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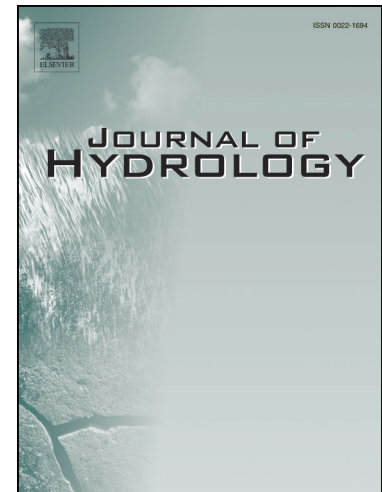
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**Development of a fine-resolution snow depth product based on
the snow cover probability for the Tibetan Plateau: Validation and
spatial-temporal analyses**

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Abstract: Accurate remotely sensed snow depth (SD) data are essential for monitoring and modeling hydrological processes in cold regions. While the available passive microwave SD data have been widely used by the community, the coarse spatial resolution (typically at 0.25°) of these data impedes the explicit representation of the hydrological processes in snow-dominated regions, especially in mountainous regions with complex terrain. To improve the spatial resolution and quality of passive microwave SD data for the Tibetan Plateau (TP), we develop a spatial-temporal downscaling method to produce a 19-year, daily 0.05° SD product by combining the existing high temporal resolution daily SD data and the high spatial resolution 8-day cloud-free Moderate Resolution Imaging Spectroradiometer (MODIS)-based snow cover probability (SCP) data, the latter of which were produced using an advanced temporal filter algorithm. Validations against the observed SD data from 92 meteorological stations suggest that the newly-developed 0.05° SD product greatly improves upon the original 0.25° version. Based on this 0.05° SD product, we found that higher SD values are mainly distributed on the southeastern and eastern TP as well as the Himalaya and Karakoram, while much lower SD values occur on the inner TP. During 2000–2018, the TP-averaged annual SD showed a slight ($p > 0.05$) increasing trend because there were little changes in SD for most grids across the TP. Regarding different basins within TP, the annual SD during 2000–2018 slightly increased over most basins except for the Amu Dayra, Ganges, Brahmaputra, and Inner TP, where the basin-scale SD showed insignificant decreasing tendencies. In general, the spatial-temporal variations in the SD across the TP were very heterogeneous because SD was

44 affected by multiple climatic factors. The newly-developed 0.05° SD product could
45 facilitate our understanding of the hydrological processes on the TP through a more
46 explicit representation of the gridded-based snow water information.

47 **Keywords:** snow depth, downscaling, snow cover probability, Tibetan Plateau

1. Introduction

Snow is a key component of the hydrological cycle and an important indicator of climate change (Pulliainen et al., 2020; Musselman et al., 2021). It also plays a key role in the energy balance because of its strong effect on the surface albedo and soil temperature, thereby modulating the local and regional weather and climate (Henderson et al., 2018; Jia et al., 2021; You et al., 2020). As the snowpack can store a large amount of the precipitation that falls during the cold season, it also plays a vital role in the spring runoff formulation (Barnett et al., 2005; Huninga and AghaKouchaka, 2020), impacting the downstream agricultural production, which relies on irrigation (Qin et al., 2020). The snow depth (SD) is the most important variable that describes the amount of snow for a given region (Kinar and Pomeroy, 2015; Matiu et al., 2021). Hence, reliable high-quality SD datasets are essential for the above applications related to the weather and climate, water resource management, and flood monitoring in cold regions.

Several approaches have been extensively used to monitor the SD, including field observations, land surface modeling, optical remote sensing, and passive microwave remote sensing. Although meteorological stations can provide accurate SD observation data for a long time series (Ma et al., 2020; Matiu et al., 2021), the number of stations in mountainous regions where the snow often occurs remains low (Lundquist et al., 2019), impeding the understanding of snow dynamics in high-elevation areas. In terms of the model-based SD estimates, including the lumped conceptual models (e.g., Snow-17 model) and the physically-based land surface models (e.g., those from the Global

Land Data Assimilation System Version 2.1), the uncertainties in the modeling forcing and the parameters may bring potential errors in regional scale SD estimation, which is especially true for remote areas where ground observed meteorological data are very sparse (Bian et al., 2019; Ma et al., 2020). While certain atmospheric reanalysis data, e.g., the Japanese 55-year Reanalysis (JRA-55), has also assimilated the ground observations in deriving the gridded SD data, they are typically at the relatively coarse spatial resolutions with an order of 0.5° or larger (Bian et al., 2020; Orsolini et al., 2019). Although snow cover information can be extracted from optical remote sensing data under clear sky conditions (Hall et al., 2007; Bhatti et al., 2016; Zhang et al., 2014), it is less accurate and more difficult to estimate the SD using the visible and infrared bands (Dai et al., 2018). With the rapid development of passive remote sensing over the last four decades, this technique has become widely used for detecting SD information by taking advantage of the difference in the microwave brightness temperature at different frequencies regardless of cloud contamination since the 1970s (Chang et al., 1987; Che et al., 2008; Liang et al., 2015; Tait, 1998; Tedesco et al., 2004). This is because the deeper the snowpack is, the more positive the microwave energy difference detected between the horizontally polarized brightness temperatures of the 19 (or 18) GHz and 37 (or 36) GHz bands (Kelly et al., 2003; Che et al., 2008; Xiao et al., 2018).

