing with the temporal representation of samples. The comparison of RFC_ Static and RFR_ Static with RFC_ Dynamic and RFR_ Dynamic is to demonstrate the advantages of the proposed strategy in data utilization effect, accuracy, and computational efficiency on the basis of satisfying the spatial and temporal representation of training samples. The comparison of SNOMAP_ December, SNOMAP_ Static, SNOMAP_ Dynamic, LR_ December, LR_ Static, and LR_ Dynamic with RFC_ Dynamic and RFR_ Dynamic is to further explore the effect of the proposed strategy in solving the problem caused by the spatial and temporal heterogeneity of snow cover.

The amount of training data and temporal application domain of depends on the specific variation as described in Table IV. In addition, it should be noted that the reference FSC of the training samples is restricted from 0.1 to 0.95, to reduce the negative effects of multiple samples clustering at very low or very high FSC [52], [56]. Furthermore, equations of Linear regression and optimal NDSI thresholds of SNOMAP under different strategies are described in Table V.

IV. RESULTS AND ANALYSIS

A. Overall Performance of the Model

The effectiveness of the 16-day dynamic strategy in improving the accuracy of snow cover mapping is demonstrated. According to Table VI, it can be seen that the RF model

TABLE IV
EXPERIMENTAL DESIGN SCHEME

Task	Method	Algorithm	Training data	Temporal application domain
BSC	RFC_ December	Classification random forest	70% of the data from December 2019	The whole year
	RFC_ Static		70% of the data from the whole year	The whole year
	RFC_ Dynamic		70% of the data from each 16 days across the whole year	Each 16 days across the whole year
	SNOMAP_ December	SNOMAP	70% of the data from December 2019	The whole year
	SNOMAP_ Static		70% of the data from the whole year	The whole year
	SNOMAP_ Dynamic		70% of the data from each 16 days across the whole year	Each 16 days across the whole year
FSC	RFR_ December	Regression random forest	70% of the data from December 2019 limited by “ $0.1 \leq FSC \leq 0.95$ ”	The whole year
	RFR_ Static		70% of the data from the whole year limited by “ $0.1 \leq FSC \leq 0.95$ ”	The whole year
	RFR_ Dynamic		70% of the data from each 16 days across the whole year limited by “ $0.1 \leq FSC \leq 0.95$ ”	Each 16 days across the whole year
	LR_ December	Linear regression	70% of the data from December 2019 limited by “ $0.1 \leq FSC \leq 0.95$ ”	The whole year
	LR_ Static		70% of the data from the whole year limited by “ $0.1 \leq FSC \leq 0.95$ ”	The whole year
	LR_ Dynamic		70% of the data from each 16 days across the whole year limited by “ $0.1 \leq FSC \leq 0.95$ ”	Each 16 days across the whole year

TABLE V
EQUATIONS OF LINEAR REGRESSION AND OPTIMAL NDSI THRESHOLDS OF SNOMAP UNDER DIFFERENT TRAINING STRATEGIES

Strategy	Temporal domain	Optimal NDSI thresholds of SNOMAP	Equations of linear regression
December	The whole year	0.34	$FSC = 0.56 \times NDSI + 0.36$
	Static	The whole year	$FSC = 0.51 \times NDSI + 0.35$
			$FSC = 0.40 \times NDSI + 0.35$
			$FSC = 0.42 \times NDSI + 0.37$
			$FSC = 0.39 \times NDSI + 0.36$
			$FSC = 0.39 \times NDSI + 0.35$
			$FSC = 0.34 \times NDSI + 0.33$
			$FSC = 0.42 \times NDSI + 0.37$
			$FSC = 0.52 \times NDSI + 0.41$
			$FSC = 0.49 \times NDSI + 0.39$
			$FSC = 0.47 \times NDSI + 0.38$
			$FSC = 0.55 \times NDSI + 0.37$
			$FSC = 0.52 \times NDSI + 0.36$
			$FSC = 0.59 \times NDSI + 0.36$
			$FSC = 0.55 \times NDSI + 0.36$
			$FSC = 0.57 \times NDSI + 0.34$
			$FSC = 0.54 \times NDSI + 0.32$
			$FSC = 0.54 \times NDSI + 0.34$
Dynamic	20191224-20200108	20200109-20200124	$FSC = 0.48 \times NDSI + 0.33$
			$FSC = 0.52 \times NDSI + 0.35$
			$FSC = 0.52 \times NDSI + 0.34$
			$FSC = 0.52 \times NDSI + 0.33$
			$FSC = 0.47 \times NDSI + 0.36$
			$FSC = 0.45 \times NDSI + 0.36$
			$FSC = 0.37 \times NDSI + 0.34$

