Using Multisource Satellite Data to Assess Recent Snow-Cover Variability and Uncertainty in the Qinghai–Tibet Plateau[✉]

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ABSTRACT

Snow cover in the Qinghai–Tibet Plateau (QTP) is a critical component in the water cycle and regional climate of East Asia. Fractional snow cover (FSC) derived from five satellite sources [the three satellites comprising the multisensor synergy of FengYun-3 (*FY-3A/B/C*), the Moderate Resolution Imaging Spectroradiometer (MODIS), and the Interactive Multisensor Snow and Ice Mapping System (IMS)] were intercompared over the QTP to examine uncertainties in mean snow cover and interannual variability over the last decade. A four-step cloud removal procedure was developed for MODIS and FY-3 data, which effectively reduced the cloud percentage from about 40% to 2%–3% with an error of about 2% estimated by a random sampling method. Compared to in situ snow-depth observations, the cloud-removed *FY-3B* data have an annual classification accuracy of about 94% for both 0.04° and 0.01° resolutions, which is higher than other datasets and is recommended for use in QTP studies. Among the five datasets analyzed, IMS has the largest snow extent (22% higher than MODIS) and the highest FSC (4.7% higher than MODIS), while the morning-overpass MODIS and *FY-3A/C* FSC are similar and are around 5% higher than the afternoon-overpass *FY-3B* FSC. Contrary to MODIS, IMS shows increasing variability in snow cover and snow duration over the last decade (2006–17). Differences in variabilities of FSC and snow duration between products are greater at 5–6 km than lower elevations, with seasonal snow-cover change showing the largest uncertainty in snowmelt date.

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1. Introduction

The snow cover in the Qinghai–Tibet Plateau (QTP) provides critical information for the evaluation of water resources, crop production, and disaster possibilities (Qin et al. 2006). It is the main water source for major Asian rivers and significantly affects the modeling and forecasting of the Asian hydrologic system (Immerzeel et al. 2009, 2010), such as the Asian monsoon through snow albedo–atmosphere interactions, and also plays an important role in the regional climate system (Liu and Yanai 2002; Luo and Wang 2019; Vernekar et al. 1995; Wang et al. 2018; Zhang et al. 2004). Therefore, it is important to understand the long-term evolution and associated uncertainties of QTP snow cover.

In situ observations showed that the snow depth in QTP increased from the 1960s to 1980s (Qin et al. 2006; Xu et al. 2017; Zhang et al. 2004), but has declined since the 1980s (Xu et al. 2017). However, the vast area of QTP only has about 83 atmospheric observation stations, which are mainly located in the eastern QTP with elevation lower than 5000 m (Fig. 1). Because the data-scarce high mountains of QTP contain the majority of the snow cover in the region (Pu et al. 2007), it is necessary to use remote sensing products to analyze the snow cover for the entire QTP.

Snow-cover change over the QTP in the last decade has been mainly analyzed using the Moderate Resolution Imaging Spectroradiometer (MODIS) snow-cover data. Pu and Xu (2009) found a small declining change for the snow cover over the QTP from 2000 to 2006 using MODIS 8-day snow-cover data. A similar trend was also found for MODIS daily snow cover in 2001–14 (Huang et al. 2017; Li et al. 2018). Those studies selected MODIS snow cover to analyze the snow-cover changes in QTP mainly for its high classification accuracy. For Canada, Simic et al. (2004) found the monthly classification accuracy for 500-m MODIS snow cover ranged from 80% to 100%. Higher classification accuracy of about 94.2% and 98.5% for daily 500-m MODIS in clear sky was found during the snow season in the Rio Grande basin (Klein and Barnett 2003) and in northern Xinjiang (Liang et al. 2008), respectively. For QTP, the classification accuracy of 8-day 0.05° MODIS snow cover was shown to be around 90% (Pu et al. 2007), while it was higher than 96% for the clear-sky daily 500-m MODIS data in winter (Yang et al. 2015).

Although the daily high-resolution MODIS snow-cover products showed better accuracy than the 8-day data, one major factor limiting the application of daily data is cloud cover. Numerous methods have been developed to fill cloud pixels, such as the adjacent temporal filter, and

FIG. 1. Elevation height of the study area and the locations of in situ observation stations (GMTED2010; https://www.usgs.gov/centers/eros/science/usgs-eros-archive-digital-elevation-global-multi-resolution-terrain-elevation?qt-science_center_objects=0#qt-science_center_objects).

usually they are applied together (Da Ronco and De Michele 2014; Gafurov and Bárdossy 2009; Paudel and Andersen 2011). For example, Hall et al. (2010) developed a cloud-gap-filled MODIS snow-cover product using the age of cloud and snow, which is close to open access and introduced in the MODIS snow products of collection 6 (Riggs and Hall 2015). In the QTP, Huang et al. (2014) combined the *Terra* and *Aqua* MODIS data, and used an adjacent-two-days temporal filter, snow line filter, and then combined a snow water equivalent product to produce a cloudless MODIS snow cover with an overall classification accuracy of 90.7%. Though the cloud-removing methods are efficient, it is difficult to statistically quantify the biases introduced by the method itself, and how they influence the uncertainty of snow-cover changes in the QTP.

On the other hand, considering the algorithm uncertainties of satellite data, the snow-cover variations based on a single data source is not sufficiently robust. For example, Wang et al. (2017) did not find evidence of widespread snow-cover decline in the QTP using a dataset combining MODIS and the Interactive Multi-sensor Snow and Ice Mapping System (IMS) snow cover, which is different from the results using MODIS snow-cover data (Huang et al. 2017; Li et al. 2018; Pu et al. 2007). The IMS data have a classification accuracy around 89.9% in the QTP (Yang et al. 2015) and are totally cloud free (Brubaker et al. 2005; Xie et al. 2018). The optical snow-cover data of FengYun-3 showed around 1% higher classification accuracy than MODIS in QTP as well (Zhang et al. 2017).