Previous studies have dedicated much effort to developing and calibrating numerous SD estimation algorithms for use with passive microwave remote sensing data. For example, the relationship between the SD and the brightness temperature gradients of the 18 and 37 GHz bands was used for SD retrievals from Nimbus-7

Scanning Multichannel Microwave Radiometer (SMMR) data (Chang et al., 1987). Considering the effects of forested areas and crystal size on SD estimation, Foster et al. (1997) presented an algorithm to improve the original one proposed by Chang et al. (1987) for North America and Eurasia. The Chang et al. (1987) algorithm was also adjusted to consider several factors influencing the SD retrieval to achieve a more accurate result in China (Che et al., 2008). This valuable effort produced a Chinese long-term SD dataset based on this algorithm for the last four decades using three passive microwave remote sensing sensors, i.e., the SMMR, Special Sensor Microwave/Imager (SSM/I), and Special Sensor Microwave Imager/Sounder (SSM/I/S) (Che et al., 2008; Dai et al., 2015; 2017). Although the microwave remote sensing SD data allow us to eliminate cloud contamination, its coarse spatial resolution (mostly at 0.25°) is too coarse to capture the fine-scale characteristics of SD, which is especially true in mountainous areas with a complex terrain. In addition, the coarse resolution of such SD products is not adequate for hydrological modeling studies in small watersheds where the runoff is often simulated at the kilometer scale.

The combination of optical snow cover products and microwave snow products is an important step in developing accurate snow cover and SD products. To mitigate the uncertainty of microwave remote sensing snow products (e.g., SD and snow water equivalent) due to its low spatial resolution, it may be preferable to blend the existing coarse resolution microwave remote sensing SD products and other auxiliary datasets with higher spatial resolutions to improve the spatial resolution of the SD product. To this end, various types of snow cover information, e.g., binarized snow cover, fractional

snow cover, and annual snow cover duration, usually have much higher spatial resolutions and thus are widely used to enhance passive microwave snow products (Gao et al., 2010; Tang et al., 2016; Huang et al., 2016; Dai et al., 2018; Wei et al., 2021).

The three main factors derived from the optical-based snow cover information were used to enhance the coarse resolution microwave SD and snow water equivalent datasets. First, a binarized snow cover image was used. Gao et al. (2010) redistributed the snow water equivalent information using the number of snow-covered pixels from the Moderate Resolution Imaging Spectroradiometer (MODIS) data in a passive microwave pixel. However, a binarized snow cover image classified using a threshold tends to underestimate patchy snow cover information to a large extent (Zhang et al., 2019). Thus, compared to the binarized snow cover, the fractional snow cover should be given priority to enhance the coarse resolution microwave SD. Second, the spatial information about the daily fractional snow cover was used. Tang et al. (2016) used a daily fractional snow cover product to enhance the daily microwave SD data based on the strong relationship between these two snow parameters. By combining ground emissivity, land surface temperature, and fractional snow cover, the SD data was further improved using a novel spatial dynamic method with a higher spatial resolution on the TP (Dai et al., 2018). However, the accuracy of the daily snow cover product is largely affected by cloud cover (Zhang et al., 2019). Third, the annual snow cover duration was used (Mhawej et al., 2014; Huang et al., 2016; Wang et al., 2019; Wei et al., 2021) because there is a strong relationship between the snow cover duration and the SD during a given year. The annual snow cover duration obtained from MODIS data was

introduced to redistribute the microwave snow water equivalent data (Mhawej et al., 2014) and the SD data (Huang et al., 2016). The relationships between the SD and several factors (e.g., longitude, latitude, terrain, and snow cover duration) were built using multi-factor regression models in order to reconstruct the high-resolution SD products (Wang et al., 2019; Wei et al., 2021). However, using the annual snow cover duration to reconstruct the daily passive microwave SD pixels is problematic because of the temporal difference.

While progress in downscaling the SD (snow water equivalent) has been made by taking advantage of more factors, less attention has been paid to enhancing the SD product by taking advantage of the high spatial resolution MODIS snow cover probability (SCP) product in previous studies. In short, neither the annual snow cover duration nor the daily snow cover product, e.g., the binarized snow cover and fractional snow cover, are suitable for use as a downscaling factor to produce SD datasets with high temporal-spatial resolutions. The utilization of the MODIS SCP information during several days can provide new opportunities, thereby improving the spatial resolution of the passive microwave SD data.