TABLE VI
VALIDATION ACCURACIES OF VARIOUS METHODS FOR
BSC MAPPING OVER THE WHOLE YEAR

Method	<i>F1</i>	<i>CE</i>	<i>OE</i>
SNOMAP_December	0.9278	0.0720	0.0724
SNOMAP_Static	0.9275	0.0683	0.0765
SNOMAP_Dynamic	0.9292	0.0707	0.0709
RFC_December	0.9456	0.0552	0.0536
RFC_Static	0.9518	0.0390	0.0573
RFC_Dynamic	0.9596	0.0315	0.0491

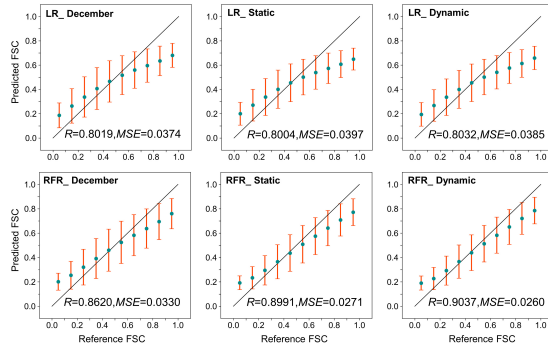


Fig. 5. Validation accuracies of various methods for FSC mapping over the whole year. Mean predicted FSC values within each 10% reference FSC range are calculated and shown as the solid circles, and the corresponding standard deviations are indicated by the vertical bars.

achieves apparently higher accuracy than the SNOMAP algorithm for BSC mapping no matter which training strategy is applied. The different training strategies would lead to the different accuracies for both RF and SNOMAP algorithm, in which the 16-day dynamic strategy achieves better performance than the other two. It is noted that the different training strategies have a greater effect on the RF than the SNOMAP algorithm by comparing the *F1* gap of 0.0140 between RFC_Dynamic and RFC_December with the *F1* gap of only 0.0017 between SNOMAP_Dynamic and SNOMAP_Static.

The FSC accuracies are presented in Fig. 5, in which the accuracy differences among different methods are similar with those in BSC mapping. The RF model also achieves apparently higher FSC accuracies than the linear regression model with the *R* gap of approximate 0.1, the improvement mainly comes from the reduction of the underestimation of high FSC values and the overestimation of the low FSC values. The 16-day dynamic strategy achieves the highest FSC accuracies in the three strategies for both the RF and the linear regression models, but the improvement (0.0417 of *R*) is apparently higher for RF model than that (0.0013 of *R*) for linear regression model.

The BSC and FSC accuracy differences in Table VI and Fig. 5 demonstrate the importance of the representation of training samples to the effect of the RF model. First, in terms of both BSC and FSC mapping, the accuracy improvement by 16-day dynamic strategy for RF model is greater than that for

SNOMAP and linear regression model. This is because the RF model is more complicated with more integrated features and more parameters, which makes it have higher capacity to learn more knowledge from the training samples for snow cover mapping. Accordingly, the better representation of the training samples would promote the greater accuracy improvement for RF model. Second, the accuracy improvement for FSC mapping is higher than that for BSC mapping by applying 16-day dynamic strategy to RF model. This is because the task of FSC mapping is more difficult than BSC mapping, which requires a higher quality in terms of the representation of training samples. Third, the accuracies achieved by RF model continuously improve from training strategy of monthly static, yearly static, to 16-day dynamic. This is because the representation of training samples in the strategy monthly static is apparently not as good as that of yearly static and 16-day dynamic. As for the difference between 16-day dynamic and yearly static, it shows that the 16-day dynamic strategy can fit the data better than the yearly static since the representation of training samples is similar between the two strategies. The results of repeated measures analysis of variance (RANOVA) [57] show that the improvement of 16-day dynamic strategy compared with the yearly static strategy in BSC mapping is statistically insignificant, while in FSC mapping is statistically significant. The primary reason is that BSC mapping is easier than FSC mapping. Yearly static strategy can be competent for BSC mapping tasks, while has still room for improvement in FSC mapping tasks.

B. Spatiotemporal Variety of Model Performance

In this section, we aim at comprehensively validating the BSC and FSC accuracies in different snow periods and different regions to illustrate the spatiotemporal variety of the model performance. According to the temporal variety of the model performance, the necessity and advantages of the 16-day dynamic strategy are further clarified for dealing with the rapid change of snow cover. Through the spatial variety of the model performance, the effectiveness of the 16-day dynamic strategy is explored on reducing the errors caused by the spatial heterogeneity of snow cover and further highlights the importance of the representation of the training samples for machine learning-based snow cover mapping.

