Accuracy assessment of cloud removal methods for Moderate-resolution Imaging Spectroradiometer (MODIS) snow data in the Tianshan Mountains, China (Postprint)

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Abstract

Snow cover plays a critical role in global climate regulation and hydrological processes. Accurate monitoring is essential for understanding snow distribution patterns, managing water resources, and assessing the impacts of climate change. Remote sensing has become a vital tool for snow monitoring, with the widely used Moderate-resolution Imaging Spectroradiometer (MODIS) snow products from the Terra and Aqua satellites. However, cloud cover often interferes with snow detection, making cloud removal techniques crucial for reliable snow product generation. This study evaluated the accuracy of four MODIS snow cover datasets generated through different cloud removal algorithms. Using real-time field camera observations from four stations in the Tianshan Mountains, China, this study assessed the performance of these datasets during three distinct snow periods: the snow accumulation period (September–November), snowmelt period (March–June), and stable snow period (December–February in the following year). The findings showed that cloud-free snow products generated using the Hidden Markov Random Field (HMRF) algorithm consistently outperformed the others, particularly under cloud cover, while cloud-free snow products using near-day synthesis and the spatiotemporal adaptive fusion method with error correction (STAR) demonstrated varying performance depending on terrain complexity and cloud conditions. This study highlighted the importance of considering terrain features, land cover types, and snow dynamics when selecting cloud removal methods, particularly in areas with rapid snow accumulation and melting. The results suggested that future research should focus on improving cloud removal algorithms through the integration of machine learning, multi-source data fusion, and advanced remote sensing technologies. By expanding validation efforts and refining cloud removal strategies, more accurate and reliable snow products can be developed, contributing to enhanced snow

monitoring and better management of water resources in alpine and arid areas.

Full Text

Preamble

Accuracy assessment of cloud removal methods for Moderate-resolution Imaging Spectroradiometer (MODIS) snow data in the Tianshan Mountains, China

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Abstract: Snow cover plays a critical role in global climate regulation and hydrological processes, making accurate monitoring essential for understanding snow distribution patterns, managing water resources, and assessing climate change impacts. Remote sensing has become a vital tool for snow monitoring, particularly through the widely used Moderate-resolution Imaging Spectroradiometer (MODIS) snow products from Terra and Aqua satellites. However, cloud cover persistently interferes with snow observations, making cloud removal techniques crucial for reliable snow product generation. This study evaluated the accuracy of four MODIS snow cover datasets generated through different cloud removal algorithms using real-time field camera observations from four stations in the Tianshan Mountains, China. The performance of these datasets was assessed during three distinct snow periods: the snow accumulation period (September–November), snowmelt period (March–June), and stable snow period (December–February of the following year). The findings showed that cloud-free snow products generated using the Hidden Markov Random Field (HMRF) algorithm consistently outperformed the others, particularly under cloud cover, while products using near-day synthesis and the spatiotemporal adaptive fusion method with error correction (STAR) demonstrated varying performance depending on terrain complexity and cloud conditions. This study highlighted the importance of considering terrain features, land cover types, and snow dynamics when selecting cloud removal methods, particularly in areas with rapid snow accumulation and melting. The results suggest that future research should focus on improving cloud removal algorithms through the integration of machine learning, multi-source data fusion, and advanced remote sensing technologies. By expanding validation efforts and refining cloud removal strategies, more accurate and reliable snow products can be developed, contributing to enhanced snow monitoring and improved water resource management in alpine and arid regions.

Keywords: real-time camera; cloud removal algorithm; snow cover; Moderate-resolution Imaging Spectroradiometer (MODIS) snow data; snow monitoring

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1 Introduction

Snow cover is a critical natural resource and essential variable in climate studies that has long been central to global climate change research and Earth surface process investigations. The Moderate-resolution Imaging Spectrometer (MODIS), mounted on Terra and Aqua satellites, provides high-frequency, high-resolution data whose powerful acquisition capabilities make it indispensable for studying global and regional snow cover dynamics [?, ?, ?]. Nevertheless, MODIS snow data utility is constrained by inherent limitations, chiefly cloud coverage that persistently interferes with snow observations. Studies indicate that the global average frequency of completely cloud-free sky coverage is only 20.70% [?, ?]. Clouds and shadows complicate accurate ground information retrieval, leading to errors in snow spectral data extraction and presenting significant challenges for snow data analysis.

In recent years, numerous algorithms have been developed to enhance MODIS cloud-free snow datasets through time-series analysis, spatial feature extraction, and multi-source data fusion, each tailored to specific regional conditions and snow characteristics [?, ?, ?]. Time-series approaches include maximum-value compositing from Terra and Aqua observations [?, ?], near-day synthesis methods [?, ?], and multi-day combination techniques [?, ?], which improve temporal continuity. Spatial methods exploit snow cover spatial autocorrelation to interpolate cloud-contaminated pixels based on surrounding clear-sky observations [?, ?, ?]. More advanced spatiotemporal strategies, such as those based on spatiotemporal data cubes, have also been proposed to more effectively eliminate cloud contamination [?, ?]. To reduce elevation-induced misclassification, several studies have combined snow-elevation models with snowline extraction techniques [?, ?, ?, ?] or applied altitude-based gradient methods [?, ?, ?, ?]. In certain regions, classification techniques distinguishing "perennial snow" from "snow-free land" have improved snow detection accuracy [?, ?, ?]. Furthermore, multi-source fusion methods integrating optical, microwave, and ground-based observations have shown promise for improving both spatial completeness and accuracy of cloud removal [?, ?, ?, ?, ?, ?, ?].

