Evaluation and Intercomparison of Multiple Snow Water Equivalent Products over the Tibetan Plateau

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ABSTRACT

Snow cover affects the thermal conditions of the Tibetan Plateau through snow–albedo feedback and snowmelt, which, in turn, modulates the Asian summer monsoon climate. An accurate estimation of the snow condition on the Tibetan Plateau is therefore of great importance in both seasonal forecasts and climate studies. Estimation of snow water equivalent (SWE) over the Tibetan Plateau is challenging due to the high altitude, complex terrain, and insufficient in situ observations. Multiple SWE products derived from satellite estimates, reanalyses, regional climate model simulations, and land data assimilations are intercompared in terms of daily, seasonal, and annual variations and are then evaluated against in situ SWE observations. The results show a relatively consistent seasonal to interannual variability of the SWE estimates among the products. The discrepancies in magnitude are large, however, especially in winter and spring. Evaluation against in situ SWE observations indicates that none of these products is capable of accurately characterizing both the spatial pattern and temporal variations.

1. Introduction

Snow plays a crucial role in water balance and surface energy budgets due to snowmelt and its high albedo (Zhang 2005). The Tibetan Plateau, the world's highest plateau with an average elevation > 4000 m, is known as the Third Pole (Qiu 2008). The snow cover on the Tibetan Plateau significantly alters the thermal conditions of the plateau, which, in turn, influences

both the Asian and global climate (Chen et al. 1985; Yanai et al. 1992; Qin et al. 2014; Ma et al. 2017)—for example, the winter and spring snow cover on the Tibetan Plateau modulates the summer precipitation in eastern China (Qian et al. 2003; Wang et al. 2017).

The Tibetan Plateau is considered to be the water tower of Asia because it is the source of all the large rivers (e.g., the Indus, Ganges, Yellow, and Yangtze Rivers; Immerzeel et al. 2010). Snowmelt accounts for >20% of the annual flow of both the Yellow and the Yangtze Rivers, playing a key part in sustaining them (Zhang et al. 2013). Snow over the Tibetan Plateau is undergoing rapid changes under the background of the global change (Kang et al. 2010). Accurate and reliable monitoring of the snow water equivalent (SWE), which represents the amount of water available once the snow cover has melted, is crucial

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for ecosystems, hydrological forecasting, the management of water resources, and seasonal climate predictions (Dawson et al. 2016).

Direct measurements of the SWE (i.e., in situ and field SWE measurements) are considered to be the most reliable way to monitor the SWE. However, single-point SWE measurements cannot appropriately represent the SWE over an area (Erxleben et al. 2002). In addition, although much effort has been made to establish in situ measurements over the Tibetan Plateau, few SWE measurement sites are available in this region due to the high altitude, complex terrain, and harsh environment. With advances in remote sensing, large-scale estimates of the SWE are possible, although several factors limit the accuracy of the SWE retrieved by remote sensing, such as the presence of liquid water in the snow, vegetation in and above the snow, and complex terrain (Frei et al. 2012). Reanalysis products offer an alternative. Some reanalysis products also have offline land surface model (LSM) rerun versions, which estimate the SWE with improved LSMs and/or forcings. Land data assimilation, which statistically combines model simulations with observed land information based on their uncertainties, is a promising approach to estimating the regional and continental SWE (Su et al. 2010; De Lannoy et al. 2012).

Mudryk et al. (2015) found substantial uncertainties in the SWE in the Alpine region within five datasets, including satellite retrievals, the Global Land Data Assimilation System (GLDAS), physical snow models, and reanalysis products. Snauffer et al. (2016) and Terzago et al. (2017) conducted an intercomparison among gridded SWE products in British Columbia, Canada, and the Alps, respectively. Few studies have focused on the Tibetan Plateau in spite of its global importance.

Zhang et al. (2014) and Zhao and Yang (2018) developed a multisource land data assimilation system that can individually and/or jointly assimilate multiple satellite observations to estimate the SWE. The multisource land data assimilation products have not yet been compared with other independent satellite retrievals and reanalysis products. Intercomparison and evaluation of these products over the Tibetan Plateau may give an insight into their relative performance and have implications for future land data assimilation studies.