1) *Temporal Variety of Model Performance*: The BSC and FSC accuracies of all the methods are related to the state of snow cover because of the lower accuracies in months with rapid snow changes such as June, July, and August than the months with relatively stable snow cover, such as November, December, January, and February, as shown in Fig. 6. Besides, the performance differences among different models and different training strategies are similar with those in Section IV-A in each month. Specifically, the RF model achieves higher accuracies than SNOMAP and linear regression model. The accuracy differences caused by different training strategies are higher for RF model than for SNOMAP and linear regression algorithm. Applying the 16-day dynamic training strategy to RF model achieves the highest accuracies for both BSC and FSC mapping.

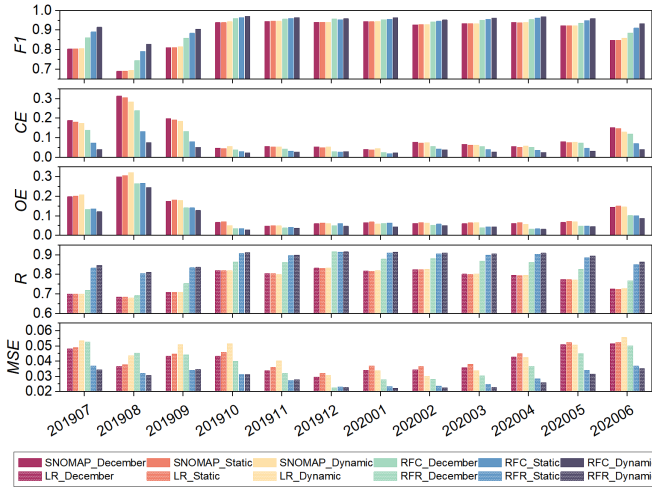


Fig. 6. BSC and FSC accuracies of different models trained by different strategies in each month.

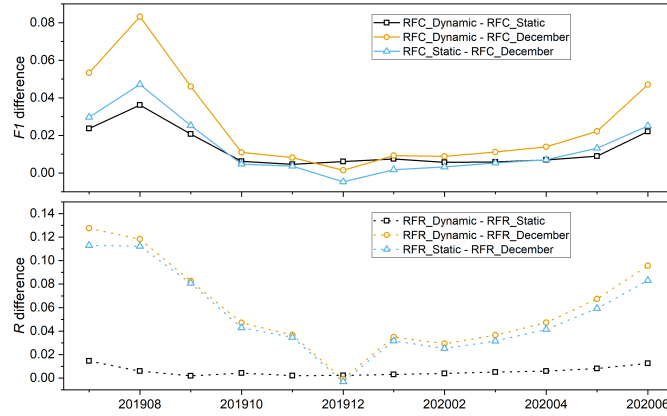


Fig. 7. $F1$ and R differences of RF models trained by different strategies in each month.

The BSC and FSC accuracy differences by applying the different training strategies to the RF model also vary in different months and appear relating to the state of snow cover, as shown in Fig. 7. Generally, the accuracies of applying the 16-day dynamic strategy are higher than the yearly static strategy and followed by the monthly static strategy throughout the year. The accuracy differences among the different strategies are the smallest in December with stable state and tend to increase in the months far away from December. For example, the $F1$ difference between the 16-day dynamic strategy and the monthly static strategy for BSC mapping increase from near 0 in December to over 0.08 in August, and the R difference for FSC mapping increase from near 0 in December to near 0.13 in July, as shown in Fig. 7. This demonstrates that the 16-day dynamic strategy can effectively alleviate the problems brought by the temporal heterogeneity to snow cover mapping. In addition, the accuracy difference between the yearly dynamic strategy and the monthly static strategy is larger than that between the 16-day dynamic strategy and the yearly static strategy, especially for FSC estimation, which shows the higher importance of the training sample representation than the model fitting performance for applying RF model to snow cover mapping.