Traditional cloud removal methods have evolved from basic interpolation to advanced reconstruction algorithms. Early efforts primarily relied on simple interpolation techniques such as cubic spline interpolation [?, ?, ?, ?, ?]. These methods have since evolved into more sophisticated approaches like image reconstruction algorithms utilizing variational interpolation theorem [?, ?], enabling automated generation of daily cloud-free MODIS snow data. Recent advances have integrated temporal interpolation and spatiotemporal weighting with piecewise cubic Hermite interpolation to effectively fill data gaps in Normalized Difference Snow Index (NDSI) [?, ?, ?]. Probabilistic modeling techniques, such as the Hidden Markov Random Field (HMRF) model, have also been employed to improve cloud removal accuracy by capturing snow cover spatial and temporal continuity [?, ?].

In the current era of rapid artificial intelligence advances, machine learning-based cloud removal algorithms have demonstrated remarkable potential for enhancing MODIS snow cover product accuracy and continuity. [?, ?] developed rule-based classification models incorporating multiple features such as terrain, time, and cloud conditions to refine snow detection under cloud cover. Ensemble learning approaches, including extreme gradient boosting [?, ?] and random forests [?, ?], utilize decision tree frameworks to enhance predictive performance, particularly in complex terrain. Support vector machines have also been applied to classify snow-covered and snow-free areas with improved reliability [?, ?]. In parallel, deep learning techniques have gained attention due to their powerful feature extraction capabilities. Convolutional neural networks have been used to automatically learn spatial features from satellite imagery [?, ?, ?], while recurrent neural networks, particularly long short-term memory variants, are increasingly applied for time-series prediction of snow cover beneath clouds [?, ?, ?]. These models exploit temporal dependencies inherent in MODIS data, offering improved performance in dynamic snow environments.

The aforementioned cloud removal methods depend on data temporal continuity and snow distribution stability, exhibiting limited adaptability to complex terrains. Therefore, understanding the error sources in various cloud removal algorithms can improve their accuracy and enhance cloud-free dataset availability.

This study employed four publicly available daily cloud-free snow cover datasets —each generated from MODIS data using different cloud removal techniques—

and validated their performance using time-matched images from four real-time cameras installed by our research team in remote, uninhabited areas of the Tianshan Mountains, Xinjiang Uygur Autonomous Region (hereafter Xinjiang), China. Our objectives are to: (1) evaluate the accuracy of these cloud-free products under both clear-sky and cloudy conditions; (2) assess their strengths and limitations across various environmental settings; and (3) analyze their performance in relation to terrain complexity and land cover heterogeneity. These findings provide critical insights for improving cloud removal techniques in mountainous environments and contribute to more accurate snow monitoring and enhanced water resource management in alpine areas.

2.1 Study Area

The Tianshan Mountains, located in central Xinjiang, form one of Central Asia's most prominent mountain systems and act as a significant climatic and ecological divide. Stretching east-west, the range is characterized by complex topography including high peaks, deep valleys, and extensive foothill zones [**?**, **?**]. This geographical pattern creates distinct climate differences between mountains and basins. Comprehensive analysis reveals fluctuating terrain, particularly the complex arrangement of mountains and basins, posing challenges to snow cover research. Snow distribution is intimately tied to terrain conditions, vegetation coverage, and climate changes, while undulating terrain significantly impacts snowmelt processes. Thus, understanding MODIS snow product accuracy in central Xinjiang is important.

Four real-time cameras were established in uninhabited mid-to-high altitude areas of the Tianshan Mountains, central Xinjiang, China (Fig. 1 [Figure 1: see original paper]; Table 1). Monitoring began in September 2016, with photography sessions conducted primarily between 09:00 and 16:00 LST. The stations –Luotuobozi, Shuidian, Shenglidaoban, and Chahanwusu–were strategically located in sparsely populated or uninhabited mid-to-high altitude mountainous areas, minimizing human activity influence and enabling observation of natural snow and vegetation dynamics. These sites span elevation zones from subalpine to alpine conditions and encompass varied terrain types including grassland and barren or sparsely vegetated land, providing essential data support for studying natural environments and plant phenology in high-altitude uninhabited areas.

2.2.1 Daily Snow Cover MODIS Products

Four daily MODIS snow cover datasets were selected for accuracy assessment, each derived using different cloud-removal algorithms based on MODIS Terra and Aqua observations.

Dataset 1: MODIS/Terra CGF Snow Cover Daily L3 Global 500

m SIN Grid (MOD10A1F). This global Level-3 dataset provides a daily composite of snow cover and albedo derived from MOD10A1. In this dataset, observation points covered by clouds in the current day' s snow cover data are replaced with cloud-free points from the previous day. The snow cover variable CGF_{{{NDSI}}*{{Snow}}*}{Cover} ranges from 1 to 100, indicating snow presence, while 0 denotes no available snow information. To ensure consistency with real-time camera observations, we extracted data covering September 6, 2016 to July 1, 2020.