Therefore, we used five high-resolution optical snow-cover products from three data sources [i.e., the multi-sensor synergy of FengYun-3 (*FY-3A/B/C*), MODIS, and IMS] to assess 1) the statistical uncertainties in different cloud removal methods; 2) the uncertainties in daily snow-cover extent, fraction, and duration in

TABLE 1. Satellite data description.

	Temporal resolution	Spatial resolution	Observation period	Satellites
MODIS	Daily	500 m	24 Feb 2000–present	<i>Terra</i>
			4 Jul 2002–present	<i>Aqua</i>
FY-3		0.01°	2 Aug 2009–31 Dec 2011	<i>FY-3A</i>
			26 Dec 2010–present	<i>FY-3B</i>
			4 Feb–30 May 2015 and 15 Aug 2016–present	<i>FY-3C</i>
IMS (Geo TIFF)		1 km	2 Dec 2014–present	Multidata sources
		4 km	1 Jan 2006–present	

different optical satellite datasets; and 3) the snow-cover variation in the last decade considering the above uncertainties. This paper is organized as follows: the datasets used are described in section 2, section 3 details the data processing methods and results, section 4 evaluates the bias introduced by data processing and the data accuracy, and the analysis of snow-cover distribution and variation in QTP and their uncertainties are shown in section 5. Conclusions and discussions are presented in section 6.

2. Data description

a. Study area and in situ observation data

The study area covers the QTP and its surrounding areas from 26° to 40°N and from 75° to 105°E (Fig. 1), with terrain elevations ranging from below 2000 to over 8000 m. The northwestern QTP with higher elevation is mainly arid and semiarid areas, and the southeastern QTP is mainly semiarid and semihumid areas (Yang et al. 2011).

Daily snow-depth data from ground stations in the study area maintained by the China Meteorological Administration (CMA) from 2010 to 2015 were used for the evaluation of satellite datasets (Fig. 1). However, all the stations are located below 4800 m, and only 83 stations are located at elevations higher than 3000 m and mostly in the eastern QTP.

b. Satellite data

Five satellite snow-cover datasets from three data sources were used in this study: the multisensor synergy of FengYun-3 (*FY-3A/B/C*), MODIS, and IMS (Table 1).

MODIS is a 36-channel visible to thermal-infrared sensor of the NASA Earth Observation System (EOS) (Hall et al. 2002). Two MODIS satellites, *Terra* and *Aqua*, provide daily 500-m snow-cover products at approximately 1030 and 1330 local time, respectively (MOD10A1, <https://nsidc.org/data/mod10a1>; MYD10A1, <https://nsidc.org/data/myd10a1>). The MODIS *Aqua*

snow-cover data were mainly used to remove cloud in section 3a, so the following MODIS snow-cover data are mainly from the *Terra* (MOD10A1). The products include the normalized difference snow index (NDSI) with a cloud mask, ocean mask, and night mask overlaid (Fig. 2). In this study, the most-recent Collection 6 MODIS data were used (Riggs and Hall 2015).

FY-3A, *FY-3B*, and *FY-3C* are three Chinese FengYun-3 second-generation polar-orbiting meteorological satellites (Dong et al. 2009). The *FY-3A* and *FY-3C* satellites are on a similar morning orbit as *Terra*, and the *FY-3B* satellite has an afternoon overpass orbit like *Aqua*. FY-3 optical snow-cover products, an 0.01° multisensor synergy (MULSS) daily maximum snow cover data, are integrated by Visible and Infrared Radiometer (VIRR) and Medium Resolution Spectral Imager (MERSI) sensors (<http://satellite.nsmc.org.cn/PortalSite/Data/Satellite.aspx>; Table 1), and use digital integers to represent snow cover, snow-free land, and clouds.

IMS snow and ice chart is a combination of multiple data sources, including various satellite datasets and observations (Helfrich et al. 2007; Ramsay 1998) provided by the NOAA National Environmental Satellite, Data, and Information Service (NESDIS; version 1, <https://doi.org/10.7265/N52R3PMC>). Note that the data sources and analysis methods used to generate IMS data vary over time. IMS snow maps were primarily produced by the visible imagery of the geostationary orbiting environmental satellites in winter (around 60%) and the polar operational environmental satellites in summer (around 65%) (Helfrich et al. 2007). Microwave satellite datasets were used for areas covered by cloud or with low solar illumination angles. Elevation dependence correlations were used to chart snow maps dynamically to remove cloud as well (Helfrich et al. 2007). Thus, unlike MODIS and FY-3, IMS snow-cover products are totally cloud free (Fig. 2). IMS also uses digital integers to represent snow or no-snow. The 4-km daily products during 2006–16 and 1-km resolution in 2015 were used in this study (Table 1).

FIG. 2. Snow-cover maps on 1 Mar 2015 for 0.01° FY-3A/B/C, 4-km IMS, and 500-m MODIS Terra and Aqua before reclassification and data processing. The “missing” categories of FY-3A/B/C and MODIS were remapped from a number of original categories representing missing data, mainly the cloud.

An example of the snow-cover maps on 1 March 2015 is shown in Fig. 2. It shows that all the datasets present similar snow-cover area during clear-sky conditions except for a significant missing region covered by clouds in FY-3A/B/C and MODIS Terra/Aqua snow-cover maps (Fig. 2). The average annual cloud-cover percentage for FY-3A/B/C ranges from 40.8% to 45.8% and even higher (up to 56.1%) for MODIS Terra, which presents a significant source of uncertainty in snow cover analysis and needs to be reduced by a series of cloud-removal procedures. Given that snow cover is the focus here, all the datasets were reclassified to contain four types—water, snow, snow-free (land without snow), and missing (mainly from clouds) before cloud removal (Fig. 3).