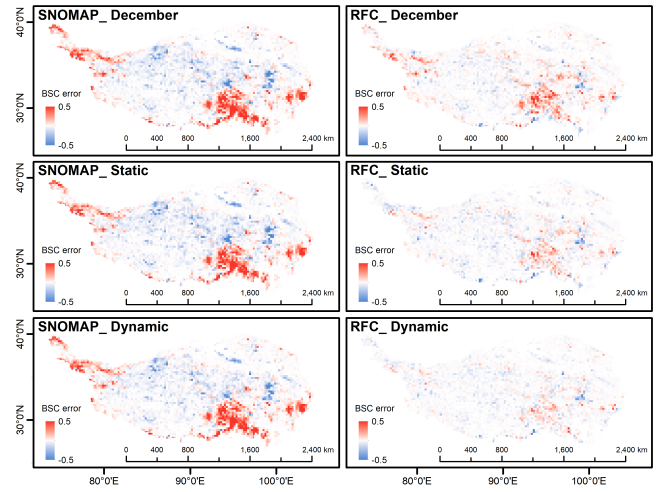


Fig. 8. BSC error distribution of the different models trained by different strategies, where larger positive BSC error values indicate more serious misclassification of non-snow pixels as snow pixels in a 25 km^2 grid, and smaller negative BSC error values indicate more serious misclassification of snow pixels as non-snow pixels.

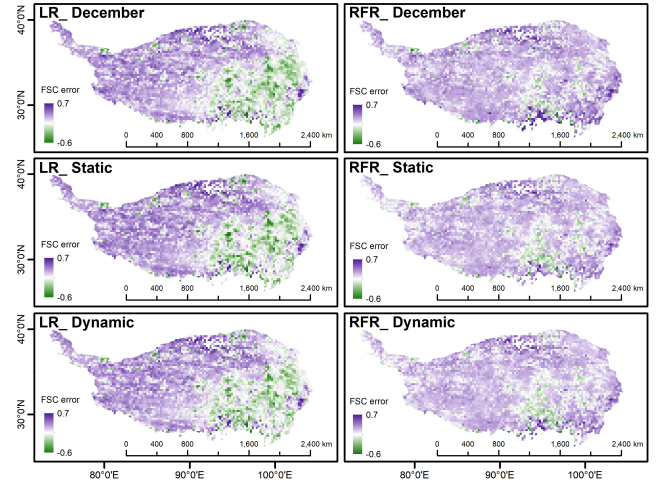


Fig. 9. FSC error distribution of the different models trained by different strategies, where the FSC error value larger than 0 indicates the overestimation in a 25 km^2 grid and that lower than 0 indicates the underestimation.

2) *Spatial Variety of Model Performance*: We perform spatial statistical analysis on the results of different methods and thus present the error distribution in Figs. 8 and 9 for BSC and FSC mapping, respectively.

As for the spatial statistical analysis of the BSC result (see Fig. 8), we subtract the BSC reference value from the BSC prediction value for each 500 m validation sample, and then count the average value within each 25 km^2 grid to obtain the error distribution. Fig. 8 shows that the misclassification of non-snow pixels as snow pixels in the southeast and northwest Tibetan Plateau with complex terrain and the misclassification of snow pixels as non-snow pixels in other areas by SNOMAP algorithm are apparently reduced by RF model, and the application of the training strategies of 16-day dynamic and yearly static further reduces the misclassifications.

As for the spatial statistical analysis of the FSC result (see Fig. 9), we subtract the FSC reference value from the

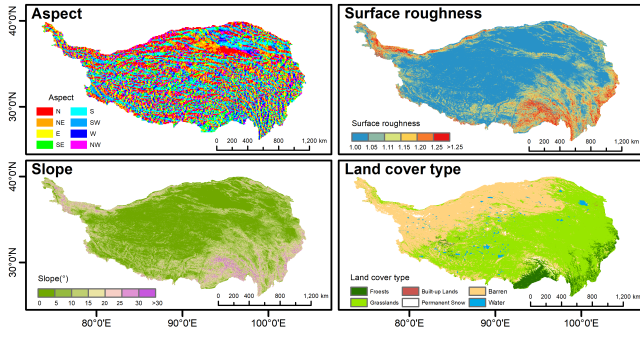


Fig. 10. Aspect, surface roughness, slope, and land cover types of the study area.

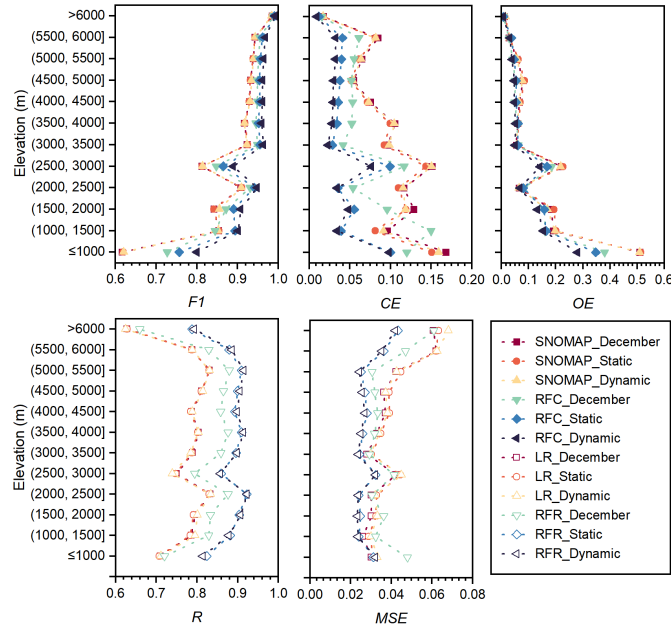


Fig. 11. BSC and FSC accuracies in different elevations.