Dataset 2: Chinese MODIS Daily Cloudless 500 m Snow Cover Area Product Dataset, provided by the National Cryosphere Desert Data Center (NCDC). This dataset is generated using a multi-index combined snow discrimination algorithm adapted for different land cover types. It utilizes MODIS surface reflectance products (MOD09GA and MYD09GA) and combines Terra and Aqua observations for initial cloud removal. Cloud gaps are subsequently filled using a Hidden Markov Random Field (HMRF) model, and microwave-derived snow depth products are integrated to further enhance spatial completeness [**?**, **?**]. Dataset values include: 0 for land, 1 for satellite-detected snow, 2 for interpolated snow from cloud removal, and 3 for snow estimated from snow depth. In this study, values of 1, 2, and 3 were considered snow cover. To ensure consistency with real-time camera observations, we extracted data covering September 6, 2016 to July 1, 2020.

Dataset 3: China' s Cloud-Free MODIS NDSI Dataset (2001-2020), provided by NCDC, is generated from MOD10A1 and MYD10A1 using the Spatiotemporal Adaptive Fusion method with Error Correction (STAR). This method integrates Spatiotemporal Adaptive Fusion (STAF) with Error Correction (EC) to eliminate clouds while preserving spatial heterogeneity in snow cover [**?**, **?**]. Data values from 1 to 100 represent snow presence, while 0 indicates no snow information. To ensure consistency with real-time camera observations, we extracted data covering September 6, 2016 to July 1, 2020.

Dataset 4: Daily Snow Cover Extent Dataset over High Asia (2002-2018). This dataset is developed using MOD10A1 and MYD10A1 as source data and is tailored for high-altitude areas across Asia. A stepwise cloud-removal approach is employed, including MODIS Terra-Aqua observation combination, 3-day consecutive composite, short-term minimum snow cover approach, adjacent-pixel method, and 8-day maximum land cover mask [**?**, **?**]. This process generates a daily low-cloud snow cover dataset for high-altitude Asian areas. Snow values from 1 to 100 indicate snow presence, 225 indicates snow-free information, and 250 indicates cloud cover. In this study, we extracted data covering September 6, 2016 to May 5, 2018.

2.2.2 Classification of Clear-Sky and Cloudy Conditions

To evaluate cloud-removal algorithm performance, it was essential to distinguish between clear-sky and cloudy conditions during the study period, enabling stratified accuracy assessment of the four cloud-free MODIS snow cover products under distinct atmospheric conditions. We used the MODIS/Terra Snow Cover Daily L3 Global 500 m SIN Grid, Version 6.1 (MOD10A1) dataset to classify each observation day as either clear-sky or cloudy. In MOD10A1, pixels with values ranging from 0 to 100 represent valid snow cover information under clear-sky conditions, while a pixel value of 250 indicates cloud contamination. A day was classified as clear-sky if more than 90.00% of pixels within a selected validation area (matching the real-time camera field of view) were marked as snow or land (values 0–100). Conversely, a day was classified as cloudy if more than 50.00% of pixels in that area were flagged as cloudy (value 250).

2.2.3 Real-Time Camera Observation Data

Between September 6, 2016 and July 1, 2020, our research group established four outdoor camera observation points in the Tianshan Mountains, central Xinjiang (Fig. 1; Table 1). Among these, Shenglidaoban Station (3,317.75 m) is located in a high-altitude area, while Luotuobozi (2,395.19 m), Shuidian (2,955.58 m), and Chahanwusu (1,962.19 m) stations are situated in mid-to-high altitude areas. Images were manually interpreted to determine snow cover presence or absence. To ensure reliability, we only selected images taken between 12:00 and 13:00 LST. Days with ambiguous visibility due to cloud obstruction or low illumination were excluded from analysis. For validation purposes, each camera' s field of view was spatially aligned with the footprint of corresponding MODIS pixels. The interpreted snow presence from field imagery served as ground truth for assessing the accuracy of the four MODIS snow cover datasets under both clear-sky and cloudy conditions.

2.3 Data Analysis

To quantitatively evaluate the four MODIS snow cover datasets, this study extracted snow cover information using ENVI v.5.2 (Exelis Visual Information Solutions, Boulder, USA) and ArcGIS v.10.2 (Environmental Systems Research Institute Inc. (ESRI), Redlands, USA). The extracted data were converted into binary format (snow and snow-free) using Python and used to generate snow cover time series. Binary snow cover information from real-time camera images was obtained through manual visual interpretation for further analysis.

To systematically evaluate cloud-removal method effectiveness, we used confusion matrices (Table 2) and statistical accuracy metrics. As shown in Equations

1-6, we utilized accuracy, precision, recall, overestimation error (OE), underestimation error (UE), and f (the harmonic mean of accuracy and recall) to evaluate cloud removal and snow cover detection method performance.

Table 2. Confusion matrix for precision validation

MODIS product	Observation Snow	Observation Snow-free
Snow	TP	FP
Snow-free	FN	TN

Note: TP, true positive; FN, false negative; FP, false positive; TN, true negative.