With an average altitude higher than 4000 m above sea level (a.s.l.), the Tibetan Plateau (TP) is the source region of several major Asian rivers, including the Indus, Ganges, Brahmaputra, Salween, Mekong, Yellow, and Yangtze rivers (Fig. 1), which is therefore known as the Asian Water Tower (Immerzeel et al., 2010). In this context, snow is extremely important because it is one of the key water resources that supply more than 1.6 billion people downstream in China, India, Pakistan, Nepal, Bhutan, and

Bangladesh (Immerzeel et al., 2020). However, in-situ observations of snow information are particularly sparse on the TP because of its complex terrain and harsh climate (Ma et al., 2020). For this reason, satellite-observed SD products for the TP have attracted increasing attention because of their ability to estimate the snow water resources in this inaccessible region with formidable natural conditions (Tang et al., 2016; Xiong et al., 2017; Zhang and Ma, 2018). However, the development of high-resolution (both spatially and temporally) remote sensing SD data in the Tibetan Plateau is challenging because of its heterogeneous landscape and scarce ground observations (Bian et al., 2019; Orsolini et al., 2019). Having recognized this need, the objectives of this study are (i) to develop a spatiotemporal downscaling method by taking advantage of the spatial information of the MODIS SCP and the temporal information of the passive microwave SD during an 8-day period to produce a finer resolution (i.e., 0.05°) SD product across the TP; (ii) to determine whether the accuracy of this newly-developed 0.05° SD product is better than that of the previous coarse-resolution SD dataset; and (iii) to investigate the spatial and temporal variations in SD over TP during the last two decades.

2 Data

2.1 Fractional snow cover and clear index

The MODIS snow cover data version 006 from 2000 to 2018 from the Terra (MOD10C1) and Aqua (MYD10C1) satellites were downloaded (accessible from the National Snow and Ice Data Center (NSIDC), <http://nsidc.org>). The spatial and

temporal resolutions are 0.05° and daily, respectively (Hall et al., 2002). Both datasets are comprised of three sub-datasets, i.e., the fractional snow cover (FSC), cloud obscuration percentage, and clear index (CI) data, ranging from 0% to 100%. Each sub-dataset of the MODIS snow cover data includes the following categories: lake ice, inland water, ocean, cloud obscured water, data not mapped, and data filled (Table 1). Because lake ice, inland water, ocean, and cloud obscured water have no snow cover information, these variables were reclassified to 100% in the clear index data. The data that were not mapped and the filled data were considered as cloud cover, so they were reclassified to 0% in clear index data. The FSC and CI were calculated as follows (Hall et al., 1995; Salomonson et al., 2006):

$$FSC_{Terra} = 1.45 \times \frac{\rho_{Green} - \rho_{SWIR1}}{\rho_{Green} + \rho_{SWIR1}} - 0.01, \quad (1)$$

where FSC_{Terra} is the fractional snow cover obtained using the MODIS Terra instrument; ρ_{Green} is the reflectance of the green band; and ρ_{SWIR1} is the reflectance of the SWIR1 band.

$$FSC_{Aqua} = 1.91 \times \frac{\rho_{Green} - \rho_{SWIR2}}{\rho_{Green} + \rho_{SWIR2}} - 0.64, \quad (2)$$

where FSC_{Aqua} is the fractional snow cover obtained using the MODIS Aqua instrument; ρ_{Green} is the reflectance of the green band; and ρ_{SWIR2} is the reflectance of the SWIR2 band.

200

$$CI = 1 - FCC, \quad (3)$$

201 where CI is the daily clear index data; and FCC is the daily fractional cloud cover.

202

203 **2.2 Gridded SD product**

204 The long-term daily, 0.25° SD dataset from 2000 to 2018 was downloaded from the
 205 National Tibetan Plateau Data Center (<https://data.tpdc.ac.cn/zh-hans/>). This dataset
 206 was obtained by the SMMR, SSM/I, and SSMI/S (Che et al., 2008; Che, 2015; Dai et
 207 al., 2015; 2017). To improve the consistency of the passive microwave remote sensing
 208 data derived from the various sensors, the brightness temperature data derived from
 209 these instruments (SMMR, SSM/I, and SSMI/S) were cross-calibrated (Dai et al., 2015).
 210 This SD dataset has long been regarded as the most accurate snow depth estimation for
 211 China and thus has been widely used not only in previous studies related to SD
 212 downscaling (Huang et al., 2016; Tang et al., 2016; Wei et al., 2021) but also in
 213 understanding the effects of snow changes on regional runoff (Xu et al., 2009) and that
 214 on vegetation dynamics (Yu et al., 2013).

215

216 **2.3 Ground measured SD data from meteorological stations**

217 The daily SD data during 2000-2010 observed at 92 meteorological stations (Fig.
 218 1) of the China Meteorological Administration were used as the “ground-truth” values
 219 for assessing the accuracy of the gridded SD product (Wang and Wan, 2018). With
 220 elevations ranging from 1000 to 4800 m above sea level, most meteorological stations

are located on the southern and eastern parts of the TP. The in-situ SD measurements are the most accurate record of the SD, and therefore, they are widely used for evaluating not only satellite-based SD products (Tang et al., 2016) but also the snow products in reanalysis over the TP (Orsolini et al., 2019).

3. Method

3.1 Definition of the snow hydrological year

According to the seasonal cycle of the SD in TP, the lowest monthly mean SD occurs in September over the TP. Therefore, the snow year was defined as September 1 to August 31 of the following year. For example, the snow year of 2000 was from September 1 of 2000 to August 31 of 2001. It should be noted that all analyses in the present study are based on the snow year instead of the calendar year.