The general goals of this study were to analyze the SWE discrepancy among the satellite estimates, reanalyses, regional climate model simulations, and land data assimilation products on daily to annual time scales and to determine which product performs the

best in terms of capturing the magnitude and temporal variability of the SWE. Section 2 briefly describes the products used in this study. Section 3 presents the discrepancy among the products on multiple time scales and compares the performance of the products with in situ observations. Section 4 discusses the results and presents our conclusions.

2. Data and methods

a. Data

Table 1 summarizes the datasets used in this study, including the in situ observations, satellite estimates, reanalyses, regional climate model simulations, and land data assimilation products. All the datasets are available from 1 January 2003 to 31 December 2009.

1) IN SITU OBSERVATIONS

The China Meteorological Administration provides daily in situ SWE, 2-m air temperature, and total precipitation observations from 40 operational meteorological stations over the Tibetan Plateau. Figure 1a shows the geographical locations of these stations and their altitudes. Figure 1b shows the terrain roughness index as defined by Riley et al. (1999).

2) SATELLITE ESTIMATES

The Advanced Microwave Scanning Radiometer for Earth Observing System (AMSR-E) *Aqua* satellite provides passive microwave SWE observations retrieved using the algorithm proposed by Chang et al. (1987) and updated by Kelly et al. (2003). The AMSR-E/*Aqua* daily L3 Global Snow Water Equivalent EASE-Grid data were downloaded from the National Snow and Ice Data Center (Tedesco et al. 2004).

3) REANALYSES AND GLDAS PRODUCTS

The National Centers for Environmental Prediction Climate Forecast System Reanalysis (CFSR; Saha et al. 2010) is obtained from a global, high-resolution, coupled atmosphere–ocean–land surface–sea ice system with two sets of global precipitation analyses used in the CFSR land surface analysis—namely, the Climate Prediction Center (CPC) Merged Analysis of Precipitation (CMAP; Xie and Arkin 1997) and the CPC Unified global daily gauge analysis (CPCU) datasets (Xie et al. 2010). The snow field was simulated by the Noah LSM (Ek et al. 2003) and constrained by CFSR snow analysis. If the Noah snow field was more than twice (or less than half) of the CFSR snow analysis, then the Noah snow field was set to twice (half) the CFSR snow analysis; otherwise, the Noah snow field was not modified.

TABLE 1. Summary of the datasets used in this study. In addition to the snow water equivalent (SWE), we also obtained 2-m air temperature (T2), total precipitation (TP), and snowfall (SF) data when available.

Dataset	Resolution	Variables	Land model	Snow model	TP correction	Snow data assimilation
Obs	40 stations	SWE, T2, TP	No	No	No	No
AMSR-E	25 km	SWE	No	No	No	No
CFSR	$0.5^\circ \times 0.5^\circ$	SWE, T2, TP	Noah	Single	CMAP, CPCU	SNODEP, IMS
ERA5	$0.25^\circ \times 0.25^\circ$	SWE, T2, TP, SF	HTESSEL	Single	No	No
ERA-I	$0.25^\circ \times 0.25^\circ$	SWE, T2, TP, SF	TESSEL	Single	No	IMS
ERA-I/L	$0.25^\circ \times 0.25^\circ$	SWE, T2, TP, SF	HTESSEL	Single	GPCP	No
JRA-55	$1.25^\circ \times 1.25^\circ$	SWE, T2, TP, SF	SiB	Single	SSM/I PW	Station, SSM/I, SSMIS
MERRA2	$0.5^\circ \times 0.625^\circ$	SWE, T2, TP, SF	Catchment	Multiple	CMAP, CPCU	No
GLDAS2	$0.25^\circ \times 0.25^\circ$	SWE, T2, TP, SF	Noah	Single	GPCP, TRMM	No
GLDAS21	$0.25^\circ \times 0.25^\circ$	SWE, T2, TP, SF	Noah	Single	GPCP	No
HAR	30 km	SWE, T2, TP, SF	Noah	Single	No	No
HAR-10	10 km	SWE, T2, TP, SF	Noah	Single	No	No
OL	$0.9^\circ \times 1.25^\circ$	SWE	CLM	Multiple	GPCP	No
MOD	$0.9^\circ \times 1.25^\circ$	SWE	CLM	Multiple	GPCP	MODIS
GRAMOD	$0.9^\circ \times 1.25^\circ$	SWE	CLM	Multiple	GPCP	MODIS, GRACE