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + FP + TN}, \quad (1)$$

$$\text{Precision} = \frac{TP}{TP + FP}, \quad (2)$$

$$\text{Recall} = \frac{TP}{TP + FN}, \quad (3)$$

$$f = \frac{2TP}{2TP + FN + FP}, \quad (4)$$

$$\text{OE} = \frac{FP}{FP + TN}, \quad (5)$$

$$\text{UE} = \frac{FN}{TP + FN}, \quad (6)$$

where TP represents pixels where the true value contains snow and the cloud-removal processed data also contains snow; FN represents pixels where the true value contains snow but the processed data shows no snow; FP represents pixels where the true value is snow-free but the processed data shows snow; TN represents pixels where the true value is snow-free and the processed data is also snow-free. Accuracy is the proportion of correctly classified observations (both snow and snow-free) relative to total observations. Precision is the proportion of correctly classified snow observations relative to total predicted snow observations. Recall is the proportion of correctly predicted snow observations relative to total actual snow observations. The f-score is the harmonic mean of accuracy and recall, with values between 0 and 1, where higher values indicate better snow classification algorithm performance. OE is the probability of erroneously predicting snow based on total actual non-snow observations, and UE is the probability of missing actual snow presence based on total actual snow observations.

3.1 Accuracy of Cloud-Free Snow Cover Datasets Under Different Periods

The accuracy of the four cloud-free MODIS snow cover datasets was evaluated under various temporal conditions, including the snow accumulation period (September–November), snowmelt period (March–June), and stable snow period (December–February of the following year).

3.1.1 Snow Cover Accuracy Over the Full Year

Comprehensive evaluation of the cloud-free snow dataset is detailed in Table S1, which presents accuracy metrics for daily snow data generated by the four MODIS snow datasets across all time periods. Dataset 1 exhibited high accuracy (0.948) and precision (0.996) at Luotuobozi Station, although a certain proportion of snow was missed, resulting in a UE of 0.098 under clear-sky conditions. At Shenglidaoban Station, snow information accuracy under cloudy conditions was actually higher than under clear-sky conditions. Dataset 2 demonstrated balanced overall performance, achieving particularly high accuracy (0.941) and precision (0.990) at Shenglidaoban Station, indicating stronger snow recognition ability under cloudy conditions. Dataset 3 showed high accuracy (0.927) at Shenglidaoban Station but generally lower performance compared with other datasets. Dataset 4 had lower accuracy than other snow datasets, showing relatively poor performance in both accuracy and recall.

3.1.2 Accuracy During the Snow Accumulation Period

During the snow accumulation period (details presented in Table S2), Dataset 1 displayed high accuracy and precision at Luotuobozi and Shenglidaoban stations. Dataset 2 exhibited similar performance to Dataset 1 at Luotuobozi Station. Dataset 3 had lower precision (0.897) and recall (0.839) at Luotuobozi Station, while Dataset 4 displayed low values for both accuracy and recall. Under persistent cloud cover and unstable snow conditions, snow cover under clear-sky conditions is easier to predict with higher accuracy. However, long-term cloud cover makes complete cloud removal difficult and decreases accuracy. Dataset 2 performed best under these conditions with higher accuracy compared with other datasets. During the snow accumulation period, delays in reconstructing snow cover under cloud conditions contributed to higher UE, which is particularly important for identifying snow coverage. Datasets 2 and 3 showed lower UE during the snow accumulation period, making them more effective for reconstructing snow accumulation data.

3.1.3 Accuracy During the Snowmelt Period

Table S3 presents confusion matrix results for snow cover during the snowmelt period (March–June). Dataset 1 displayed balanced accuracy and precision at

Luotuobozi and Shuidian stations. Dataset 2 exhibited good performance at all stations, though at Chahanwusu Station its OE (0.016) was higher compared with other datasets. Dataset 2 had higher accuracy and lower UE than other datasets under cloud coverage. Dataset 4 had low recall at Luotuobozi Station (0.606). At Shenglidaoban Station, overall accuracy was 1.000; however, recall was low and UE was 0.250, indicating that Dataset 4 did not overestimate snow but failed to detect snow when present. This may be because patchy snow cover during the snowmelt period was not captured by the MOD10A1-based remote sensing data used in Dataset 4. The datasets appeared to show the snowmelt period occurring earlier than it actually did when capturing the snowmelt process. Dataset 2 outperformed other datasets under cloudy conditions with higher accuracy and lower UE.

3.1.4 Accuracy During the Stable Snow Period

Confusion matrix results for the stable snow period (December–February of the following year) are presented in Table S4. Accuracy was relatively high, with Luotuobozi, Shuidian, and Shenglidaoban stations exhibiting high accuracy and low UE. In contrast, at Chahanwusu Station, where land cover and terrain create unstable snow conditions, all four datasets showed lower accuracy with missed snow detections. These results indicated that the four datasets have limitations in capturing short-term snow cover, warranting further improvement. Notably, at Shuidian and Shenglidaoban stations, snow detection accuracy was higher under cloud cover than under clear-sky conditions during snow fluctuation periods (i.e., snow accumulation and snowmelt periods). The false negative rate, where real-time camera observations detected snow but datasets did not, was higher under clear-sky conditions. This discrepancy could be attributed to snow patches and light snow cover at these stations that MOD10A1 (used in Datasets 1, 3, and 4) failed to recognize. In Dataset 2, exclusion of some snow information may result either from source data inability to detect snow or from overly high snow classification thresholds during cloud removal.

Overall, Dataset 2 demonstrated superior snow recognition ability under cloud cover, while Dataset 4 showed notable limitations. There were no significant differences between Dataset 1 and Dataset 3. During the snow accumulation period, Dataset 2 consistently outperformed other datasets with higher accuracy and lower UE. Similar trends were observed during the snowmelt period, where Dataset 2 maintained higher accuracy and lower UE. During the stable snow period, Datasets 1, 2, and 3 all performed well, showing consistent results.