FSC prediction value for each 500 m validation sample, and then count the average value within each 25 km² grid to obtain the error distribution. Larger positive FSC error values indicate the more serious overestimation in the grid, and the smaller negative FSC error value indicates the more serious underestimation. Fig. 9 shows that the underestimation in the southeast and the overestimation in the other area are also relieved by RF model together with the training strategies of 16-day dynamic and yearly static.

To further illustrate the effectiveness of the 16-day dynamic strategy under different spatial conditions, we make a detailed analysis of the accuracies in different terrains and land cover types. To facilitate the analysis, the aspect, slope, surface roughness, and land cover types of the study area are shown in Fig. 10, and the elevation of the study area has been shown in Fig. 1.

The BSC and FSC accuracies by different methods within each 500-m elevation range are shown in Fig. 11. The BSC accuracies of all the methods tend to improve with the increased elevation except for the abrupt drop in elevations between 2500–3000 m, which is caused by the commission

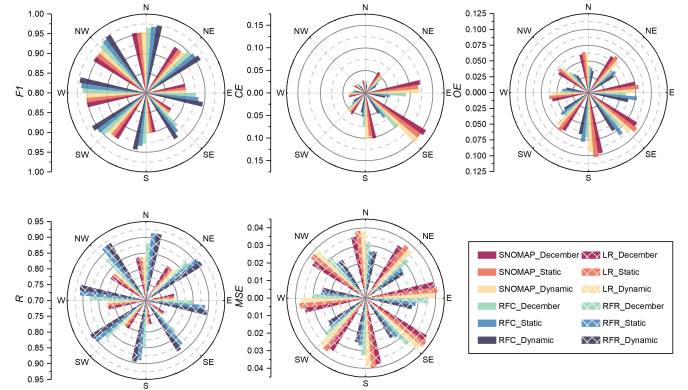


Fig. 12. BSC and FSC accuracies in different aspects.

errors in the southeast as shown in Fig. 8. Applying the 16-day dynamic training strategy to RF model achieves the highest accuracy in different elevations, but the accuracy differences to other methods tend to be small with the increased elevation. Applying the 16-day dynamic training strategy to RF model also achieves the highest FSC accuracy in different elevations, and the accuracy differences to other methods remains almost unchanged in different elevations. The FSC accuracies do not show a monotonic change trend with elevation as that of BSC accuracies. The FSC accuracies in the elevations of <1000 m, 2500–3000 m, and >6000 m appear to be apparently lower than other elevations, which is mainly caused by the overestimation, underestimation, and overestimation, respectively, as shown in Fig. 9.

We divided the aspect into eight directions in the interval of 45°, and calculate the BSC and FSC accuracies of each aspect as shown in Fig. 12. Applying the 16-day dynamic training strategy to RF model can effectively improve both the BSC and FSC accuracies in all the aspects. In addition, in the east, southeast, and south aspects, SNOMAP and linear regression model have apparently lower accuracies because of the stronger shortwave radiation leads to the relatively rapid changes of snow cover in these aspects. However, the accuracy improvement by applying the 16-day dynamic training strategy to RF model is higher in the east, southeast, and south aspects than others, which results in the similar accuracies in different aspects and thus demonstrates the effectiveness of the proposed method on improving snow mapping accuracy with greater difficulty caused by rapid changes of snow cover.

We divided the slope into seven ranges in the interval of 5°, and calculate the BSC and FSC accuracies of each slope range as shown in Fig. 13. Applying the 16-day dynamic training strategy to RF model achieves the highest accuracies in terms of both BSC and FSC mapping in each slope range. In addition, the BSC and FSC accuracies by SNOMAP and linear regression model decrease apparently as the slope increase, which is because the steep slope leads to the greater difficulty of snow cover mapping. However, the accuracy improvement by applying the 16-day dynamic training strategy to RF model is higher in steeper slope ranges, which results in the similar accuracies in different slope ranges. This further demonstrates the effectiveness of the proposed method on improving snow