3. Data processing

a. MODIS merge and simple cloud removal

For a given day, Terra and Aqua MODIS data are obtained about 3 h apart, so their information can be combined to reduce short-lived clouds (Xie 2009). If a Terra pixel is cloudy while the same pixel in Aqua is cloudless at the same day, the identification of Aqua pixel was given to that cloudy-Terra pixel. Thus, the merged MODIS snow cover is mainly from the Terra data. By merging Terra and Aqua data, the average cloudy percentage in 2002–16 decreased from 56.1% to 39.2% (Table 2) and is similar to that of the FY-3 MULSS snow cover products, which are the combination of two sensors as well. Then, the MODIS NDSI was converted to fractional snow cover (FSC) by Eq. (1) in the MODIS Snow Products Collection 6 User Guide (Riggs and Hall 2015):

$$\text{FSC} = [-0.01 + (1.45 \times \text{NDSI})] \times 100.0, \quad (0.0 \leq \text{NDSI} \leq 1.0). \quad (1)$$

b. Further cloud removal procedure applied to MODIS and FY-3 products

Four steps were developed to further remove cloudy pixels in the merged MODIS and FY-3A/B/C snow-cover data using various temporal and spatial filters. The output of each step after cloud removal was the input of the next step. The details of each step are described in the first section of the supplemental material.

Figure 3 shows an example of the snow-cover data before cloud removal on 1 March 2015 (Figs. 3a1–d1) and the subsequent data after applying each step of the cloud-removal technique. Similar cloud-removed regions between different datasets demonstrates the consistency in cloud-removal methods. After applying the four-step cloud removal approach, the annual mean cloud percentage decreased from about 40% to 2.5%, 3.3%, 2.2%, and 2.4% for FY-3A, FY-3B, FY-3C, and MODIS, respectively (Table 2). Steps 1, 3, and 4 sequentially removed 13.8%, 12.4%, and 12.1% of the cloudy pixels when averaged over all datasets. Step 2 only removed about 1% cloudy pixels mainly because of its conservative method and the large cloud extent in Tibet. We also employed other methods of cloud removal, such as the snow line method (Parajka et al. 2010) and the snow season approach (Da Ronco and De Michele 2014; Gafurov and Bárdossy 2009), but they are less applicable in QTP than the methods used in this study.

FIG. 3. Snow-cover maps on 1 Mar 2015 (a1)–(d1) before and after cloud-removal (a2)–(d2) step 1, (a3)–(d3) step 2, (a4)–(d4) step 3, and (a5)–(d5) step 4 for 0.01° FY-3A/B/C and 0.005° MODIS.

c. Spatial resolution conversion

Multiple datasets with different resolutions are less comparable. Thus, FY-3A/B/C and MODIS were re-sampled to a common 0.04° latitude–longitude grid to facilitate comparisons. For the 500-m MODIS data, first the data were resampled to 0.005° , then 0.04° FSC was calculated from the average FSC in the neighboring 64 pixels. For FY-3A/B/C data with digital integers, the total number of snow pixels was divided by the total cloudless pixels in neighboring 16 pixels to calculate the 0.04° FSC values. This approach was only applied when the cloudless pixels were more than 30% of a given 0.04° pixel, otherwise the point was identified as cloud.

4. Evaluations of the cloud-removed snow-cover data over QTP

a. Evaluating the cloud removal biases by random sampling

To statistically quantify the uncertainty introduced by the cloud-removal methods and also explore which method is more reliable, a random sampling analysis

combined with a cloud generation method was used to estimate the biases of each cloud removal methods. Since IMS is cloudless, “fake” clouds were inserted into the product randomly based on the cloud persistence. Then, the cloud removal steps were applied to remove the fake clouds to simulate the cloud removing process. Therefore, the differences between the fake cloud-filled results and the original cloudless IMS data are the biases introduced by the cloud-removal procedures. Details of this new procedure and its uncertainty controlling methods can be found in the second section of the supplemental material.

Biases were estimated only for the cloud-removal steps 1, 3, and 4 due to their high effectiveness in

TABLE 2. The cloud percentage in the study area averaged in each observation periods of FY-3A/B/C and MODIS before and after using the four steps of the cloud removal procedure.

	Before	Merge	Step 1	Step 2	Step 3	Step 4
FY-3A	40.8%	—	27.5%	26.0%	15.4%	2.5%
FY-3B	45.8%	—	31.8%	30.8%	15.0%	3.3%
FY-3C	41.8%	—	27.1%	25.7%	14.2%	2.2%
MODIS	56.1%	39.2%	26.1%	25.5%	14.0%	2.4%

cloud removing. We defined the incorrect percentage (PI) of the missing filled days of each step as

$$PI = \frac{D_{inc}}{D_{filled}} \times 100, \quad (2)$$

where D_{inc} is the total days when the missing filled results of random sampling are incorrect compared to the original IMS value, and D_{filled} is the total missing filled days of each step. Results of random sampling show that the average PI is 0.9%, 2.5%, and 10.8% for cloud-removed pixels of step 1, step 3, and step 4, respectively (Table 3). Then, the real biases of cloud removal for *FY-3A/B/C* and MODIS were derived by multiplying PI to their real cloud removed percentages (Table 3). Therefore, as shown in Table 3, the total biases introduced by cloud removal step 1, step 3, and step 4 are 1.86%, 1.89%, 1.80%, and 1.75% for *FY-3A*, *FY-3B*, *FY-3C*, and MODIS, respectively. To decrease total bias introduced by cloud removal, the three cloud removal methods were applied one by one with biases from low to high.

Other studies using cloud-generation methods applied to the *Terra* and *Aqua* snow cover showed that the error of the adjacent-two-day filter was about 1% for the Kokcha basin of Afghanistan (Gafurov and Bárdossy 2009) and for the adjacent-one-day filter about was 0.56% for the Trans-Himalayan region of Nepal (Paudel and Andersen 2011). Their results for the adjacent-pixels spatial filter also showed low biases.

b. Evaluating the classification accuracy using in situ observations

Surface daily snow-depth observations located above 3000 m were used as independent evaluation data over the available period of 2010–15. All the 0.04° datasets and higher-resolution *FY-3B* and MODIS after cloud removal were evaluated. Given that the observation is snow depth at a point, the value of the nearest pixel of satellite data was extracted to represent the snow cover of that point. The frequency of agreement between the observation and the extracted satellite data is considered the classification accuracy.