3.2 Cloud removal method for estimating the spatial probability of the snow cover

Cloud contamination of optical remote sensing products greatly limits the usage of daily MODIS snow cover datasets. To remove the clouds from the original MODIS snow cover product, the ratio of the number of snow pixels to the number of cloud-free pixels during a 15-day period was used to estimate the spatial probability of the snow cover by combining the regional snowline and an elevation zone with a 100 m interval (Li et al., 2017). However, the snow pixels were identified via binarization processing of the Normalized Difference Snow Index (NDSI) image data, with a specific threshold on the regional scale, which causes uncertainties in estimating the area of the snow

cover (Zhang et al., 2019). To achieve a more accurate spatial probability of snow, the binary snow images with snow pixels and non-snow pixels were replaced by the FSC images in this study. Similarly, the binary cloud-free images with cloud pixels and non-cloud pixels were replaced by the clear index (CI) images.

The ratio of the sum of the fractional snow cover (FSC_{sum}) data to the sum of the clear index (CI_{sum}) data during a period is an improved method for estimating the spatial probability of the snow cover, which makes full use of the snow cover and cloud information from the original MODIS snow product. The new advanced SCP dataset was generated by combining MODIS Terra and Aqua data for 2002–2018 at a spatial resolution of 0.05° over the entire TP. During 2000–2001, only the MODIS Terra data were used because Aqua is not available. Detailed descriptions of the three steps of the new method are provided below (Figs. 2 & 3).

Step 1: The sum of FSC and the sum of the clear index during an 8-day period for both the daily MODIS Terra and MODIS aqua datasets covering each pixel of the entire TP was calculated as follows:

$$CI_{sum} = \sum_{i=1}^n CI_i, \quad (4)$$

where CI_{sum} is the sum of the daily clear index data during an 8-day period.

$$FSC_{sum} = \sum_{i=1}^n FSC_i, \quad (5)$$

where FSC_{sum} is the sum of the fractional snow cover from the original daily MODIS snow cover product during an 8-day period.

Step 2: If the sum of the daily clear index for a pixel was higher than 0 within the 8-day period, the spatial probability of snow cover in this pixel was estimated as

262 follows:

$$SCP = \frac{FSC_{sum}}{CI_{sum}} = \frac{\sum_{i=1}^n FSC_i}{\sum_{i=1}^n CI_i}, \quad (6)$$

263 where SCP is the 8-day cloud-free snow cover probability.

264 The above two steps effectively remove most of the clouds in the original MODIS
265 snow cover product during an 8-day period. If CI is zero in all of the pixels from the
266 Terra and Aqua sensors during this period, a backup forecasting method was used in
267 the next step.

268 **Step 3:** If the pixel was completely (100%) covered by clouds during the entire 8-
269 day period, the spatial probability of snow cover was estimated using the cloud-free
270 spatial probability of snow cover for the preceding 8-day period (PSCP) and that of the
271 following 8-day period (FSCP) as follows:

$$SCP = \begin{cases} (PSCP + FSCP)/2, & \text{PSCP and FSCP are available} \\ PSCP, & \text{FSCP is not available} \\ FSCP, & \text{PSCP is not available} \end{cases}. \quad (7)$$

272 Using the above three steps, we were able to estimate the SCP regardless of almost all
273 of the cloud cover, with a time span of 24 days.

274 The results of the SCP estimation are shown in [Fig. 4](#). The SCP could be easily
275 estimated using Step 2 when the sum of the CI in the pixels is greater than 0 during an
276 8-day period. When a small part of the pixels is fully covered by clouds for all time
277 within a given period, the preceding and the subsequent 8-day cloud-free SCP data for
278 the same pixels estimated using Step 3 are employed to fill such a gap. As a result, an
279 8-day SCP dataset without cloud cover could be produced using the above three steps.

280

281 **3.3 Relationship between passive microwave SD product and SCP**

282 Snow cover information with a high spatial resolution is a key factor and has been
283 widely used as a spatial weight when redistributing passive microwave SD pixels in
284 previous studies. These studies identified a positive correlation between the FSC and
285 SD over the TP (Tang et al., 2016; Dai et al., 2018), indicating that the FSC can be used
286 to determine the detailed spatial information for the passive microwave SD pixels.
287 Therefore, the SCP generated from the FSC has the potential ability to redistribute
288 passive microwave SD pixels.

289 To illustrate, we selected two typical regions with a large amount of snow in the
290 TP. The 8-day mean SD and SCP values from 300 grid points during winter 2000 were
291 randomly extracted for the western TP and for the southeastern TP, which are the two
292 main snow-covered regions on the TP. Thus, a total of 600 grid points were sampled to
293 test the relationship between the SD and SCP in the cold season. A simple linear
294 regression model was then established based on these collected SCP and SD data. In
295 each region, we found a significant positive relationship between the SD and SCP, as
296 can be seen from the R values of 0.74 for the western TP and 0.88 for the southeastern
297 TP ($p < 0.001$ in both cases) (Fig. 5). Thus, the SCP was determined to be an appropriate
298 factor for downscaling the coarse-resolution SD data used in this study.