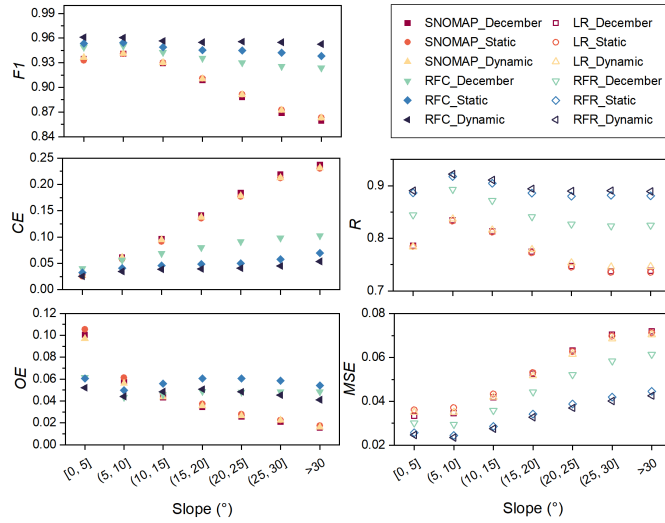


Fig. 13. BSC and FSC accuracies in different slopes.

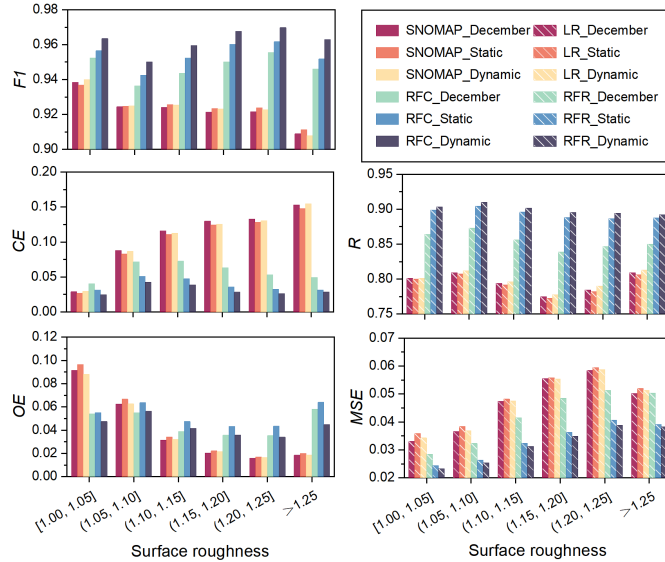


Fig. 14. BSC and FSC accuracies with respect to different surface roughness.

mapping accuracy with greater difficulty caused by steep slope.

We divided the surface roughness into six ranges in the interval of 0.05, and calculate the BSC and FSC accuracies of each surface roughness range as shown in Fig. 14. Applying the 16-day dynamic training strategy to RF model achieves the highest accuracies in terms of both BSC and FSC mapping in each surface roughness range. In addition, the BSC and FSC accuracies by SNOMAP and linear regression model varies apparently in different surface roughness ranges. However, the accuracy improvement by applying the 16-day dynamic training strategy to RF model is higher when the SNOMAP and linear regression model have relatively lower accuracies, which results in the similar accuracies in different surface roughness ranges. This further demonstrates the effectiveness of the proposed method on improving snow cover mapping accuracy with greater difficulty caused by terrain variety.

Fig. 15 shows the BSC and FSC accuracies under different land cover types, where the IGBP classification scheme is

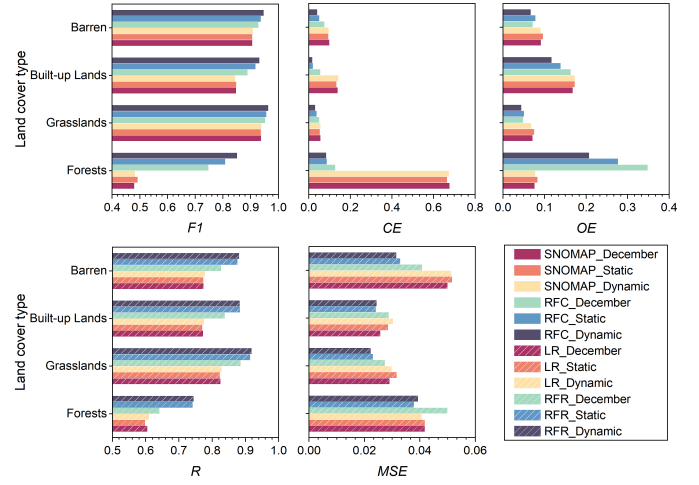


Fig. 15. BSC and FSC accuracies with respect to different land cover types.

reclassified into four land cover types of built-up lands, grasslands, forests, and barren for simplicity. Applying the 16-day dynamic training strategy to RF model also achieves the highest BSC and FSC accuracies in each land cover type. The SNOMAP and linear regression model achieve the highest accuracies in grasslands, followed by barren and built-up lands, and the apparently lower accuracies in forests. However, the accuracy improvement by applying the 16-day dynamic training strategy to RF model changes to the contrary with the largest improvement in forests among the four land cover types. This further demonstrates the effectiveness of the proposed method on overcoming snow cover mapping difficulty caused by complicated land cover, e.g., forests.