Results show that, among different datasets, the classification accuracies of 0.01° and 0.04° *FY-3B*, and 0.005° MODIS after cloud removal are highest (~94%) when considering all days (i.e., annual mean), while they are lowest for *FY-3A* and 0.04° MODIS (Table 4). IMS has intermediate annual mean classification accuracy, but its accuracy reduces considerably in winter (Table 4). Compared to previous studies, our new *FY-3B* and 0.005° MODIS datasets,

TABLE 3. The annual mean PI relative to the total cloud filled days of random sampling averaged in seven snow-day bands for cloud-removal step 1, step 3, and step 4. For the *FY-3A/B/C* and MODIS, the incorrect percentage of cloud removal is calculated by multiplying PI to the real cloud removed percentage listed in Table 2.

	PI	Mean PI relative to real data			
		<i>FY-3A</i>	<i>FY-3B</i>	<i>FY-3C</i>	MODIS
Step 1	0.9%	0.12%	0.13%	0.13%	0.12%
Step 3	3.0%	0.32%	0.47%	0.35%	0.35%
Step 4	11.0%	1.42%	1.29%	1.32%	1.28%
Total	—	1.86%	1.89%	1.80%	1.75%

after cloud removal, have higher classification accuracy. For instance, Huang et al. (2014) found a classification accuracy for MODIS around 90.7% after cloud removal. Thus, when available, *FY-3B* snow cover data are recommended for its higher and consistent accuracies at both spatial resolutions.

Table 4 also shows that the uncertainty introduced by resampling to the 0.04 grid depends on the native resolution of dataset. The 0.04° MODIS snow cover has much lower classification accuracy than 0.005° MODIS, but the 0.01° and 0.04° *FY-3B* have similar accuracy. Many studies omitted MODIS FSC lower than 15% or 20% because they found the 500-m MODIS snow-cover with low FSC to be unreliable (Huang et al. 2017; Painter et al. 2009; Rittger et al. 2013). Using those unreliable low FSC reduced the classification accuracy of 0.04° MODIS in this section, because we used the threshold of higher than 0% FSC as snow cover to keep consistency with other datasets instead of 15% that results in the overestimation.

5. Analysis of snow-cover uncertainties in the QTP

We used five elevation zones ranging from 2 to over 6 km (2–3, 3–4, 4–5, 5–6, >6 km) to analyze the distributions and variations of FSC and snow duration, respectively, as well as their uncertainties. For IMS, annual FSC is the ratio between the snow pixels and the total pixels at each elevation band or the ratio between the snow days and the total days in a year.

Although we have five snow-cover datasets, not all datasets are available to be used in a relatively long-period analysis. The temporal overlap of daily FSC of the five 0.04° snow-cover datasets is shown in Fig. 4. It shows that the *FY-3A* FSC has a steep reduction on 20 April 2016 and results in near-zero FSC at all elevation zones. The problem first occurred around 1 July 2013 (not shown) with a FSC reduction of about 10%–15% in regions higher than 6 km. This is probably caused by the instruments degradation of the MERSI

TABLE 4. Mean snow classification accuracy between the satellite datasets and the in situ observations of snow depth in the QTP in 2010–15.

	0.04° × 0.04° (or 4 km)				MODIS (0.005°)	FY-3B (0.01°)
	IMS	FY-3B	FY-3A	MODIS		
Winter mean	87.4%	91.8%	84.2%	84.7%	93.0%	91.4%
Annual mean	92.1%	94.2%	88.7%	82.0%	93.9%	94.6%

(Hu et al. 2012). Thus, the *FY-3A* snow-cover data after 2012 are not recommended for snow cover analysis.

Figure 4 also shows that the *FY-3C* and MODIS data are very similar, and the *FY-3A* FSC before 2013 is close to MODIS FSC as well (not shown). The *FY-3A/C* and MODIS are 4.8%, 5.2%, and 5.6% higher than the *FY-3B* FSC, likely due to different satellite orbital overpass times. The *Terra* and *Aqua* MODIS snow cover also have similar overpass-related differences in other studies (Xie 2009). Therefore, in addition to the algorithm of remote sensing products, the detecting time and the instrumental problems also contribute to the uncertainties of FSC value.

Given that the available and reliable period of *FY-3A/C* snow cover is too short, the 0.04° *FY-3B* and MODIS and 4-km IMS snow-cover data were selected for the following analysis of long-term snow-cover spatial distribution, variation, and uncertainty in the QTP.

a. Multiyear mean FSC

Snow-cover distribution in the QTP was analyzed using the multiyear mean value of three datasets in their available periods: *FY-3B* in 2012–17, MODIS in 2002–17, and IMS in 2006–17. Results show that high FSC in all seasons is primarily located in mountain areas with high elevation, such as Mt. Himalaya, Kunlun,

FIG. 4. Daily FSC of 0.04° *FY-3A/B/C*, MODIS, and 4-km IMS snow cover from 1 Jan 2016 to 1 Jan 2018.

FIG. 5. Spatial distribution of seasonal mean FSC for the 0.04° *FY-3B* (2012–17), MODIS (2002–17), and 4-km IMS (2006–17) snow-cover data. The FSC of IMS is the ratio between the snow days and the total days in a specific season.

Karakoram, Tanggula, and Nychen Tanggula (Fig. 5), similar to Pu and Xu (2009). IMS generally has a larger snow-covered area with higher FSC than *FY-3B* and MODIS. The annual snow-cover area (FSC > 5% for IMS and *FY-3B*, and FSC > 15% for MODIS) of IMS is about 22% and 28% larger than *FY-3B* and MODIS, respectively. Those differences are mainly located in the northwestern QTP and low-elevation regions of the eastern QTP, and are even larger in winter.