3.2 Snow Cover Dataset Time Series at Real-Time Camera Stations

At Luotuobozi Station, real-time camera observations revealed snow onset dates between late October and early November. However, due to cloud contamination, all four datasets failed to detect snow in early November 2016, resulting in delayed snow onset (Fig. 2a [Figure 2: see original paper]). On December 1, 2017, persistent cloud cover in MOD10A1 data prevented all datasets from detecting snow, causing delayed snow detection. Snowmelt was observed from late May to early June in both real-time camera images and datasets, though slight timing discrepancies were observed between camera data and dataset predictions.

At Shuidian Station, real-time camera observations showed snow onset dates between late September and early October (Fig. 2b [Figure 2: see original paper]). In early October 2016, Dataset 1 failed to detect snow due to cloud contamination, suggesting delays in its cloud removal algorithm. Although Datasets 2, 3, and 4 successfully detected snow onset dates in early October 2016, long-term cloud cover resulted in intermittent snow-free periods, indicating challenges with extended cloudy conditions. Real-time camera observations recorded snowmelt at Shuidian Station in early June, whereas all datasets exhibited earlier snowmelt onset during June in both 2016 and 2017, revealing discrepancies between real-time observations and dataset predictions.

At Shenglidaoban Station, real-time camera observations recorded snow onset dates from late September to early October, which largely aligned with dataset timings (Fig. 2c [Figure 2: see original paper]). However, during the stable snow period from November 2017 to May 2018, Dataset 4 exhibited intermittent gaps in snow detection due to incomplete cloud removal. Despite these gaps, snowmelt onset was recorded from mid-May in the datasets, though discrepancies suggested that Dataset 4 struggled with cloud contamination during the stable snow period, limiting its accuracy.

At Chahanwusu Station, real-time cameras indicated short snow duration with rapid melting (Fig. 2d [Figure 2: see original paper]). However, Datasets 2 and 3 suggested longer snow cover periods compared with real-time camera data. This discrepancy highlighted the difficulty of accurately capturing short snow events in areas with rapid snowmelt and limited snow cover duration. The differences between real-time camera data and datasets underlined challenges in reconstructing snow cover dynamics in regions with variable snow conditions.

3.3.1 Snow Accumulation Period

During the snow accumulation period, different cloud removal methods exhibited varying accuracies at different stations. Since snow cover was continuously increasing, high recall was usually expected, requiring greater accuracy to capture changes during the fluctuating snow accumulation period. Figure 3 [Figure 3: see original paper] illustrates the complex terrain surrounding Luotuobozi Real-time Camera Station. The station is located in a valley between two mountains, a gently sloping area at the foothill of the Southern Mountain. Between 12:22:33 and 12:50:06 LST on November 5, 2017, the real-time camera captured patchy snow cover on the ground, while none of the four datasets detected any snow presence. Figure 4 [Figure 4: see original paper] shows that each dataset exhibited varying snow cover boundaries, with some having broader and more ambiguous coverage. Dataset 1 replaced cloud-covered points with cloud-free data from the previous day, leading to missed snow detection in areas with short-term snow accumulation. Dataset 2 had discrepancies in complex mountainous areas due to extended cloud pixels in its spatiotemporal operations, which resulted in expanded snow boundaries or absence of snow information.

In Dataset 3, the cloud removal algorithm employed a spatiotemporal adaptive fusion method. Choices for spatial partitioning and conditional thresholding may lead to increased snow pixels in NDSI assignment. However, during cloud gap-filling, tracing correlation with the target area using an 8-day window (both before and after) produced reliable snow predictions in areas with prolonged cloud cover. Dataset 4 showed higher UE due to insufficient spatiotemporal processing and retention of residual cloud information. At Chahanwusu Station, a gravel surface and steep south-facing slope, combined with unstable snow periods and rapid accumulation, led to high UE for all datasets. These findings indicated that the datasets were not suitable for such terrain, highlighting the need for improved cloud removal algorithms that account for surface conditions and elevation.

3.3.2 Snowmelt Period

Cloud removal datasets also exhibited varying accuracy characteristics at different stations and conditions during the snowmelt period. Snow cover beneath clouds was prone to significant and rapid changes that impacted both accuracy and recall (Table S3). Reducing UE during this period was essential for accurately capturing snow cover decrease. As shown in Figure 5 [Figure 5: see original paper], a snow event was observed at Luotuobozi Real-time Camera Station at 12:22:32 LST on April 19, 2018. However, none of the four datasets detected snow on this date because original MODIS data failed to detect snow and severe cloud cover prevailed, resulting in inaccurate cloud removal for all datasets (Fig. 6 [Figure 6: see original paper]). Although this was a rare phenomenon, it highlighted the challenge of snow detection under complex conditions. Similar to the snow accumulation period, Dataset 2 effectively captured snow dynamics under continuous cloud cover, exhibiting higher accuracy compared with other datasets and reducing UE compared with Dataset 3. However, Dataset 2 displayed a more uniform distribution of binary snow cover, causing entire areas to be incorrectly classified as snow-covered, particularly in mountainous terrains and valleys (Fig. 6b [Figure 6: see original paper]).

Limitations of real-time cameras in mountainous areas led to undetected snow, restricting snow cover spatial accuracy. Dataset 4 significantly underestimated snow cover during the snowmelt period, resulting in higher UE.