The CFSR snow analysis is based on the U.S. Air Force Weather Agency's SNODEP model (Kopp and Kiess 1996) and snow cover from the National Environmental Satellite Data and Information Service Interactive Multisensor Snow and Ice Mapping System (IMS; Helfrich et al. 2007). The SNODEP model uses in situ observations combined with the Special Sensor Microwave Imager (SSM/I)-based detection algorithm and its own climatology to generate a global analysis of snow depth at 47-km resolution. It should be noted that the SNODEP model lacks the capability to measure the SWE accurately due to the sparse nature of the in situ observations (Foster et al. 2011). The IMS snow cover data at 24-km resolution are assimilated from February 1997 and the IMS snow cover at 4-km resolution are assimilated from February 2004. The analyzed snow depth was set to 2.5 cm or the SNODEP value if the IMS indicated snow cover. Conversely, the analyzed snow depth was set to zero if the IMS data indicated that the region was snow free. The analyzed

snow depth data were converted to SWE using a 10:1 ratio.

We used three reanalysis datasets generated by the European Centre for Medium-Range Weather Forecasts (ECMWF), including the ERA-Interim (ERA-I; Dee et al. 2011), ERA-Interim/Land (ERA-I/L; Balsamo et al. 2015), and ERA5. The land component of ERA-I, the Tiled ECMWF Scheme of Surface Exchanges over Land (TESSEL), is driven by ECMWF forcing with the snow scheme based on Douville et al. (1995). The snow analysis is updated based on a Cressman analysis of station observations of snow depth, although no station on the Tibetan Plateau is used. The IMS 24-km resolution snow cover is assimilated from 2004 (Drusch et al. 2004). ERA-I/L is produced with the offline Hydrology Tiled ECMWF Scheme of Surface Exchanges over Land (HTESSEL) model using atmospheric forcing from the ERA-Interim dataset, with precipitation corrected based on the Global Precipitation Climatology Project (GPCP; Adler et al. 2003).

FIG. 1. (a) Topography (m) of the Tibetan Plateau. The locations of the 40 stations are shown with colored circles indicating the range in altitude. (b) Terrain roughness index (m) of the Tibetan Plateau: level, 0–80 m; nearly level, 81–116 m; slightly rugged, 117–161 m; intermediately rugged, 162–239 m; moderately rugged, 240–497 m; highly rugged, 498–958 m; and extremely rugged, 959–4367 m. Station locations are indicated by black dots.

HTESSEL is an extension of TESSEL with a new snow scheme based on Dutra et al. (2010). ERA-I/L does not assimilate any observational snow information. ERA5 is the latest generation of reanalysis datasets produced by the ECMWF. ERA5 uses the same land component and snow scheme as ERA-I/L. The snow analysis is updated based on a two-dimensional optimal interpolation of station observations of snow depth and the IMS 4-km resolution snow cover. Unlike ERA-I, the IMS snow cover is not used above 1500 m, which means that no IMS snow cover is used over the Tibetan Plateau. ERA5 does not use any station on the Tibetan Plateau.

The Japanese 55-year Reanalysis (JRA-55; Kobayashi et al. 2015) uses the offline Simple Biosphere (SiB) model (Sellers et al. 1986) as its LSM, forced with precipitation corrected by precipitable water (PW) retrieved from the SSM/I brightness temperature (Onogi et al. 2005). Its snow analysis is generated once a day with two-dimensional optimal interpolation using synoptic snow depth observations and daily snow cover retrievals from the SSM/I and the Special Sensor Microwave Imager Sounder on a 0.25° latitude–longitude grid. Note that JRA-55 assimilated a few stations over the eastern Tibetan Plateau from 1971 to 2006 (Onogi et al. 2005). The SiB snow field over an ice sheet is replaced with either the climatological depth or 2 cm, whichever is greater due to the absence of physical processes for ice sheets in the SiB.