In conclusion, through the spatial statistical analysis of model performance in different terrains and land cover types, it is demonstrated that applying the 16-day dynamic training strategy to RF model achieves the highest BSC and FSC accuracies in different terrains and land cover types. In addition, applying the 16-day dynamic training strategy to RF model can effectively overcome the difficulties of snow cover mapping caused by steep slope, sunny slope, terrain variety, and forests by integrating various auxiliary data and enhancing the representation of the training samples. Accordingly, it can achieve a higher improvement of accuracies in regions where SNOMAP and linear regression models have lower accuracies.

V. DISCUSSION

A. Computational Efficiency Comparison

We make a comparison of the computation time by applying different training strategies to RF model for producing the whole-year daily BSC and FSC maps. The analyses are carried on a personal computer with two 2.4 GHz intel¹ Xeon CPU E5-2640 V4 processor and 128 GB 2133 MHz DDR3 RAM and the results are shown in Table VII.

In terms of BSC, the total time of monthly static strategy is the shortest. The second is that of 16-day dynamic strategy and the extra time is mainly used for training models. The

¹Registered trademark.

TABLE VII
COMPARISON OF COMPUTATION TIME (MIN) FOR PRODUCING
A WHOLE-YEAR DAILY BSC AND FSC MAPS IN TIBETAN
PLATEAU BY APPLYING DIFFERENT TRAINING
STRATEGIES TO RF MODEL

Method	Number of observations	Training time	Predicting time	Total time
RFC_ December	9,138,330	37.04	1051.20	1088.24
RFC_ Static	91,588,204	790.42	1422.04	2212.46
RFC_ Dynamic	91,588,204	333.73	1036.24	1369.97
RFR_ December	269,055	2.43	1464.38	1466.81
RFR_ Static	1,904,598	20.78	2105.32	2126.10
RFR_ Dynamic	1,904,598	37.72	1141.72	1179.44

total time of yearly static strategy is the longest. In terms of FSC, the total time of 16-day dynamic strategy is the shortest. The second is that of monthly static strategy and the extra time is mainly used for predicting. The total time of yearly static strategy is also the longest.

From the perspective of comprehensive accuracy and running time, the 16-day dynamic strategy achieves apparently higher accuracies and similar computational efficiency compared with the monthly static strategy, and achieves higher accuracies and apparently higher computational efficiency than the yearly static strategy in both BSC and FSC mapping. In addition, it is noted that the computational efficiency of the 16-day dynamic strategies can be further improved because it is convenient to perform parallel computation by dividing the time-series tasks into independent 16-day tasks.

B. Application Potential and Limitations

The proposed strategy provides a framework for training machine learning models for relatively low-resolution snow cover mapping by utilizing relatively high-resolution images as training samples. In terms of the target low-resolution images, it can be extended to other satellite images, such as NOAA AVHRR and FY-3. In terms of the high-resolution images, we can integrate more from other sensors, which could help shorten the duration of the dynamic strategy to better deal with the rapid changes of snow cover, and provide more samples for training the machine learning models.

The proposed strategy is only validated in the Tibetan Plateau for a single year. As an extension of time, since the validation of the whole year covers the different periods for seasonal snow cover, and the small tasks in the proposed strategy are independent with each other, the proposed method can directly be extended to other years for snow cover mapping. As an extension of space, e.g., to the global scope, the data volume will surge and the snow situation will become more complex and diverse, which brings great challenges to train the machine learning model for snow cover mapping. To deal with the challenges, we can divide the large-size area into multiple regions and training spatially local models independently.

Besides, it deserves to explore a machine learning model, e.g., deep learning model, with higher complexity and capacity to deal with the complex and diverse situations for snow cover mapping.

Accurately identifying and removing cloud is critical to producing cloud-free MODIS snow cover products. There is cloud/snow confusion in the official cloud mask products of MODIS [58]. The proposed strategy has the potential to recognize cloud, but has not yet achieved this capability, because the accurate cloud labels cannot be obtained automatically, due to the difference between the cloud position of the MODIS and Landsat-8 images. In this study, we focused on exploring methods to improve the accuracy of snow cover mapping without paying additional attention to identifying and removing cloud, but reducing snow/cloud confusion is worthy of attention in the future.