3.3.3 Stable Snow Period

During the stable snow period, cloud removal datasets exhibited distinct accuracy characteristics at different stations and under diverse conditions. Snow cover remained stable with minimal changes in distribution and status, resulting in higher accuracy and recall, as well as lower OE and UE. According to real-time camera observations, there was no snow cover at 12:19:07 LST on December 21, 2016 at Chahanwusu Station (Fig. 7 [Figure 7: see original paper]). However, snow maps generated by Datasets 1 and 3 erroneously indicated snow cover (Fig. 8 [Figure 8: see original paper]). This misclassification occurred because original MODIS snow data contained snow information, causing Datasets 1 and 3 to mistakenly fill gaps with snow. Despite this incorrect prediction at Chahanwusu Station, Dataset 1 performed well throughout the stable snow period with low UE. Accurately predicting short-term and unstable snow cover remains a critical challenge.

In summary, method performance varied across stations. Dataset 2 performed well at most stations, while Datasets 1 and 3 showed relatively balanced performance. However, when cloud cover frequently changes and snow cover fluctuates, overly simplified time-series models (such as Dataset 1) cannot fully capture dynamic changes in regional snow cover, limiting their effectiveness. Cloud removal method selection requires careful consideration of geographical and climatic conditions specific to the application scenario and study stations. If the goal is to minimize missed snow accumulation, Dataset 3 with its higher recall may be preferred. However, if the goal is to maintain overall high accuracy and precision to avoid false positives, Dataset 2 may be a better choice.

4.1 Validation and Performance of Snow Detection Products

Recent advancements in snow cover remote sensing retrieval technologies have significantly enhanced multi-source dataset applicability across complex terrains and diverse surface conditions. For Dataset 1, [?, ?] demonstrated notable accuracy improvements in updated versions compared with legacy products. According to [?, ?], intermittent short-term cloud cover has little impact on Dataset 1 accuracy, but long-term cloudy periods can reduce snow prediction accuracy when snow cover conditions change. This is consistent with snow patterns observed by real-time cameras and our study conclusions.

For Dataset 2, [?, ?] reported 93.15% overall accuracy across China, and [?, ?] emphasized its superior cloud removal performance and high Cohen' s Kappa (CK) value of 0.609 for China, corresponding to 97.00% accuracy. Similarly, [?, ?] demonstrated that Dataset 2 exhibited superior performance on the Xizang

Plateau compared with alternative methods, achieving a CK of 0.820. This finding aligns with our validation results, confirming Dataset 2' s reliable performance in accuracy and consistency.

In this study, real-time camera observations revealed that during transient snowfall events with minimal accumulation, thin snow layers may briefly appear on the surface. However, due to cloud contamination, Dataset 1 erroneously indicated clear-sky conditions based on MOD10A1 cloud information, highlighting limitations of relying solely on a single satellite for snow detection. To improve snow detection accuracy, integrating observations from both Terra and Aqua satellites is essential. [?, ?] emphasized that combining MOD10A1 and MYD10A1 daily snow products significantly enhances accuracy, especially in areas below 5,000 m elevation, thereby reducing cloud-induced errors across varying terrain conditions. [?, ?] pointed out inconsistencies in cloud masking and acquisition timing between Terra and Aqua satellite data. Therefore, combining snow cover data from both satellites can effectively improve cloud removal accuracy, consistent with this study' s conclusions.

4.2 Optimization and Application of Cloud-Free Snow Cover Algorithm

Accuracy validation of snow products remains critical for methodologies. [?, ?] demonstrated that camera networks are effective validation tools for improving remote sensing satellite products, highlighting a key challenge—decreased accuracy of cloud-filling algorithms under prolonged cloudy conditions. Their study also established MOD10A1 NDSI thresholds through camera data validation, particularly useful for identifying errors related to canopy occlusion and cloud filling. Addressing validation method limitations, [?, ?] proposed that high spatial and temporal resolution albedo products derived from camera networks and unmanned aerial vehicle (UAV) technology—providing centimeter-level resolution—offer reliable benchmarks for satellite product calibration. However, time-lapse imagery spatial representation in the study area remains limited, underscoring the need for further validation efforts [?, ?].

Future research should aim to establish a coordinated "point-to-area" validation framework by expanding the phenological camera network and integrating multispectral data from Landsat-8 and Sentinel-2. Special emphasis should be placed on optimizing camera placement to account for slope orientation and elevation variations in complex mountainous terrains. Expanding localized observations to regional snow information will enhance snow dataset evaluation, providing further evidence to support our findings. Once additional phenological camera station data are incorporated, a comprehensive assessment of multiple snow datasets will be conducted to improve research accuracy and analyze topography and snow heterogeneity impacts on inversion results.

Regarding algorithm optimization, [?, ?] developed a method for monitoring snow-covered areas and vegetation phenology using real-time cameras. [?, ?] demonstrated that integrating MODIS data with time-lapse photography and machine learning significantly improves binary snow classification accuracy in forest areas. [?, ?] and [?, ?] effectively enhanced cloud removal efficiency and snow cover discrimination in complex scenes by integrating real-time cameras with remote sensing data. Time-lapse cameras also accurately capture temporal dynamics of snow accumulation and melting [?, ?], particularly in areas prone to rapid snowmelt events such as central Xinjiang. This necessitates development of algorithms with dynamic adaptability, requiring further integration of instantaneous environmental parameters and multi-source remote sensing data to balance processing efficiency and accuracy.