The LSM used in the Modern-Era Retrospective Analysis for Research and Applications version 2 (MERRA2; Reichle et al. 2017) is the Catchment model (Koster et al. 2000) forced with precipitation corrected using CMAP and CPCU data, which are also used for precipitation correction in CFSR. The snow dynamics in response to the surface meteorological conditions are modeled in three layers (Stieglitz et al. 2001). No snow data assimilation is performed in MERRA2.

The Noah LSM is used to produce the Global Land Data Assimilation System version 2 (GLDAS2) and version 2.1 (GLDAS21) (Rodell et al. 2004). GLDAS2 uses the Princeton meteorological forcing data (Sheffield et al. 2006), which is generated by combining a suite of global observation-based datasets with the National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis dataset. For precipitation, it is disaggregated in space to 1.0° using relationships with the GPCP daily product and in time from daily to 3-hourly using relationships with the Tropical Rainfall Measuring Mission (TRMM) 3-hourly product (Huffman et al. 2007). GLDAS21 was forced with a combination

of Global Data Assimilation atmospheric analysis fields and the spatially and temporally disaggregated GPCP precipitation product. No snow data assimilation is performed in either GLDAS2 or GLDAS21.

4) HIGH ASIA REFINED ANALYSIS

Regional climate model simulations via the Weather Research and Forecasting (WRF) Model over mountainous areas could provide useful snow information (Wrzesien et al. 2017, 2018). The High Asia Refined analysis dataset (MauSSION et al. 2014) is generated by the WRF Model with the Noah model as the land surface component over East Asia. It was forced with the Final Analysis data from the Global Forecasting System. No assimilation of observations is conducted. The dataset has two resolutions: 30 km in East Asia (hereafter HAR) and 10 km on the Tibetan Plateau (hereafter HAR-10). Since the HAR-10 Tibetan Plateau domain is not fully overlapped with the Tibetan Plateau domain in this study and covers 28 stations west of 100°E among our 40 stations, only the HAR dataset was used for comparison with other gridded datasets and the observations from the 40 stations. The HAR and HAR-10 datasets are evaluated against the observations from the 28 stations to investigate the influence of resolution on snow simulations.

5) DART/CLM4 LAND DATA ASSIMILATION PRODUCTS

We made use of the open-loop run and two snow data assimilation products generated from a multisource land data assimilation system (Zhang et al. 2014; Zhao and Yang 2018). This system consists of the Data Assimilation Research Testbed and the Community Land Model version 4 (DART/CLM4) and is forced with atmospheric reanalysis data generated by DART/CAM4 (Raeder et al. 2012). CAM4 is a general circulation model widely used in climate studies. Zhang et al. (2014) performed a correction for DART/CAM4 precipitation using GPCP. The Moderate Resolution Imaging Spectroradiometer (MODIS) daily snow cover fraction (SCF) and monthly total water storage (TWS) observations from the Gravity Recovery and Climate Experiment (GRACE; Sakumura et al. 2016) are assimilated into the offline DART/CLM4. We used OL to represent the offline DART/CLM4 simulation without assimilating observations, MOD for the offline DART/CLM4 simulation assimilating MODIS SCF, and GRAMOD for the offline DART/CLM4 jointly assimilating MODIS SCF and GRACE TWS. Using MOD and GRAMOD to constrain land initialization, Lin et al. (2016) found that MOD and GRAMOD

FIG. 2. Interannual variation of the annual mean SWE averaged for the Tibetan Plateau in different datasets.

improve seasonal temperature predictions, especially in high latitudes and on the Tibetan Plateau.

b. Methods

Following the method reported in Sun et al. (2018), we intercompared the 12 gridded datasets (CFSR, ERA5, ERA-I, ERA-I/L, JRA-55, MERRA2, GLDAS2, GLDAS21, HAR, OL, MOD, and GRAMOD). All the datasets were regridded into a unified resolution ($0.9^\circ \times 1.25^\circ$) and then normalized at each grid location. Normalization refers to the subtraction of a minimum SWE from all the datasets and then dividing the difference between the maximum and minimum, which rescales the values into the range 0.0–1.0. We used the range between the 75th and the 25th percentiles of the normalized SWE to represent the discrepancy among the all datasets, referred to as the discrepancy index. The performance of the gridded products and AMSR-E with respect to the in situ observations was quantified using the correlation coefficient, mean bias, and root-mean-square error (RMSE).