299

300 **3.4 Downscaling algorithms**

301 **3.4.1 Spatial downscaling algorithm**

The above analysis suggests that a higher SCP value may indicate a higher SD value. Therefore, it is reasonable to use the SCP derived from the FSC product to improve the spatial resolution of the SD grids. To maintain the same temporal resolution for the SD and SCP, the total SD (SD_{sum}) during an 8-day period dataset was produced by summing the daily SD data for each 8-day period by:

$$SD_{sum} = \sum_{i=1}^8 SD_i, \quad (8)$$

The area of a 0.25° passive microwave SD pixel is 25 times that of an 0.05° SCP pixel. Thus, each 0.25° SD pixel was equally divided into 25 subpixels by taking into consideration the spatial weight derived from the 0.05° SCP in the same location. Dividing the sum of the 0.05° SCP in the extent of the 0.25° SD pixel by each 0.05° SCP pixel is an effective way to estimate each spatial weight that is used to redistribute the 0.25° SD pixels. In this case, the 8-day SD_{sum} grids must be multiplied by 25 before multiplying by the subpixel-level spatial weight value. In this way, an 8-day SD_{sum} dataset with the 0.05° resolution subpixel spatial information was produced for 2000–2018 over the TP (Fig. 6). The equations of spatial downscaling algorithm are as follows:

$$WS = \frac{SCP_j}{\sum_{j=1}^{25} SCP_j} = \begin{bmatrix} W_{11} & \cdots & W_{15} \\ \vdots & \ddots & \vdots \\ W_{51} & \cdots & W_{55} \end{bmatrix}, \quad (9)$$

$$(SD_{sum})_{sub} = 25 \times SD_{sum} \times W_s = \begin{bmatrix} 25 \times SD_{sum} \times W_{11} & \cdots & 25 \times SD_{sum} \times W_{15} \\ \vdots & \ddots & \vdots \\ 25 \times SD_{sum} \times W_{51} & \cdots & 25 \times SD_{sum} \times W_{55} \end{bmatrix}, \quad (10)$$

where $(SD_{sum})_{sub}$ is the sum of the subpixel snow depth at 0.05° during an 8-day period, SD_i is the snow depth on the i th day during an 8-day period ($1 \leq i \leq 8$), W_s is the spatial weight for redistributing the passive microwave snow depth pixel, and SCP_j is the snow cover probability in the j th pixel in the area of each 0.25° snow depth pixel ($1 \leq j \leq 25$).

3.4.2 Temporal downscaling algorithm

In the process of downscaling the passive microwave SD, the advantage of its high temporal resolution has long been disregarded in previous studies. Using the ratio of daily SD to the 8-day SD_{sum} , the daily temporal weight can be calculated to improve the temporal resolution of the 8-day SD_{sum} dataset containing subpixel spatial information. A subpixel SD dataset with a daily temporal resolution during 2000–2018 in the study region was produced by multiplying the 8-day SD_{sum} subpixel dataset and each daily temporal weight. The flowchart of the temporal downscaling algorithm is shown in Fig. 7, and the equations are as follows:

$$Wt = \frac{SD_i}{\sum_{i=1}^8 SD_i} = \left[\frac{SD_1}{\sum_{i=1}^8 SD_i} \quad \cdots \quad \frac{SD_8}{\sum_{i=1}^8 SD_i} \right], \quad (11)$$

$$(SD_i)_{sub} = (SD_{sum})_{sub} \times Wt = \left[(SD_{sum})_{sub} \times W_1 \quad \cdots \quad (SD_{sum})_{sub} \times W_8 \right] = \quad (12)$$

$$\left[(SD_{sum})_{sub} \times \frac{SD_1}{\sum_{i=1}^8 SD_i} \quad \dots \quad (SD_{sum})_{sub} \times \frac{SD_8}{\sum_{i=1}^8 SD_i} \right],$$

336

337 where $(SD_i)_{sub}$ is the subpixel daily snow depth on the i th day, $(SD_{sum})_{sub}$ is the sum of
 338 the subpixel snow depth during an 8-day period, W_t is the temporal weight, and SD_i is
 339 the snow depth on the i th day during an 8-day period ($1 \leq i \leq 8$).

340

341 3.5 Statistical metrics for assessing the SD product

342 The daily in-situ SD data measured at 92 meteorological stations of the China
 343 Meteorological Administration (CMA) were used to evaluate the accuracy of the new
 344 daily 0.05° SD product and the original 0.25° one for 2000–2010. For each product, the
 345 SD value of the grid in which the station is located was compared against that observed
 346 by the meteorological stations. Based on the elevations of the stations, the comparisons
 347 were also aggregated into four elevation zones with a 1000 m interval. The root-mean-
 348 square-error (RMSE) and the mean-absolute-error (MAE) values were calculated to
 349 quantitatively evaluate the accuracy of these two products, i.e.,

350

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - y_i)^2}, \quad (13)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |x_i - y_i|, \quad (14)$$

351

352 where x_i is the i th in-situ snow depth value, and y_i is the i th passive microwave snow
 353 depth value.