Furthermore, effects of topographic complexity (e.g., slope orientation and elevation) and snow dynamics (e.g., transient snow events) on inversion results remain insufficiently quantified in existing studies. This highlights the need to incorporate multi-source auxiliary data such as land surface temperature and vegetation indices, as well as dynamic environmental parameters [?, ?]. Vegetation cover, an important factor influencing snow accumulation and melting, must also be considered. Under different land surfaces, temperature and moisture conditions of surface soil and soil layers change, while vegetation can reflect solar radiation with varying absorption rates depending on land surface type. Solar radiation amount directly affects temperature, thereby influencing snow accumulation and melting [?, ?]. [?, ?] effectively mitigated snow information overestimation by incorporating meteorological fields such as minimum temperature and precipitation alongside ground observations.

4.3 Future Development and Optimization Strategies

To address challenges of delays in cloud removal data processing, future research should focus on improving algorithm accuracy for specific stations such as Chahanwusu and other arid Xinjiang areas including the Tarim Basin. Additionally, snow cover variability and stability must be considered. Combining time-series models with machine learning-based cloud removal strategies can enhance model adaptability to complex terrain conditions and dynamic snow cover variations. Future studies should continue exploring integration of multi-source data fusion technologies with machine learning and artificial intelligence methods. Advances in intelligent and efficient cloud removal processing will unlock greater potential for practical applications. Furthermore, manual visual interpretation of real-time camera data is crucial, particularly for analyzing transient snow cover phenomena such as sudden accumulation, rapid disappearance, and thin snow layers, and their impact on snow-derived water resources. These findings offer new insights and potential solutions for processing snow data in central Xinjiang, especially in areas characterized by complex topography and rapidly changing snow conditions.

5 Conclusions

This study evaluated the performance of four cloud-free MODIS snow cover datasets in the complex mountainous terrain of the Tianshan Mountains, central Xinjiang, China, providing insights into cloud removal algorithm effectiveness in these challenging environments. Results highlighted that Dataset 2 performed consistently well across different snow periods, while other datasets such as Dataset 1 and Dataset 3 showed variable accuracy, particularly under prolonged cloud cover. Analysis of real-time camera observations further underscored challenges posed by cloud contamination and terrain complexity, especially in areas with unstable snow cover such as Chahanwusu Station.

In addition to validating snow products under clear-sky and cloudy conditions, this study emphasizes the need for more refined cloud removal strategies that account for terrain variability, land cover heterogeneity, and snow dynamics. Integration of multi-source data fusion technologies and machine learning-based approaches holds considerable potential for enhancing cloud-free snow detection product performance. Future research should focus on expanding validation efforts, incorporating more phenological camera networks, and integrating advanced remote sensing techniques like UAVs and multispectral data to improve snow monitoring accuracy in mountainous areas. These findings provide a solid foundation for improving snow cover monitoring and water resource management in alpine regions, contributing valuable perspectives to the development of more advanced cloud removal methods.

Conflict of interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table S1. Accuracy assessment of the four cloud removal methods

Station	Dataset	TP	FN	TN	Accuracy	Precision	Recall	f	OE	UE
Luotuobozi Station	Clear-sky Dataset 1									
	Cloudy									
	All sky									
	Clear-sky Dataset 2									
	Cloudy									
	All sky									
	Clear-sky Dataset 3									
	Cloudy									
	All sky									
	Clear-sky Dataset 4									
	Cloudy									
	All sky									
Shuidian Station	Clear-sky Dataset 1									
	Cloudy									
	All sky									
	Clear-sky Dataset 2									
	Cloudy									
	All sky									

Station	Dataset	TP	FN	TN	Accuracy	Precision	Recall	f	OE	UE
	Clear-sky									
	Dataset 3									
	Cloudy									
	All sky									
	Clear-sky									
	Dataset 4									
	Cloudy									
	All sky									
Shenglidaban Station	Clear-sky									
	Dataset 1									
	Cloudy									
	All sky									
	Clear-sky									
	Dataset 2									
	Cloudy									
	All sky									
	Clear-sky									
	Dataset 3									
	Cloudy									
	All sky									
	Clear-sky									
	Dataset 4									
	Cloudy									
	All sky									

Station	Dataset	TP	FN	TN	Accuracy	Precision	Recall	f	OE	UE
Chahanwusu Station	Clear-sky Dataset 1									
	Cloudy									
	All sky									
	Clear-sky Dataset 2									
	Cloudy									
	All sky									
	Clear-sky Dataset 3									
	Cloudy									
	All sky									
	Clear-sky Dataset 4									
	Cloudy									
	All sky									

Note: TP, true positive; FN, false negative; FP, false positive; TN, true negative; f, harmonic mean of accuracy and recall; OE, overestimation error; UE, underestimation error.

