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Key Points:

- Compared with ERA5 data set, WRF/Noah-MP output has reduced the root mean square error and mean bias of the snow depth estimation by 95.74% and 93.02%, respectively
- The climatological March snow mass measured 97.85 (± 16.60) Gt in the Tianshan Mountains with a negligible tendency
- The total precipitation during the cold season controlled the variation of March snow mass

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Variation of Snow Mass in a Regional Climate Model Downscaling Simulation Covering the Tianshan Mountains, Central Asia

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Abstract Mountain snow is a fundamental freshwater supply in the arid regions. Climate warming alters the timing of snowmelt and shortens the snow cover duration, which greatly influences the regional climate and water management. However, a reliable estimation of snow mass in the Tianshan Mountains (TS) is still unclear due to the scarcity of extensive continuous surface observations and a complex spatial heterogeneity. Therefore, a long-time snow simulation from 1982 to 2018 was performed in WRF/Noah-MP to quantify snow mass in the TS, forced by ERA5 reanalysis data and real-time updated leaf area index and green vegetation fraction. Meanwhile, March snow mass (close to the annual peak snow mass), snow cover fraction (SCF), and their associated trends were investigated in the TS. The results indicated a good accuracy of the simulated snow water equivalent (root mean square error [RMSE]: 7.82 mm/day) with a slight overestimation (2.84 mm/day). Compared with ERA5 data set, the RMSE and mean bias of the daily snow depth from WRF/Noah-MP downscaling were significantly reduced by 95.74% and 93.02%, respectively. The climatological March snow mass measured 97.85 (± 16.60) Gt in the TS and exhibited a negligible tendency during the study period. The total precipitation during the cold season controlled the variations of March snow mass. The increased precipitation in the high-altitude regions contributed to an extensive snow mass, which could offset the loss in the TS lowland. In contrast, rapidly rising air temperature caused a significant reduction of March SCF, particularly in the Southern TS.

1. Introduction

The seasonal snowpack plays an essential role in the water resources budget of the global mountainous area and provides freshwater supply for over 1/6 of the world's population (Barnett et al., 2005; Huning & AghaKouchak, 2020), which has a profound effect on the food production of irrigated agriculture and snowmelt runoff regimes in the snow-dominated basin (Qin et al., 2020). It also strongly affects regional climate system, alpine phenology, and biogeochemical processes through regulation of the land-atmospheric exchanges of water and energy (Arndt et al., 2020; Tomaszewska et al., 2020; Zhang, 2005). In addition, snow attracts recreational activities and is an important resource of winter tourism (Deng et al., 2019), but it also causes snow-related disasters, such as snow avalanches and snowmelt flooding (Ballesteros-Cánovas et al., 2018; Schweizer et al., 2003). Although the role of snow is irrefutable, present approaches show a large uncertainty regarding snow mass estimation in a global mountainous area due to the presence of orographic barriers, its strong vertical and horizontal variability, diverse vegetation cover, and representative sites for snow measurement (Dong, 2018; Dozier et al., 2016; Mudryk et al., 2015). The accuracy of snow mass map based on in-situ observations interpolation methods depends on the number and representativeness of the ground observations, while a sparse network of snow observations usually exists in the mountainous environment, especially in the area with dense vegetation and a complex topography (Dozier et al., 2016; Mortimer et al., 2020). The passive microwave sensors could provide a nearly real-time global snow mass

estimation by means of the algorithms of microwave brightness temperatures, but a poor performance was reported in the presence of forest, wet snow, deep snow, and large snow grains (Che et al., 2016; Takala et al., 2011). Notably, most gridded snow water equivalent (SWE) products from passive microwave instruments exclude the alpine area or exhibit an underestimation (Bormann et al., 2018; Pulliainen et al., 2020; Takala et al., 2011). The sensor's inconsistencies from different passive microwave platforms might lead to uncertainty in the detected trends of long-time snow mass products (Smith & Bookhagen, 2016). Moreover, a further improvement of snow mass estimation in passive microwave measurements (~25 km) and global reanalysis data sets (>30 km) is restricted in the mountainous regions with a large varying heterogeneity of snow physical characteristics due to the coarse spatial resolution (Dalož et al., 2020), and tend to be underestimated (Mudryk et al., 2015; Wrzesien et al., 2019). In contrast, although the active microwave remote sensing has been used to retrieve snow mass with a finer spatial resolution (Lievens et al., 2019), the low accuracy is caused by the repeat-pass interval and a complex underlying surface (Dong, 2018). Similarly, the large-scale application of continuous snow mass measurements from the Unmanned Aerial Vehicles and airborne LiDAR is limited by flight time and sight (Dozier et al., 2016). Furthermore, the snow physical module within the land surface models (LSMs) has a large potential to estimate the snow processes on the complex terrain (Holtzman et al., 2020; Wrzesien et al., 2018), but a lack of both accurate forcing data and multiparameters calibration constrains its application for snow mass estimation of mountainous areas (Pritchard et al., 2020; Ryken et al., 2020).