3. Results

a. Intercomparison of SWE estimates among the gridded products

1) INTERCOMPARISON OF ANNUAL MEAN SWE ESTIMATES

Figure 2 shows the interannual variation of the annual mean SWE averaged for the Tibetan Plateau derived from the different datasets. The ERA5 dataset considerably overestimates the SWE compared with the other datasets. The magnitude of the annual mean SWE averaged for the Tibetan Plateau deviated by as much as 13 mm among the datasets, even when excluding ERA5. The interannual variabilities are reasonably consistent with the maximum annual mean SWE averaged for the Tibetan Plateau in 2005 among all products, except

CFSR, MERRA2 and HAR. The CFSR dataset generates the maximum SWE in 2007, whereas there is no clear interannual variation of the SWE in MERRA2 and HAR.

Figure 3 shows the spatial distribution of the 7-yr (2003–09) averaged annual mean SWE. All the datasets capture a similar pattern, with a higher SWE in the western Tibetan Plateau and a lower SWE in the eastern and central Tibetan Plateau. ERA5 generates a higher SWE over the whole Tibetan Plateau than the other datasets. CFSR, ERA5, ERA-I, ERA-I/L, JRA-55, GLDAS2, GLDAS21, and HAR show a higher SWE in the southeastern Tibetan Plateau than GLDAS2, OL, MOD, and GRAMOD. The discrepancy index among the datasets is >0.2 in most regions of the Tibetan Plateau, with a slightly greater discrepancy in the central and western Tibetan Plateau than in the eastern Tibetan Plateau (Fig. 4a). We also examined the ratio of the discrepancy index to the normalized 7-yr averaged annual mean SWE. Figure 4c shows that regions with a ratio <1 are mainly located in the western Tibetan Plateau, whereas the SWE in this region is higher than in the other regions of the Tibetan Plateau.

2) INTERCOMPARISON OF SEASONAL MEAN SWE ESTIMATES

The seasonal variations in the SWE averaged for the Tibetan Plateau show that the peak SWE appears in either February or March for all products. There is a large spread in the amplitude of the peak SWE among the datasets (Fig. 5). The peak SWE varies from 5 to 26 mm over the Tibetan Plateau, with MERRA2 giving the lowest value and ERA-I giving the highest value if the ERA5 dataset, in which the peak SWE reaches 55 mm, is excluded. The SWE in ERA5 markedly exceeds that in the other datasets in all seasons, especially in December–February (DJF) and March–May (MAM). The spreads of the SWE are much larger in DJF and MAM than in September–November (SON) and June–August (JJA). The differences in DJF and MAM SWE span >17 mm, whereas the differences in SON and JJA without considering the ERA5 dataset are <5 mm.

The discrepancy among the datasets at the spatial level varies with the season (Fig. 6). The discrepancy index is generally >0.2 over a large area of the Tibetan Plateau. The discrepancy in the eastern Tibetan Plateau in JJA is significant, with a discrepancy index >0.5 . The ratio of the discrepancy index to the normalized seasonal mean SWE is >1 in most regions of the Tibetan Plateau in all seasons, except in the western Tibetan Plateau in DJF. This suggests that there is an extremely large discrepancy in the SWE estimated by different datasets.

FIG. 3. Spatial distribution of the 7-yr (2003–09) average annual mean SWE (mm) from different datasets. The values for the SWE are based on the original spatial resolution of each dataset.

3) INTERCOMPARISON OF DAILY SWE ESTIMATES

Figure 7 shows the day-to-day variation of the SWE in term of the frequency and intensity of snow ablation and snow accumulation. We use the day-to-day variation of $SWE < 0$ (> 0) to represent the snow ablation (snow accumulation). There is a large divergence (24.3%–46.3%) in the frequency of snow accumulation estimated by different datasets. The HAR dataset has the highest frequency estimate for snow accumulation, followed by OL, MOD, and GRAMOD. The estimated frequencies of snow accumulation and snow ablation are lower for JRA-55 than for most of the other products. The higher estimated frequencies of snow accumulation at higher bins ($> 1 \text{ mm day}^{-1}$) are in the ERA-I/L, ERA5, and HAR datasets, which also produce higher frequency estimates at a high snow ablation intensity ($> 1 \text{ mm day}^{-1}$) than the other datasets.