For the five elevation zones, all the datasets have similar seasonal evolution of daily FSC (Fig. 6). As expected, the snow-season length significantly increases with elevation. Compared to the results of Pu and Xu (2009) using 8-day MODIS snow cover, the seasonal evolution presented here has stronger elevation dependence because of the higher temporal resolution of daily data in this study. Despite the similar seasonal evolution of three datasets, their amplitudes are significantly different. The mean annual FSC of IMS is 4.7% and 9.5% higher than MODIS and *FY-3B*, probably because it uses 1 for snow pixel while MODIS and

FY-3B use the FSC (≤ 1.0). Moreover, the differences of daily FSC increase with the increasing elevation zones. Below 6 km, MODIS FSC is closer to *FY-3B*, but it is closer to IMS when the elevation is higher than 6 km (Fig. 6).

b. Multiyear mean snow duration

Since snow cover in some regions of the QTP is thin and usually does not have a continuous snow period over a week, the snow melting date (SMD) and snow onset date (SOD) in this section are defined as Eq. (3) according to Wang and Xie (2009):

$$\begin{aligned} \text{SMD} &= D_1 + \sum_{i=n1}^{i=m1} \text{SD}_1, \\ \text{SOD} &= D_2 - \sum_{i=n2}^{i=m2} \text{SD}_2, \end{aligned} \quad (3)$$

where D_1 and D_2 are the ending and beginning dates (in Julian date) of the snow season selected here as 1 March

FIG. 6. Multiyear mean daily FSC for 0.04° FY-3B (2012–17), MODIS (2002–17), and 4-km IMS (2006–17) snow-cover data averaged at five elevation zones (2–3, 3–4, 4–5, 5–6, >6 km).

and 1 December, SD_1 and SD_2 are the snow days during the transition season, n_1 and m_1 are the beginning and ending dates of snow melting period, and n_2 and m_2 are the beginning and ending dates of snow onset period. Transition period dates n_1 , m_1 , n_2 , and m_2 were set to be 1 March, 30 June, 1 September, and 30 November, respectively, according to the seasonal FSC shown in Fig. 6. Note that the FSC lower than 15% is set as snow-free land when calculating MODIS snow days. Snow duration was also analyzed using the multiyear mean total snow days in a year for the available periods of three datasets.

Figure 7 shows that FY-3B has the lowest snow days, which is significantly lower than the other two datasets. MODIS and IMS have generally similar extent of high snow days, while IMS has a wider extent of low snow days. Thus, compared to in situ observations in 83 stations in the QTP, IMS snow days are 9 days higher, MODIS and FY-3B snow days are around 4 and 10 days lower, respectively, using the value of the nearest pixels of observation stations. Snow-day

observations were derived from in situ snow-depth observations in 2010–15.

FY-3B also has the latest snow onset and earliest snowmelt among the three datasets (Fig. 7). Although spatial distributions of SOD and SMD are generally similar for MODIS and IMS, MODIS has a relatively earlier snow onset while IMS has relatively later snowmelt in mountainous areas. Previous studies also found that IMS holds snow too long in spring (Brown et al. 2007). Differences of snow duration and snow onset and melting dates among three datasets are mainly located in the northwestern QTP and the low-elevation regions in eastern QTP, which is similar to the location of FSC differences.

c. Variabilities of FSC and snow duration

Since the observation periods of FY-3 datasets are less than 10 years, a variation analysis in 2006–17 was applied for MODIS and IMS snow cover data. (An extra variation analysis for three datasets, FY-3B, MODIS, and IMS in 2012–17 can also be found in the third section of the supplemental material). Spatially, MODIS FSC reduces in high-mountain areas generally, while IMS FSC increases in most areas in the recent decade (Figs. 8a1,b1). Snow-day variations are consistent to that of FSC for both datasets. Figure 8 also shows that the delayed snow onset is more significant than the delayed snow melting for MODIS, while IMS snow melting is delayed more significant than snow onset. Thus, the decreasing snow duration of MODIS is mainly due to the delayed snow onset (Fig. 8a3), while the increasing snow days of IMS are mainly caused by the delay of snow melting (Fig. 8b4).

Averaged over five elevation zones, annual FSC decreases for both long-period datasets at 2–3-km elevation zone, but it decreases for MODIS and increases for IMS at higher elevation zones (Fig. 9). Variation trends of both MODIS and IMS FSC and snow duration are not significant, except for the MODIS FSC higher than 6 km with negative variations passing the significant t test at 95% confidence level. Annual FSC of 0.005° MODIS before cloud removal is also shown in Fig. 9. The highly matched variation fluctuations and tendencies before and after data processing indicate that this processing does not affect the variability. For the snow duration, MODIS-derived snow duration is shorter by 0.96 day yr^{-1} , while IMS snow duration is longer by 0.93 day yr^{-1} averaged at all elevation zones. In situ snow-depth and snow-day observations have shown a shorter snow duration in 1961–2010 (Xu et al. 2017).

An elevation dependence is found for the variations of annual FSC and snow duration below 6 km. Figures 9 and 10 shows that higher elevation zones have higher decreasing rates of annual FSC and snow days for

FIG. 7. Spatial distribution of multiyear mean snow days, SOD, and SMD for the 0.04° *FY-3B* (2012–17), MODIS (2002–17), and 4-km IMS (2006–17) snow-cover data.

MODIS, and also higher increasing rates of FSC and snow days for IMS. Thus, the 5–6-km elevation zone has the most severe drop of annual FSC and snow duration for MODIS, and most severe increasing FSC and snow duration for IMS. It also has the highest increasing rate for both SOD and SMD. Pu and Xu (2009) found a notable decreasing rate of FSC ($-0.58\% \text{ yr}^{-1}$) over 5000 m in the snow minimum season (August) band using MODIS *Terra* 8-day maximum FSC as well.