The land surface-atmosphere coupling in regional climate models (RCMs), such as the Weather Research and Forecasting (WRF) model (Skamarock & Klemp, 2008), could precisely estimate snow mass in mountainous regions by reproducing correctly the orographic precipitation at a high spatial resolution (S. Chen et al., 2019; Minder et al., 2016; Wrzesien et al., 2017). More specifically, the advanced model structures and parameterization schemes in the RCM LSMs, such as the sophisticated microphysics schemes, the multi-layer snowpack, and separate vegetation canopy model have been proven to produce a reasonable snowfall estimation and snow-related water-heat exchange processes (X. Cai et al., 2014; Niu et al., 2011; Tomasi et al., 2017). Indeed, as the typically third-generation LSM, the Noah LSM with Multiparameterization Options (Noah-MP) model (Niu et al., 2011) within WRF has a better ability to describe the snow processes in a mixed forest cover and complex terrain environment compared with in-situ and remote sensing observations, particularly in the snow ablation season (Liu et al., 2019; Musselman et al., 2018; Wrzesien et al., 2019). Most land surface parameters of snow process in Noah-MP model are obtained from look-up tables, coarse gridded data sets, and empirical formulas, which might not fully capture the dynamical heterogeneity of the snowpack characteristics in the extensive mountains (Y. Jiang et al., 2020; You, Huang, Yang, et al., 2020). For example, the vegetation parameters, such as the leaf area index (LAI) and green vegetation fraction (FVC) are determined by vegetation types or prescribed from climatological data sets with no real-time update, which trigger large uncertainties in snow mass estimation (Kumar et al., 2019; Tomasi et al., 2017). More realistic vegetation parameters and schemes exhibited a more accurate snow characteristics estimation in the LSMs (Kumar et al., 2019; Ma et al., 2019; T. Yang, Li, Chen, et al., 2020), particularly in the dense vegetation regions through the improvement of interception, sublimation and melting in the snow accumulation and ablation period (Helbig et al., 2019; Niu & Yang, 2004). Due to the limitation of computing time, the snow simulation in the RCM LSMs often runs a relatively short period, which could not reveal the long-time variation of mountainous snow (Oaida et al., 2015; Wrzesien et al., 2019). Additionally, the performance of snow mass estimation in the RCM LSMs heavily depends on the accuracy of the reanalysis forcing data (Liu et al., 2019; Terzago et al., 2020). The ERA5 is the fifth-generation global reanalysis product released from the European Centre for Medium-range Weather Forecasts (ECMWF) and has assimilated more observations with a higher spatiotemporal resolution compared with the widely used ERA-Interim reanalysis (Copernicus Climate Change Service (C3S), 2017; Hersbach et al., 2020). Hence, it is expected that a reliable long-time series of snow data sets could be obtained from the RCM LSMs in poorly gauged mountainous regions forced by more accurate reanalysis data and updated vegetation parameters.

Having the function of both the ecological barrier and water tower of Central Asia, the Tianshan Mountains (TS) are located in the hinterland of the Eurasian arid regions (Farinotti et al., 2015). The glaciers/snow-melt water is the base freshwater source for the regional mountain-oasis-desert system (Sorg et al., 2012). An accurate snow mass estimation and variations significantly affect the surrounding irrigated agriculture, ecosystem services, and water resources management (Unger-Shayesteh et al., 2013; T. Yang et al., 2019).