VI. CONCLUSION

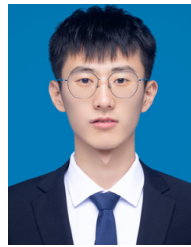
We proposed an m -day dynamic strategy to train machine learning models for improving MODIS snow cover mapping, which can ensure the representation of training samples for machine learning models to overcome the difficulties of snow cover mapping caused by the strong spatiotemporal heterogeneity and the rapid changes of snow. The strategy was applied to BSC and FSC mapping on the Tibetan Plateau using Landsat-8 OLI images as equivalent ground references. Its m was set as 16 based on the spatiotemporal law of Landsat and MODIS imaging and thus named as 16-day dynamic strategy. A large number of validation experiments on the Tibetan Plateau demonstrate that applying the 16-day dynamic strategy to RF model achieves the highest BSC and FSC accuracies in different periods, terrains, and land cover types, whose $F1$ of BSC mapping achieves 0.9596, and R and MSE of FSC mapping achieve 0.9037 and 0.0260, respectively. In addition, applying the 16-day dynamic strategy to RF model achieves an apparent improvement for both BSC and FSC accuracies compared with the SNOMAP and linear regression algorithm in the regions with mapping difficulties caused by sunny and steep slope, surface roughness, and complicated land cover. The 16-day dynamic strategy for RF model also achieves a better balance in terms of mapping accuracies and computational efficiency than the static strategies, which has the potential to be used for improving large-scale and long-time snow cover mapping from relatively low-resolution satellite images. In the future, we would like to further validate and improve the proposed strategy in other regions with a goal of applying it to snow cover mapping worldwide. We also plan to integrate more images from other sensors to further strengthen the proposed strategy for both BSC and FSC.

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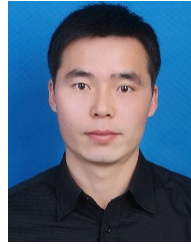
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Wenbo Luan received the B.E. degree in resource exploration engineering from the China University of Mining and Technology, Xuzhou, China, in 2020. He is currently pursuing the M.S. degree in cartography and geographic information system with Nanjing University, Nanjing, China.

His research interests include remote sensing of snow cover and deep learning for remote sensing.



Xueliang Zhang (Member, IEEE) received the B.S. degree in geographical information system and the Ph.D. degree in remote sensing of resources and environment from Nanjing University, Nanjing, China, in 2010 and 2015, respectively.

From 2014 to 2015, he was a Visiting Student with the Informatics Institute, University of Missouri, Columbia, MO, USA. From 2016 to 2018, he was an Associate Researcher with the Department of Geographic Information Science, Nanjing University, where he is currently an Associate Professor.

His research interests include high-resolution remote sensing image analysis, semantic segmentation, and deep learning for remote sensing.



Pengfeng Xiao (Senior Member, IEEE) received the B.M. degree in land resource management from Hunan Normal University, Changsha, China, in 2002, and the Ph.D. degree in cartography and geographical information system from Nanjing University, Nanjing, China, in 2007.

From 2007 to 2009, he was a Lecturer with the School of Geography and Ocean Science, Nanjing University, where he was an Associate Professor from 2010 to 2018. He was a Visiting Scholar with the Department of Geography, University of Giessen, Giessen, Hesse, Germany, from 2011 to 2012, and the Department of Environmental Science, Policy, and Management, University of California at Berkeley, Berkeley, CA, USA, from 2014 to 2015. Since 2019, he has been a Professor with Nanjing University. He has authored four books and more than 160 articles. His research interests include high-resolution remote sensing image analysis, remote sensing of snow cover, and land use and land cover change.



Huadong Wang received the B.E. degree in surveying and mapping engineering from Nanjing Normal University, Nanjing, China, in 2020. She is currently pursuing the M.S. degree in remote sensing of resources and environment with Nanjing University, Nanjing.

Her research interests include remote sensing of snow phenology and snow density.



Siyong Chen received the B.S. degree in geology from Chang'an University, Xi'an, China, in 2016, and the M.S. degree in cartography and geographic information system from Lanzhou University, Lanzhou, China, in 2021. He is currently pursuing the Ph.D. degree in cartography and geographic information system with Nanjing University, Nanjing, China.

His research interests include remote sensing data reconstruction, radiative transfer/geometric optical modeling, and snow parameters retrieval.