Figure 10 also shows that uncertainties of variations of FSC and snow duration increase with rising elevations below 6 km. First, we derived the linear regression slopes of all pixels in the study area for both datasets, and then calculated the mean value and the first and the third quantiles at each elevation zones, as shown in the boxes of Fig. 10. It shows that the differences of variations of FSC, snow days, and snow onset and melting dates between MODIS and IMS increase with the increasing elevation zones. Higher-elevation zones (<6 km) have larger ranges between the first and the

third quantiles for the variations of FSC and snow day as well (Fig. 10). However, for the extremely high elevation zones over 6 km, snow cover is too stable to vary significantly. Therefore, uncertainties of FSC and snow-day variations between MODIS and IMS snow cover data increase with the increasing elevation zones below 6 km.

6. Conclusions and discussions

Five satellite snow-cover products—*FY-3A/B/C*, MODIS, and IMS—were used to analyze the snow-cover variations and their uncertainties in the recent decade. A four-step cloud-removal approach was developed to reduce cloudy-pixel percentage from 40.8%–56.1% to 2.2%–3.3% for *FY-3A/B/C* and MODIS with an averaged error of about 2% estimated by a random sampling method. The main findings of this study are as follows:

- 1) The mean annual classification accuracy of cloud-removed *FY-3B* at the native 0.01° and the aggregated 0.04° resolutions are 94.4% compared with

FIG. 8. Spatial distribution of the variation trends (linear regression slopes) of annual FSC ($\% \text{ yr}^{-1}$), snow days (days yr^{-1}), and SOD and SMD (days yr^{-1}) in 2006–17 for the 0.04° MODIS and 4-km IMS snow-cover data.

in situ observations, which is higher than that of MODIS, IMS, and *FY-3A*. Thus, we recommend the *FY-3B* snow cover data for its higher and consistent accuracy than other datasets and relatively longer observation period than *FY-3C*. In addition, the snow cover data of *FY-3A* after 2012 cannot be used because of instrument degradation.

- 2) IMS snow-cover data have the largest snow extent (28% and 22% higher than MODIS and *FY-3B*), and the highest daily FSC (4.7% and 9.5% higher than the MODIS and *FY-3B*). Moreover, the morning-overpass *FY-3A*, *FY-3C*, and MODIS have similar

daily FSC while the afternoon-overpass *FY-3B* FSC is around 5% lower. *FY-3B* also has significantly lower snow days (around 10 days less than in situ observations) with later snow onset and earlier snowmelt.

- 3) In the last decade (2006–17), both IMS and MODIS data show decreasing FSC and snow duration in the elevation zone below 3 km. However, over 3 km, MODIS FSC decreases with shorter snow duration and delayed snow onset, while IMS FSC increases with longer snow duration and delayed snowmelt in recent decade.

FIG. 9. Annual mean (a1)–(a5) FSC and (b1)–(b5) snow days at five elevation zones in 2006–17 for the 0.04° MODIS and 4-km IMS snow-cover data, the annual mean FSC of 0.005° MODIS before data processing is also shown (MODIS_ori). Dashed lines are the least squares fitted lines of each dataset, their slopes are labeled with the same color, and the significant values are marked in bold ($P < 0.05$).

4) Higher elevation has higher uncertainties for the variations of annual FSC and snow duration below 6 km since snow cover over 6 km is stable. Elevation dependence is also found for the mean snow cover and its variations in QTP below 6 km. Higher elevation has higher FSC, longer snow duration, and also higher variation trends of FSC and snow duration. Thus, the 5–6-km elevation zone has the fastest changing FSC and snow duration with highest spatial variation. Seasonally, the uncertainty of snow-melting trends in spring is higher than that of the snow-onset trends.

Despite the use of various methods to reduce the biases of data processing, snow-cover products at present all have high uncertainties. IMS snow cover significantly overestimates snow days and probably the FSC, leading to a lower classification accuracy and a different variation trend compared with other datasets. This overestimation problem of IMS was also documented by a number of papers in other regions of the Northern Hemisphere, which is probably due to the uncertainties of microwave satellite data and elevation effects to remove clouds, and possibly due to the overestimated threshold value to identify snow/no snow (Brown et al. 2007; Wang et al. 2005). MODIS snow cover is

FIG. 10. Boxplots for the linear regression slopes of annual FSC ($\% \text{ yr}^{-1}$), snow days (Snowday; days yr^{-1}), and SOD and SMD (days yr^{-1}) at five elevation zones in 2006–17 for the 0.04° MODIS and 4-km IMS snow-cover data. The top and bottom points of the boxes are the first and the third quartiles, respectively. The horizontal short lines are the median value. The mean values are labeled in dashed lines with solid dots.

problematic when FSC is lower than 15% (or 20%), which then introduces other problems, such as how to identify the snow cover extent and snow days. *FY-3B* snow cover has high classification accuracy, and its variation is consistent with that of MODIS data, so it is recommended for the snow-cover analysis in the QTP. However, its snow days are 5–20 days less than MODIS and IMS, and also around 10 days less than the in situ observations. Thus, *FY-3B* data underestimate the snow days, and also probably underestimate the FSC.

Therefore, significant differences were found in snow cover extent, daily FSC, snow duration, and their variations among those datasets. Uncertainties mainly come from the different algorithms of snow cover products, the detecting time of different satellite orbits (around 5%), the cloud removing (around 2%), and the resolution conversion (less than 1% for *FY-3B* and around 10% for MODIS but does not affect the variation trend). Thus, the inherent uncertainties in snow-cover products

are higher than those introduced by the data processing. Even so, we believe that those long-term cloud-removed snow cover products of MODIS and *FY-3B* has superior quality than those currently used for QTP studies, which is valuable for evaluating weather and climate models in this region.