Unfortunately, the majority of the snow-related studies focused on the variations in snow cover and snow depth (SD) in partial or entire TS utilizing the sparse in-situ observations and remote sensing measurements (Q. Li et al., 2019; Tomaszewska & Henebry, 2018). Both the observations from the meteorological stations and the passive microwave sensors demonstrated that the snow end date significantly advanced in the TS during the past decades due to climate warming (Q. Li et al., 2019; T. Yang et al., 2019). Moreover, the field observations suggested that the snow characteristics in the forest regions are significantly distinguishable from other land cover types (Lu et al., 2017; J. W. Yang, Jiang, Lemmetyinen, et al., 2020). Recently, the short time snow simulations on the SD and SWE have been well performed using the offline Noah-MP and WRF/Noah-MP model on a point scale and regional scale, respectively (T. Yang, Li, Chen, et al., 2020; You, Huang, Gu, et al., 2020; You, Huang, Yang, et al., 2020). However, as the most important quantity indicator representing the regional snow resources, snow mass and its long-time variations under a warming trend are still unclear in the entire TS due to the scarcity of accurate observation data sets.

The study aims to quantify snow mass and its variations in the entire TS from 1982 till 2018 by means of WRF/Noah-MP, which was forced by a new generation of reanalysis data sets (ERA5) and real-time updated vegetation parameters (LAI and FVC). The specific objectives are: (a) to evaluate the performance of a long-time snow mass estimation in WRF/Noah-MP; (b) to investigate the spatiotemporal variability of snow mass and snow cover fraction (SCF); (c) to identify possible causes and implications of the model uncertainty and snow variations. This is the first attempt to quantify the snow storage and its variations in the entire TS. The results will enhance the understanding of the regional snow resources and will provide a fundamental data set for the regional studies on the cryospheric, hydrological, and environmental processes.

2. Data and Methods

2.1. Study Area

As the largest mountain system in Central Asia, the TS are located at 67°E–95°E and 39°N–46°N, stretching over 2,500 km from west to east, 250–350 km from south to north, and covering over 800,000 km² (Figure 1b). The average height of the TS measures about 4,000 m above sea level (a.s.l.). Affected by the westerlies and the complex topography, the TS exhibit a distinct gradient in temperature and precipitation between the low-altitude and high-altitude regions (Figures 1c and 1d). The total average annual precipitation and mean temperature in the entire TS amount to 329.3 mm and 4.6°C, respectively (T. Yang et al., 2019). Approximately 1/3 of the total precipitation (500–700 mm) occurs as snowfall in the northern slope of the TS (Guo & Li, 2015). Grassland is the dominated land cover type (T. Yang, Li, Chen, et al., 2020) and the forest cover prevails between 1,300 and 2,800 m a.s.l. (Lu et al., 2017). Both the Western TS (WTS) and Northern TS (NTS) have a relatively moist climate, while the Eastern TS (ETS) and Southern TS (STS) exhibit a typically continental climate (Aizen et al., 1997; Sorg et al., 2012). In addition, the precipitation in the ETS and NTS concentrates during spring and early summer, which is later than that in the WTS (late winter to early spring) but earlier in the STS (summer) (Sorg et al., 2012). Abundant precipitation in the mountainous area shapes the “wet island” landscape and contributes to the rich snow and glaciers resources, which has a significant impact on the growth of the regional irrigated agriculture and industry (Farinotti et al., 2015).

2.2. Data Sets Acquisition and Processing

2.2.1. Ground-Based Surface Data

The China Meteorological Administration (CMA) and the Tianshan Station for Snow Cover and Avalanche Research (TSSAR), Chinese Academy of Sciences provided 56 meteorological stations in the target area (Figure 1b), which includes the mean daily temperature, SD, precipitation, and 5-day SWE (when SD > 5 cm). In addition, All-Russian Research Institute of Hydrometeorological Information-World Data Centre (RI-HMI-WDC) provided four stations with daily SD observations. The stations data were collected from the National Snow and Ice Data Centre (NSIDC). After exclusion of the stations with over 10% missing data, 54 stations have been adopted to process for the monthly precipitation and mean temperature, respectively. Detailed information is shown in Table 1.

Figure 1. Topography (m) of the Weather Research and Forecasting (WRF) 27-km and 9-km domains (a), location of the Tianshan Mountains (b), mean annual temperature (c), and precipitation (d) from WRF model.