4. Results

4.1 Validations of the original 0.25° SD product and the new 0.05° SD product

[Fig. 8](#) shows the validation results of the new 0.05° and the original 0.25° SD data using the ground measured SD data. As seen, the RMSE and MAE values from the former are much smaller than those from the latter, indicating a significant improvement in the 0.05° SD product across the TP. For all 92 stations, the mean RMSE and MAE values of the new 0.05° SD product are 1.54 and 0.67 cm d⁻¹, respectively. The spatial distribution for the RMSE and MAE of two SD products ([Fig. 9](#)) shows that the improvement of new SD estimates is more obvious in the eastern part of TP. For certain stations in the southeastern TP, however, the difference in the accuracy of these two products seems not obvious. This may be attributed to the inherent larger error in the original 0.25° SD product in this area where numerous forests are found.

Regarding the stations in different elevation zones ([Table 2](#)), the RMSE values of the new 0.05° SD product are all lower than those of the original 0.25° SD product. This is also true for the MAE values. The improvement is most obvious in the 3000–4000 m a.s.l. elevation zone, in which the RMSE decreases from 3.22 to 2.30 m d⁻¹ ([Table 2](#)). The above validation suggests that our newly-developed SD product with a higher spatial resolution outperforms the original 0.25° SD product regarding the accuracy.

4.2 Spatial pattern of the SD over the TP from the new and original SD products

[Fig.10](#) presents the spatial characteristics of the multiyear (2000–2018) mean SD from the new 0.05° and original 0.25° SD products over the TP. As can be seen, the two SD products exhibit similar spatial distribution characteristics. However, the new SD product with a 0.05° spatial resolution captures much more detailed information and provides more heterogeneous spatial distribution patterns compared to the original version. This is because the former assimilates the much spatial information of the SCP, the latter of which was derived from the MODIS with a high spatial resolution. The difference between these two products is most obvious in the snow-dominated regions, i.e., the southeastern TP as well as the Himalaya and Karakoram.

To further illustrate the strength of the new 0.05° SD product at the monthly scale, [Figs. 11 & S2](#) further illustrate the spatial distribution of the multiyear (2000–2018) mean monthly SD across TP. As seen, a more explicit spatial pattern of SD across TP could be detected every month by the new 0.05° SD product. With this new 0.05° SD product, we could describe the spatial characteristic of SD in a more detailed manner. On the monthly scale, the spatial pattern of the multiyear (2000–2018) average SD over the TP differs significantly in the cold and warm seasons ([Figs. 11 & S2](#)). During the cold season, the large SD values mainly occur on the northwestern and southeastern TP, while the SD values in the inner TP are much smaller. During the warm season, there is little snow on most parts of the TP, except for the high-elevation areas of Karakorum, Kunlun, Himalaya, and Pamir, where a certain amount of snow still exists during the warm season. Note that although the 0.05° SD product has an improved spatial resolution, it may be less capable of presenting the spatial information about the

snowpack in summer. This is mainly because the microwave data cannot efficiently detect the SD in regions with shallow SD values.

4.3 Seasonal cycle of the SD over the TP and its basins

The multiyear mean monthly SD averaged over the entire TP increases rapidly from September to January, leading to a peak monthly value of 3.54 cm mo⁻¹ (Fig. 12m). This is followed by a gradual decrease until September. In general, the rate of increase of the monthly SD during September-January is obviously faster than the rate of decrease of the monthly SD during January-September, which suggests that the duration of the snow melting period is likely longer than the snow accumulation period over the TP.

Figs. 12a–l illustrate the seasonal cycle of the SD in 12 basins within the TP. In general, the lowest monthly SD occurs in July or August over the basins in the eastern TP, but for the basins in the western and inner TP, the lowest monthly SD occurs in September. For most basins that are influenced by the Asian Monsoon, the maximum monthly SD occurs in December or January. However, for the Amu Dayra, Indus, and Ganges, which are obviously impacted by the westerlies, the SD is large until April. The above analysis highlights that the monsoon and westerlies play important roles in controlling the intra-annual SD variations in the different basins across TP.

4.4 Trends in the SD over the entire TP and its basins

Fig. 13a shows the spatial pattern of the trends (2000–2018) in annual SD across

the TP derived from the new 0.05° product. The SD increased significantly in some parts of the Tarim, upper Yangtze, Yellow, and Mekong River basins and the northern Himalayas, but it decreased significantly in some parts of the inner TP, eastern Brahmaputra, and the southern Himalayas. However, in most parts of TP, the trends of the annual SD were not significant during 2000–2018 (Fig. 13b). To further illustrate the strength of the new high-resolution SD data, we also show the spatial pattern of the trends in annual SD derived from the 0.25° product in Fig. S2. Although the spatial pattern of the linear trends derived from the 0.25° version is overall similar to those from the 0.05° product, the new data obviously provide a more explicit representation of the changes in SD across TP. Therefore, it is suggested that our newly-developed SD data could serve as a useful tool for investigating the spatial and temporal variations in snow over TP.