To determine the consistency of the temporal variation among all the datasets, we calculated the year-round

pairwise correlations between the daily SWE time series over the 7-yr (2003–09) period between the different datasets. The correlation coefficients among the datasets range from 0.54 to 0.88 (Table S1 in the online supplemental material). GLDAS2 shows the weakest correlation with the other datasets. Mudryk et al. (2015) calculated the correlations between pairs of SWE from the datasets GLDAS2, ERA-I/L, the European Space Agency's Global Snow Monitoring for Climate Research (GlobSnow) version 2, MERRA, and the SWE from the Crocus snow model, which also showed that the correlations between GLDAS2 and the other datasets are the weakest. Figure 8 shows the spatial distribution of the mean correlation. The correlations are high in the western and part of the eastern Tibetan Plateau, with correlation coefficients > 0.6 .

b. Evaluation against in situ SWE observations

Figure 9 compares the monthly SWE averaged over the 40 stations during 2003–09 between the in situ

FIG. 4. (a) Spatial distribution of the range of discrepancies in the normalized 7-yr (2003–09) averaged annual mean SWE among the different datasets. (b) Normalized annual mean SWE averaged across multiple SWE products. Note that we only chose the datasets between the 75th and the 25th percentiles to calculate the average to remove the impact of extreme values on the mean. (c) Ratio of the discrepancy in (a) to the normalized annual mean SWE in (b). The ratio is calculated only when the normalized annual mean SWE is > 0.2 to remove any unrealistic values induced by a small denominator.

FIG. 5. (a) Month-to-month and (b) season-to-season variations in the 7-yr (2003–09) mean SWE averaged over the Tibetan Plateau. Different colors represent different datasets.

observations and the 13 gridded datasets (AMSR-E, CFSR, ERA5, ERA-I, ERA-I/L, JRA-55, MERRA2, GLDAS2, GLDAS21, HAR, OL, MOD, and GRAMOD). The in situ observations show a very thin snow cover, which only remains for a short time in winter and spring. All the products show weak temporal correlations with the observed SWE (Fig. 10a). The highest

temporal correlation with the in situ observations is shown by MERRA2 (0.22), followed by GRAMOD (0.21) and ERA-I/L (0.20). The AMSR-E dataset shows the poorest temporal correlation with the in situ data.

Figure 11 shows the spatial distribution of the SWE on 22 March 2003, which is near the time of the

FIG. 6. As in Fig. 4, but for normalized seasonal mean SWE in SON, DJF, MAM, and JJA, over the 7-yr (2003–09) period, respectively.

FIG. 7. (a) Frequency of snow ablation (SAB) days and snow accumulation (SAC) days. (b) Frequency of snow ablation days based on snow ablation $> 0, 0.1, 1$, and 3 mm day^{-1} during 2003–09 across all grids over the Tibetan Plateau from different datasets. (c) Frequency of snow accumulation days based on snow accumulation $> 0, 0.1, 1$, and 3 mm day^{-1} during 2003–09 across all grids over the Tibetan Plateau from different datasets. Note that we use the day-to-day variation in SWE < 0 (> 0) to represent snow ablation (snow accumulation).

maximum SWE in all datasets, from both the in situ observations and the different datasets. The AMSR-E and ERA5 show patterns that are the most different from the in situ SWE observations. The RMSE and bias of each dataset are shown in Figs. 10b and 10c. All the datasets overestimate the SWE, especially the AMSR-E and ERA5 datasets with a bias of 15.5 and 15.4 mm, respectively. The overestimation of SWE by AMSR-E and ERA5 has also been addressed by Yang et al. (2015) and Dai et al. (2017), and Orsolini et al. (2019), respectively. Both the ERA-I and ERA-I/L datasets show a better performance than the ERA5 dataset. The bias of ERA-I and ERA-I/L is 3.3 and 2.7 mm, respectively. Although ERA-I performs better than ERA5, it still presents a higher bias than the other datasets, except for AMSR-E. Except for the AMSR-E, ERA5, and ERA-I, HAR has the highest bias of 3.1 mm. The MOD and GRAMOD datasets, with biases of 0.5 and 0.7 mm, respectively, both perform better than the OL dataset, for which the bias is 1.6 mm. The CFSR dataset has a bias of 1.9 mm and the JRA-55 dataset has a bias of 2.4 mm. The bias of GLDAS2 and GLDAS21 is 0.44 and 1.54 mm, respectively. GLDAS2 has the lowest bias (0.4 mm) among all the datasets,