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REFERENCES

- Brown, R., C. Derksen, and L. Wang, 2007: Assessment of spring snow cover duration variability over northern Canada from satellite datasets. *Remote Sens. Environ.*, **111**, 367–381, <https://doi.org/10.1016/j.rse.2006.09.035>.
- Brubaker, K. L., R. T. Pinker, and E. Deviatova, 2005: Evaluation and comparison of MODIS and IMS snow-cover estimates for the continental United States using station data. *J. Hydrometeorol.*, **6**, 1002–1017, <https://doi.org/10.1175/JHM447.1>.
- Da Ronco, P., and C. De Michele, 2014: Cloud obstruction and snow cover in Alpine areas from MODIS products. *Hydrol. Earth Syst. Sci.*, **18**, 4579–4600, <https://doi.org/10.5194/hess-18-4579-2014>.
- Dong, C., J. Yang, W. Zhang, Z. Yang, N. Lu, J. Shi, P. Zhang, Y. Liu, and B. Cai, 2009: An overview of a new Chinese weather satellite *FY-3A*. *Bull. Amer. Meteor. Soc.*, **90**, 1531–1544, <https://doi.org/10.1175/2009BAMS2798.1>.
- Gafurov, A., and A. Bárdossy, 2009: Cloud removal methodology from MODIS snow cover product. *Hydrol. Earth Syst. Sci.*, **13**, 1361–1373, <https://doi.org/10.5194/hess-13-1361-2009>.
- Hall, D. K., G. A. Riggs, V. V. Salomonson, N. E. Digirolamo, and K. J. Bayr, 2002: MODIS snow-cover products. *Remote Sens. Environ.*, **83**, 181–194, [https://doi.org/10.1016/S0034-4257\(02\)00095-0](https://doi.org/10.1016/S0034-4257(02)00095-0).
- , —, J. L. Foster, and S. V. Kumar, 2010: Development and evaluation of a cloud-gap-filled MODIS daily snow-cover product. *Remote Sens. Environ.*, **114**, 496–503, <https://doi.org/10.1016/j.rse.2009.10.007>.
- Helfrich, S. R., D. McNamara, B. H. Ramsay, T. Baldwin, and T. Kasheta, 2007: Enhancements to, and forthcoming developments in the Interactive Multisensor Snow and Ice Mapping System (IMS). *Hydrol. Processes*, **21**, 1576–1586, <https://doi.org/10.1002/hyp.6720>.