When averaged over the entire TP, the annual SD increased slightly with a rate of 0.005 cm yr⁻¹ ($p > 0.05$) during 2000–2018 (Fig. 14m). The annual SD generally increased during 2000–2008 and 2017–2018, and it decreased overall during 2008–2017. It should be highlighted that the trend in the SD depends highly on the temporal period analyzed since there was a sudden jump in the SD in 2018 (which is also the largest annual SD during these 19 years). For this reason, the trend in TP-averaged annual SD became a slight decreasing one with a value of -0.009 cm yr⁻¹ ($p > 0.05$) during 2000–2017 (Fig. S3m).

Figs. 14a–l also illustrate the linear trends in the annual SD during 2000–2018 for 12 basins within the TP. The annual SD increased in most of the basins in the TP, except

the Amu Dayra, Ganges, Brahmaputra, and Inner TP, in which the annual SD decreased to some extent. However, the trends are mostly insignificant, except for that of the Tarim Basin, in which the annual SD increased significantly at a rate of 0.05 cm yr^{-1} ($p < 0.05$) during the 19-year study period. When switching to the period of 2000–2017 (Fig. S3), trends in basin-scale annual SD change to some extent. In particular, trends in Indus, Salween, Mekon, Yangtze, and Qaidam become decreasing, though such trends are still not statistically significant.

5. Discussions

Although the SD dataset was improved, with a better resolution of 0.05° , the error of the representativeness is inevitable when validating pixel-based SD products based on ground-based SD measurements. This is because a sample point is less capable of representing a pixel, especially in regions with a heterogeneous underlying surface (Xiao et al., 2018). To improve the reliability of the validation results of the SD products derived from remote sensing satellites across the entire TP, progress should be made not only in developing downscaling algorithms but also in enhancing advanced sensors.

Although the SD retrieval method has been calibrated and developed using several versions (Chang et al., 1987; Foster et al., 1997; Che et al., 2008; Jiang et al., 2014), accurate knowledge of the physical properties of the snowpack, e.g., snow temperature, snow density, snow grain size, and snow water content, is not explicitly and comprehensively considered used in most of the retrieval methods using the passive

microwave remote sensing data (Dietz et al., 2012). Thus, in future studies, more dynamic SD retrieval methods should be developed to consider the various effects of these physical properties to improve the accuracy of the original SD products derived from passive microwave brightness temperature data.

It is more suitable to use passive microwave remote sensing to estimate the snow water equivalent rather than the SD. This is mainly because the microwave brightness temperature of the snowpack is affected by both SD and snow density (Kelly et al., 2003). However, most of these algorithms involved the relationship between the SD value and the passive microwave brightness temperature (Chang et al., 1987; Foster et al., 1997; Che et al., 2008; Jiang et al., 2014). Therefore, it is believed that these algorithms may also be appropriate for estimating the snow water equivalent after slight modifications. In this case, more attention should be paid to building more snow water equivalent measurement sites because of the limited global samples available for validation.

Several factors may impact the trend of the snow parameters over the TP to some extent, such as the study area and study period. The effects of the size of the TP coverage on the trends of the snow parameters have long been disregarded. For example, the TP's extent in China is less than the entire TP region in this study (Zhang et al., 2013). It is worthwhile to highlight the SD in certain areas of the western TP (e.g., the Karakoram) is higher than other parts of the TP, thus making them a significant contributor to the trend in the TP-averaged annual SD. A good example of this is that the seasonal cycle of the SD over the entire TP is influenced by the high SD values in

the western TP to a large extent, which is especially true in summer. Additionally, the trend in the annual SD is also very sensitive to the length of the study period, as can be seen from the comparisons between Fig. 14 and Fig. S3. Although the SD in most of the basins in the TP increased slightly from 2000 to 2018, it decreased slightly from 2000 to 2017. Different trends during these two different periods are also true for the TP-averaged annual SD, though both trends are not statically significant.

6. Conclusions

By combining a high temporal resolution passive microwave SD dataset with a high spatial resolution cloud-free SCP dataset, this study developed a spatial-temporal downscaling method to successfully downscale the 0.25° SD dataset to a 0.05° SD product for the TP during 2000–2018. The validation against 92 ground meteorological stations demonstrates that the new 0.05° SD product significantly improves upon the original 0.25° version. While the present study only focuses on the TP, the spatial-temporal downscaling method proposed here could be applied to other snow-dominated regions (e.g., the high latitudes) to produce new SD data with an improved spatial resolution.

Based on the new 0.05° SD product, we found that SD is typically higher in the southeastern TP as well as the Himalaya and Karakoram, while the lowest SD value occurs mainly in the inner TP. For the seasonal cycle of SD, the maximum monthly SD occurs in December or January for most basins that are influenced by the Asian Monsoon. However, for the Amu Dayra, Indus, and Ganges, which are obviously

impacted by the westerlies, the SD is large until April. This indicates that the monsoon and westerlies play important roles in controlling the intra-annual SD variations patterns across TP.

During 2000–2018, there was no significant trend in annual SD for most parts of TP. The TP-averaged annual SD showed a slight increasing trend (0.005 cm a^{-1} , $p > 0.05$). On the basin scale, the annual SD slightly decreased in the Amu Dayra, Ganges, Brahmaputra, and Inner TP, but an opposite trend was observed in the rest of the basins within TP. It should be noted that the trends reported here depend greatly on the study period since there was a sudden jump in the SD for the last year (i.e., 2018) we analyzed. However, trends are still not statistically significant after removing this year's data.