FIG. 8. Spatial distribution of the mean correlation between pairs of the daily SWE time series. Correlations are calculated using the year-round daily SWE over the 7-yr (2003–09) period for a given grid cell between all available pairs of datasets and averaged together.

followed by the MOD (0.5 mm) and MERRA2 (0.6 mm). The MERRA2 dataset has the best performance among the datasets in terms of the overall temporal variation, bias and RMSE, followed by the GRAMOD and MOD datasets.

Because the ERA-I dataset assimilates the SCF from the IMS over the Tibetan Plateau, whereas the ERA5 does not, it is reasonable that ERA-I performs relatively well. It is similar to the OL, MOD, and GRAMOD

FIG. 9. Temporal variation in monthly SWE averaged over all 40 stations from January 2003 to December 2009. The observed in situ SWE data have been multiplied by ten; other datasets are unaltered. As the AMSR-E data are missing on some days due to the orbital swath, the observed in situ SWE data in (a) were processed to keep the missing days consistent with the AMSR-E. The observed in situ SWE data in (b) and (c) are unchanged.

FIG. 10. (a) Temporal correlations, (b) RMSE, and (c) mean bias between the different datasets and the in situ observations. Correlations are calculated using the daily SWE data year-round over the 7-yr (2003–09) period and averaged over all 40 stations. The RMSE and mean bias values are calculated using daily SWE data over the 7-yr (2003–09) period and averaged over all 40 stations.

datasets. The MOD dataset assimilates SCF from MODIS. Likewise, the GRAMOD dataset jointly assimilates SCF from MODIS and TWS from GRACE based on the OL dataset. The GRAMOD dataset does not show a better performance over the Tibetan Plateau than the MOD dataset, which may be because the snow

cover over the Tibetan Plateau is shallow. As noted by Lin et al. (2016), the assimilation of TWS from GRACE offers a remarkable improvement relative to the MOD dataset at high latitudes where the snow cover is thick.

To investigate the influence of resolution on the snow simulation, we compared the HAR and HAR-10 datasets against the in situ observations. With a higher resolution, HAR-10 improves the simulation of precipitation and presents a lower snowfall than HAR, although there is little improvement in the simulation of temperature and SWE (Fig. S1). Figure 12a shows that all the datasets have a cold temperature bias relative to the in situ observations, with the HAR dataset showing the largest bias. The cold bias generated by the WRF model (Meng et al. 2018) may be an important reason for the large SWE bias in the HAR dataset. The SWE excess in the ERA5 and ERA-Interim datasets may be attributed to the missing process for the sublimation of blowing snow in the windy and dry conditions of the Tibetan Plateau and the excessive snowfall generated by the models, as suggested by Orsolini et al. (2019).

4. Discussion and conclusions

We conducted an intercomparison of multiple SWE products—including reanalysis datasets, regional climate model simulations, and land data assimilation products—on daily to annual time scales. We found that most of the products have relatively consistent interannual and seasonal variations with a large spread in

FIG. 11. Spatial distribution of SWE (mm) on 22 Mar 2003 from different datasets. Colored circles indicate the range of the in situ SWE observations. All the gridded SWE data are based on the original spatial resolution of each dataset.