Table S2. Accuracy assessment of the four cloud removal methods during the snow accumulation period (September-November)

Station	Dataset	TP	FN	TN	Accuracy	Precision	Recall	f	OE	UE
Luotuobozi Station	Clear-sky Dataset 1									

Station	Dataset	TP	FN	TN	Accuracy	Precision	Recall	f	OE	UE
	Cloudy									
	All sky									
	Clear-sky									
	Dataset 2									
	Cloudy									
	All sky									
	Clear-sky									
	Dataset 3									
	Cloudy									
	All sky									
	Clear-sky									
	Dataset 4									
	Cloudy									
	All sky									
Shuidian Station	Clear-sky									
	Dataset 1									
	Cloudy									
	All sky									
	Clear-sky									
	Dataset 2									
	Cloudy									
	All sky									
	Clear-sky									
	Dataset 3									

Station	Dataset	TP	FN	TN	Accuracy	Precision	Recall	f	OE	UE
	Cloudy									
	All sky									
	Clear-sky									
	Dataset 4									
	Cloudy									
	All sky									
Shenglidaban Station	Clear-sky									
	Dataset 1									
	Cloudy									
	All sky									
	Clear-sky									
	Dataset 2									
	Cloudy									
	All sky									
	Clear-sky									
	Dataset 3									
	Cloudy									
	All sky									
	Clear-sky									
	Dataset 4									
	Cloudy									
	All sky									
Chahanwusu Station	Clear-sky									
	Dataset 1									

Station	Dataset	TP	FN	TN	Accuracy	Precision	Recall	f	OE	UE
	Cloudy									
	All sky									
	Clear-sky Dataset 2									
	Cloudy									
	All sky									
	Clear-sky Dataset 3									
	Cloudy									
	All sky									
	Clear-sky Dataset 4									
	Cloudy									
	All sky									

Table S3. Accuracy assessment of the four cloud removal methods during the snowmelt period (March–June)

Station	Dataset	TP	FN	TN	Accuracy	Precision	Recall	f	OE	UE
Luotuobozi Station	Clear-sky Dataset 1									
	Cloudy									
	All sky									
	Clear-sky Dataset 2									

Station	Dataset	TP	FN	TN	Accuracy	Precision	Recall	f	OE	UE
	Cloudy									
	All sky									
	Clear-sky									
	Dataset 3									
	Cloudy									
	All sky									
	Clear-sky									
	Dataset 4									
	Cloudy									
	All sky									
Shuidian Station	Clear-sky									
	Dataset 1									
	Cloudy									
	All sky									
	Clear-sky									
	Dataset 2									
	Cloudy									
	All sky									
	Clear-sky									
	Dataset 3									
	Cloudy									
	All sky									
	Clear-sky									
	Dataset 4									

Station	Dataset	TP	FN	TN	Accuracy	Precision	Recall	f	OE	UE
	Cloudy									
	All sky									
Shenglidaban Station	Clear-sky									
	Dataset 1									
	Cloudy									
	All sky									
	Clear-sky									
	Dataset 2									
	Cloudy									
	All sky									
	Clear-sky									
	Dataset 3									
	Cloudy									
	All sky									
	Clear-sky									
	Dataset 4									
	Cloudy									
	All sky									
Chahanwusu Station	Clear-sky									
	Dataset 1									
	Cloudy									
	All sky									
	Clear-sky									
	Dataset 2									

Station	Dataset	TP	FN	TN	Accuracy	Precision	Recall	f	OE	UE
	Cloudy									
	All sky									
	Clear-sky Dataset 3									
	Cloudy									
	All sky									
	Clear-sky Dataset 4									
	Cloudy									
	All sky									

Note: During the snowmelt period, there were almost no snow data, and TP and FN were 0 at Chahanwusu Station. "-" indicates no value.

Table S4. Accuracy assessment of the four cloud removal methods during the stable snow period (December–February of the following year)

Station	Dataset	TP	FN	TN	Accuracy	Precision	Recall	f	OE	UE
Luotuobozi Station	Clear-sky Dataset 1									
	Cloudy									
	All sky									
	Clear-sky Dataset 2									
	Cloudy									
	All sky									

Station	Dataset	TP	FN	TN	Accuracy	Precision	Recall	f	OE	UE
	Clear-sky									
	Dataset 3									
	Cloudy									
	All sky									
	Clear-sky									
	Dataset 4									
	Cloudy									
	All sky									
Shuidian Station	Clear-sky									
	Dataset 1									
	Cloudy									
	All sky									
	Clear-sky									
	Dataset 2									
	Cloudy									
	All sky									
	Clear-sky									
	Dataset 3									
	Cloudy									
	All sky									
	Clear-sky									
	Dataset 4									
	Cloudy									
	All sky									

Station	Dataset	TP	FN	TN	Accuracy	Precision	Recall	f	OE	UE
Shenglidaban Station	Clear-sky Dataset 1									
	Cloudy									
	All sky									
	Clear-sky Dataset 2									
	Cloudy									
	All sky									
	Clear-sky Dataset 3									
	Cloudy									
	All sky									
	Clear-sky Dataset 4									
	Cloudy									
	All sky									
Chahanwusu Station	Clear-sky Dataset 1									
	Cloudy									
	All sky									
	Clear-sky Dataset 2									
	Cloudy									
	All sky									

Station	Dataset	TP	FN	TN	Accuracy	Precision	Recall	f	OE	UE
	Clear-sky									
	Dataset 3 Cloudy									
	All sky									
	Clear-sky									
	Dataset 4 Cloudy									
	All sky									

Note: During the stable snow period, there were almost no snow-free data, and FP and TN were 0 at Luotuobozi, Shenglidaoban, and Shuidian stations. "-" indicates no value.

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

Source: ChinaXiv —Machine translation. Verify with original.