The demand for high-resolution remote sensing-based SD datasets can be met to some extent by the current SD data downscaling algorithms. Therefore, it is believed that the new fine-resolution SD dataset not only provides an accurate data source for estimating snow water storage and its variations over the TP, but also presents new opportunities for hydrological and climatological studies related to the seasonal snowpack. More importantly, the response mechanism of SD to ongoing climate change on the TP is expected to be clarified in the future by using such an improved SD dataset.

Author Contributions

Dajiang Yan: Conceptualization, Methodology, Formal analysis, Software, Investigation, Resources, Data curation, Writing-original draft, Visualization. **Ning Ma:**

Investigation, Formal analysis, Writing-original draft, Funding acquisition. **Yinsheng**

Zhang: Writing-review & editing, Funding acquisition, Supervision.

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Conflicts of Interest

The authors declare that there are no potential conflicts of interest.

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TABLES

Table 1 The attributes and reclassified values of the MOD10C1 (Terra) and MYD10C1 (Aqua) products.

Attributes	Value	Reclassified values in clear index	Reclassified values in fractional snow cover
Fractional snow cover	0–100	/	0–100
Clear index value	0–100	0–100	/
Lake ice	107	100	0
Inland water	237	100	0
Ocean	239	100	0
Cloud obscured water	250	100	0
Data not mapped	253	0	0
Filled	255	0	0

Table 2 The RMSE and MAE values of the newly-developed 0.05° and the original 0.25° SD products in the different elevation zones

Elevation (m a.s.l.)	RMSE (cm d ⁻¹)		MAE (cm d ⁻¹)	
	0.25° SD	0.05° SD	0.25° SD	0.05° SD
	product	product	product	product
1000–2000	0.77	0.76	0.22	0.19
2000–3000	1.98	1.16	1.07	0.54
3000–4000	3.22	2.30	1.78	1.08
4000–4800	1.44	1.29	0.63	0.45
All stations	2.15	1.54	1.12	0.67

FIGURES CAPTIONS

Fig. 1 Spatial domain of the Tibetan Plateau and its 12 basins. The unfilled circles denote the 92 meteorological stations of the China Meteorological Administration where the snow depth was observed.

Fig. 2 Flowchart of estimating the cloud-free snow cover probability from the MODIS Terra snow cover product during 2000–2001.

Fig. 3 Flowchart of estimating the cloud-free snow cover probability from the MODIS Terra and Aqua snow cover products during 2002–2018.

Fig. 4 Flowchart and the results of the SCP estimation based on the fractional snow cover and clear index during 1–8 January 2003 using the MODIS Terra and Aqua products.

Fig. 5 Relationship between the SD and SCP based on 300 grid points during winter 2000 in the (a) western and (b) southeastern TP.

Fig. 6 Flowchart of the spatial downscaling method.

Fig. 7 Flowchart of the temporal downscaling method.

Fig. 8 (a–b) RMSE and (c–d) MAE values of the newly-developed 0.05° and the original 0.25° SD products when validated against the ground-observed SD data from 92 meteorological stations across the TP.

Fig. 9 Spatial patterns of the (a–b) RMSE and (c–d) MAE of the newly-developed 0.05° and the original 0.25° SD products from the validations against the ground-observed SD data from 92 meteorological stations across the TP.

Fig. 10 Spatial pattern of the multiyear (2000–2018) mean annual SD from the (a)

original 0.25° SD product and (b) newly-developed 0.05° SD product over the TP.

Fig. 11 Spatial pattern of the multiyear (2000–2018) mean monthly SD from September to February over the TP based on the newly-developed 0.05° and the original 0.25° SD products.

Fig. 12 Multiyear (2000–2018) mean seasonal cycle of the SD over the TP and its 12 basins based on the newly-developed 0.05° product.

Fig. 13. The spatial pattern of the (a) linear trends (2000–2018) in annual SD from the newly-developed 0.05° product and (b) significance test across the Tibetan Plateau. The trend is regarded as statistically significant when $p < 0.05$.

Fig. 14 The interannual variations and the linear trends of the basin-scale (a–l) and the TP-averaged (m) annual SD during 2000–2018.

751 **Author Contributions**

752 **Dajiang Yan:** Conceptualization, Methodology, Formal analysis, Software,
753 Investigation, Resources, Data curation, Writing-original draft, Visualization. **Ning Ma:**
754 Investigation, Formal analysis, Writing-original draft, Funding acquisition. **Yinsheng**
755 **Zhang:** Writing-review & editing, Funding acquisition, Supervision.

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758 **Conflicts of Interest:**

759 No potential conflict of interest was reported by the authors.

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Highlights:

- A new spatial-temporal downscaling method to produce a fine-resolution SD product
- Using the cloud-free snow cover probability to downscale the coarse SD dataset
- Development of a daily 0.05° SD product (2000–2018) for the Tibetan Plateau
- The TP-averaged annual SD increased slightly during 2000–2018