FIG. 12. Temporal variations of the monthly (a) 2-m air temperature (T_2), (b) total precipitation (TP), and (c) snowfall averaged over all 40 stations from January 2003 to December 2009 from the in situ observations and different datasets.

magnitude, especially in winter and spring. The ERA5 dataset considerably overestimates the SWE compared with the other datasets. The magnitude of the annual mean SWE averaged for the Tibetan Plateau deviated by as much as 13 mm among the datasets, even without considering the ERA5. The discrepancy index (represented by the range between the 75th and the 25th percentiles of the normalized SWE) of the seasonal SWE also varied with the region, with a range of discrepancy index > 0.5 in the eastern Tibetan Plateau in JJA. The ratio of the discrepancy index to the normalized seasonal mean SWE is > 1 in most regions of the Tibetan Plateau in all seasons, except in the western Tibetan Plateau in DJF.

The evaluation of the satellite estimates, reanalysis datasets, regional climate model simulation and the land data assimilation products against the in situ observations indicates that all the products poorly capture the in situ temporal variability of snow. The highest correlation was shown by the MERRA2 dataset (0.22) and the lowest correlation was shown by the AMSR-E dataset (0.07). All the datasets overestimate the SWE, especially AMSR-E and ERA5 with biases of 15.5 and 15.4 mm, respectively. Both the ERA-I and ERA-I/L datasets show a better performance than the ERA5 dataset. The bias in ERA-I and ERA-I/L is 3.3 and 2.7 mm, respectively. Apart from AMSR-E, ERA5, and ERA-I, the HAR dataset, which is generated by the

WRF regional climate model, has the highest bias (3.1 mm). Both the MOD and GRAMOD products show improved SWE estimates compared with the OL dataset, which does not assimilate any satellite observations, because the MOD dataset assimilates SCF from MODIS and GRAMOD jointly assimilates SCF from MODIS and TWS from GRACE. The bias of the OL, MOD, and GRAMOD datasets is 1.6, 0.5, and 0.7 mm, respectively. The GLDAS2 dataset has the lowest bias (0.4 mm) among all the datasets, followed by MOD (0.5 mm) and MERRA2 (0.6 mm). MERRA2 performs the best among all the datasets in terms of the overall temporal variation, bias and RMSE, followed by the GRAMOD and MOD datasets.

Notice that observational stations are very sparse on the Tibetan Plateau and most are located in valleys on the eastern Tibetan Plateau and in rugged areas (Fig. 1). Figure S2 shows the topography of the Tibetan Plateau at the original resolution of each dataset, together with the altitudes of the 40 stations. The altitudes of some stations are lower than those of the grid cells near the stations when the resolution of the dataset is coarse. Consequently, the in situ observations may underestimate the SWE in the grid cell in which the station located. High-resolution datasets could better resolve the heterogeneity of the Tibetan Plateau than coarse-resolution datasets, although discrepancy in altitude still exists. The differences in altitude and spatial resolution may cause discrepancies in the SWE between the in situ observations and the gridded datasets and among the gridded datasets (Baba et al. 2019; Magnusson et al. 2019). Although the in situ observations may underestimate the SWE, the station observations are still a reliable way to measure the SWE. More station SWE observations are needed in the Tibetan Plateau, not only for validating the satellite estimates, reanalysis datasets, model simulations and data assimilation products, but also for further hydrology, weather and climate studies. Data assimilation is a promising approach to estimate the SWE in this region. Further data assimilation or simulation studies are required using more accurate precipitation data and higher resolution models with the implementation of snow processes, for example, blowing snow (Xie et al. 2017) and snow sublimation (Orsolini et al. 2019).

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Center (https://nsidc.org/data/AE_DySno). The CFSR and JRA-55 datasets were obtained from the NCAR Research Data Archive (<https://rda.ucar.edu/>). The ERA5, ERA-Interim, and ERA-Interim/Land datasets were obtained from the ECMWF Public Datasets web interface (www.ecmwf.int/en/forecasts/datasets/browse-reanalysis-datasets). The MERRA2, GLDAS2, and GLDAS21 datasets were obtained from the NASA Goddard Earth Science Data and Information Services Center. The HAR dataset was obtained from the Chair of Climatology, TU Berlin (www.klima.tu-berlin.de/index.php?show=forschung_asien_tibet_har&lan=en). The OL, MOD, and GRAMOD products used in this study are available upon request from the corresponding author (liang@jsg.utexas.edu). We finally thank the two referees for their valuable comments which allowed us to significantly improve the paper.

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