- Hu, X., and Coauthors, 2012: Calibration for the solar reflective bands of medium resolution spectral imager onboard FY-3A. *IEEE Trans. Geosci. Remote Sens.*, **50**, 4915–4928, <https://doi.org/10.1109/TGRS.2012.2214226>.
- Huang, X., X. Hao, Q. Feng, W. Wang, and T. Liang, 2014: A new MODIS daily cloud free snow cover mapping algorithm on the Tibetan Plateau. *Sci. Cold Arid. Reg.*, **6**, 116–123.
- , J. Deng, W. Wang, Q. Feng, and T. Liang, 2017: Impact of climate and elevation on snow cover using integrated remote sensing snow products in Tibetan Plateau. *Remote Sens. Environ.*, **190**, 274–288, <https://doi.org/10.1016/j.rse.2016.12.028>.
- Immerzeel, W. W., P. Droogers, S. M. de Jong, and M. F. P. Bierkens, 2009: Large-scale monitoring of snow cover and runoff simulation in Himalayan river basins using remote sensing. *Remote Sens. Environ.*, **113**, 40–49, <https://doi.org/10.1016/j.rse.2008.08.010>.
- , L. P. H. van Beek, and M. F. P. Bierkens, 2010: Climate change will affect the Asian water towers. *Science*, **328**, 1382–1385, <https://doi.org/10.1126/science.1183188>.
- Klein, A. G., and A. C. Barnett, 2003: Validation of daily MODIS snow cover maps of the upper Rio Grande River basin for the 2000–2001 snow year. *Remote Sens. Environ.*, **86**, 162–176, [https://doi.org/10.1016/S0034-4257\(03\)00097-X](https://doi.org/10.1016/S0034-4257(03)00097-X).
- Li, C., F. Su, D. Yang, K. Tong, F. Meng, and B. Kan, 2018: Spatiotemporal variation of snow cover over the Tibetan Plateau based on MODIS snow product, 2001–2014. *Int. J. Climatol.*, **38**, 708–728, <https://doi.org/10.1002/joc.5204>.
- Liang, T., X. Zhang, H. Xie, C. Wu, Q. Feng, X. Huang, and Q. Chen, 2008: Toward improved daily snow cover mapping with advanced combination of MODIS and AMSR-E measurements. *Remote Sens. Environ.*, **112**, 3750–3761, <https://doi.org/10.1016/j.rse.2008.05.010>.
- Liu, X., and M. Yanai, 2002: Influence of Eurasian spring snow cover on Asian summer rainfall. *Int. J. Climatol.*, **22**, 1075–1089, <https://doi.org/10.1002/joc.784>.
- Luo, X., and B. Wang, 2019: How autumn Eurasian snow anomalies affect East Asian winter monsoon: A numerical study. *Climate Dyn.*, **52**, 69–82, <https://doi.org/10.1007/s00382-018-4138-y>.
- Painter, T. H., K. Rittger, C. McKenzie, P. Slaughter, R. E. Davis, and J. Dozier, 2009: Retrieval of subpixel snow covered area, grain size, and albedo from MODIS. *Remote Sens. Environ.*, **113**, 868–879, <https://doi.org/10.1016/j.rse.2009.01.001>.
- Parajka, J., M. Pepe, A. Rampini, S. Rossi, and G. Blöschl, 2010: A regional snow-line method for estimating snow cover from MODIS during cloud cover. *J. Hydrol.*, **381**, 203–212, <https://doi.org/10.1016/j.jhydrol.2009.11.042>.
- Paudel, K. P., and P. Andersen, 2011: Monitoring snow cover variability in an agropastoral area in the Trans Himalayan region of Nepal using MODIS data with improved cloud removal methodology. *Remote Sens. Environ.*, **115**, 1234–1246, <https://doi.org/10.1016/j.rse.2011.01.006>.
- Pu, Z., and L. Xu, 2009: MODIS/Terra observed snow cover over the Tibet Plateau: Distribution, variation and possible connection with the East Asian Summer Monsoon (EASM). *Theor. Appl. Climatol.*, **97**, 265–278, <https://doi.org/10.1007/s00704-008-0074-9>.
- , —, and V. V. Salomonson, 2007: MODIS/Terra observed seasonal variations of snow cover over the Tibetan Plateau. *Geophys. Res. Lett.*, **34**, L06706, <https://doi.org/10.1029/2007GL029262>.
- Qin, D. H., S. Y. Liu, and P. J. Li, 2006: Snow cover distribution, variability, and response to climate change in western China. *J. Climate*, **19**, 1820–1833, <https://doi.org/10.1175/JCLI3694.1>.
- Ramsay, B., 1998: The interactive multisensor snow and ice mapping system. *Hydrol. Processes*, **12**, 1537–1546, [https://doi.org/10.1002/\(SICI\)1099-1085\(199808/09\)12:10/11<1537::AID-HYP679>3.0.CO;2-A](https://doi.org/10.1002/(SICI)1099-1085(199808/09)12:10/11<1537::AID-HYP679>3.0.CO;2-A).
- Riggs, G., and D. Hall, 2015: MODIS snow products user guide to collection 6. NSIDC Doc., 66 pp., <https://nsidc.org/sites/nsidc.org/files/files/MODIS-snow-user-guide-C6.pdf>.
- Rittger, K., T. H. Painter, and J. Dozier, 2013: Assessment of methods for mapping snow cover from MODIS. *Adv. Water Resour.*, **51**, 367–380, <https://doi.org/10.1016/j.advwatres.2012.03.002>.
- Simic, A., R. Fernandes, R. Brown, P. Romanov, and W. Park, 2004: Validation of VEGETATION, MODIS, and GOES + SSM/I snow-cover products over Canada based on surface snow depth observations. *Hydrol. Processes*, **18**, 1089–1104, <https://doi.org/10.1002/hyp.5509>.
- Vernekar, A. D., J. Zhou, and J. Shukla, 1995: The effect of Eurasian snow cover on the Indian monsoon. *J. Climate*, **8**, 248–266, [https://doi.org/10.1175/1520-0442\(1995\)008<0248:TEOESC>2.0.CO;2](https://doi.org/10.1175/1520-0442(1995)008<0248:TEOESC>2.0.CO;2).
- Wang, L., M. Sharp, R. Brown, C. Derksen, and B. Rivard, 2005: Evaluation of spring snow covered area depletion in the Canadian Arctic from NOAA snow charts. *Remote Sens. Environ.*, **95**, 453–463, <https://doi.org/10.1016/j.rse.2005.01.006>.
- Wang, X.-W., and H. Xie, 2009: New methods for studying the spatiotemporal variation of snow cover based on combination products of MODIS Terra and Aqua. *J. Hydrol.*, **371**, 192–200, <https://doi.org/10.1016/j.jhydrol.2009.03.028>.
- Wang, X.-Y., C. Wu, H. Wang, A. Gonsamo, and Z. Liu, 2017: No evidence of widespread decline of snow cover on the Tibetan Plateau over 2000–2015. *Sci. Rep.*, **7**, 14645, <https://doi.org/10.1038/s41598-017-15208-9>.
- Wang, Z., R. Wu, S. Chen, G. Huang, G. Liu, and L. Zhu, 2018: Influence of western Tibetan Plateau summer snow cover on East Asian summer rainfall. *J. Geophys. Res. Atmos.*, **123**, 2371–2386, <https://doi.org/10.1002/2017JD028016>.
- Xie, H., 2009: Development and assessment of combined Terra and Aqua snow cover products in Colorado Plateau, USA and northern Xinjiang, China. *J. Appl. Remote Sens.*, **3**, 033559, <https://doi.org/10.1117/1.3265996>.
- Xie, Z., Z. Hu, Z. Xie, B. Jia, G. Sun, Y. Du, and H. Song, 2018: Impact of the snow cover scheme on snow distribution and energy budget modeling over the Tibetan Plateau. *Theor. Appl. Climatol.*, **131**, 951–965, <https://doi.org/10.1007/s00704-016-2020-6>.
- Xu, W., L. Ma, M. Ma, H. Zhang, and W. Yuan, 2017: Spatial-temporal variability of snow cover and depth in the Qinghai-Tibetan plateau. *J. Climate*, **30**, 1521–1533, <https://doi.org/10.1175/JCLI-D-15-0732.1>.
- Yang, J., L. Jiang, C. B. Ménard, K. Luoju, J. Lemmetyinen, and J. Pulliainen, 2015: Evaluation of snow products over the Tibetan Plateau. *Hydrol. Processes*, **29**, 3247–3260, <https://doi.org/10.1002/hyp.10427>.
- Yang, K., B. Ye, D. Zhou, B. Wu, T. Foken, J. Qin, and Z. Zhou, 2011: Response of hydrological cycle to recent climate changes in the Tibetan Plateau. *Climatic Change*, **109**, 517–534, <https://doi.org/10.1007/s10584-011-0099-4>.
- Zhang, Y.-S., T. Li, and B. Wang, 2004: Decadal change of the spring snow depth over the Tibetan Plateau: The associated circulation and influence on the East Asian summer monsoon. *J. Climate*, **17**, 2780–2793, [https://doi.org/10.1175/1520-0442\(2004\)017<2780:DCOTSS>2.0.CO;2](https://doi.org/10.1175/1520-0442(2004)017<2780:DCOTSS>2.0.CO;2).
- Zhang, Y.-H., X. Kan, W. Ren, T. Cao, W. Tian, and J. Wang, 2017: Snow cover monitoring in Qinghai-Tibetan Plateau based on Chinese Fengyun-3/VIRR data. *J. Indian Soc. Remote Sens.*, **45**, 271–283, <https://doi.org/10.1007/s12524-015-0527-4>.