2.2.2. Remote Sensing Product

The variation in the Terrestrial Water Storage (TWS) during the cold season is mainly caused by the snow evolution in the mountainous regions (Wrzesien et al., 2018). Noah-MP treats the TWS as the sum of the SWE, soil moisture contents, groundwater storage, and canopy water contents (Kumar et al., 2019). Due to a lack of in-situ observations in the alpine region, the Gravity Recovery and Climate Experiment (GRACE) of the monthly TWS anomaly product (version RL06) at a 0.5° spatial resolution was applied so as to compare it with the modeled TWS. In addition, the Moderate Resolution Imaging Spectroradiometer Satellite (MODIS) monthly SCF in the Climate Modeling Grid (MOD10CM, $0.05^\circ \times 0.05^\circ$) product was regridded to a 9-km spatial resolution and used to evaluate WRF estimated SCF.

Table 1
Information on the Validation Data Set

Data set name	Variables (resolution)	Period	Data sources
CMA V3.0	TP, T2, SD, and SWE	1982/10/01–2015/09/30	http://data.cma.cn/
TSSAR	TP,T2, SD and SWE	1982/10/01–2015/09/30	Chinese Academy of Sciences
Central Asia	TP and T2	1982/10–2000/12	https://nsidc.org/data/G02174
Former USSR	SD	1982/10/01–2015/09/30	http://aisori.meteo.ru/ClimateR
GRACE TWS	TWS ($0.5^\circ \times 0.5^\circ$)	2002/09–2017/09	https://grace.jpl.nasa.gov/data/
MOD10CM	SCF ($0.05^\circ \times 0.05^\circ$)	2000/09–2018/09	https://urs.earthdata.nasa.gov/

Note. TP, T2, SD, SWE, TWS, and SCF represent the total precipitation, air temperature at 2 m, snow depth, snow water equivalent, and Terrestrial Water Storage, respectively.

Table 2
Main Physical Parameterizations Used in the Numerical Simulation

Simulation period	1982/10/01–2018/09/30
Model Version	Version 4.01
Nest	2
Horizontal grid (D02)	9 km
Number of grids	304 × 133
Vertical levels	35
Microphysics' scheme	WSM-6
Longwave radiation scheme	RRTM
Shortwave radiation scheme	Dudhia
Surface layer	Revised MM5 Monin-Obukhov
Planetary boundary layer	YSU
Cumulus parameterization	Kain-Fritsch
Initial/lateral boundary condition	ERA5
Land cover	CCI-2000
Land surface model	Noah-MP

The WRF adapted the basis land cover (LC) containing the 2000 global annual LC map at a 300-m spatial resolution which was produced by the European Space Agency (ESA) Climate Change Initiative (CCI) project. The CCI-LC product includes the annual global land cover map from 1992 to the present with an overall accuracy of 75.4% (ESA, 2017). According to Huang et al. (2020), the CCI-LC2000 was converted into the MODIS-20 category as WRF LC. As the key vegetation parameters, the 8-day LAI and FVC products at a 0.05° spatial resolution from September 1, 1982, to September 30, 2018, have been obtained from the Global Land Surface Satellite (GLASS) products, manufactured by the Advanced Very High-Resolution Radiometer (AVHRR) reflectance data sets (Xiao et al., 2016). Compared with the other global vegetation data sets, the GLASS LAI and FVC data have been successfully applied to the land-atmosphere interaction simulation, due to their higher quality (Fang et al., 2019; Xiao et al., 2014). The 8-day GLASS LAI and FVC data sets were linearly interpolated to a daily scale at a 9-km resolution and used as the real-time updates of the LAI and FVC in WRF/Noah-MP.

2.3. Model Configuration

In this study, WRF-AWR 4.01 coupled with Noah-MP (Niu et al., 2011) model was used for the snowpack simulation in the TS and performed from September 1982 to September 2018. The model was initialized at 00:00 UTC on September 1 each year and terminated on September 30 the next year. As a tradeoff between the large computational demand of high resolution downscaling (Norris et al., 2018) and the fact that 1 month is enough for the deep soil moisture to get to the equilibrium (Berckmans et al., 2017), the model output for the first month was considered as spin-up. Hence, the 36 full cold seasons (from November to March) were retained as model output for our analysis. Previous studies demonstrated that a grid resolution smaller than 10 km could reveal the realistic orographic precipitation processes in the complex topography (Norris et al., 2015; Wrzesien et al., 2018). Considering the limited storage space and computing time, WRF was configured with tone-way double nested domains along with 35 vertical levels from the surface up to 50 hPa (Figure 1a). The outer domain (D01, 27 km grid spacing) had 317 × 145 grids in the west-east and south-north direction, and the inner domain (D02, 9-km grid spacing) was nested with 304 × 133 grids. As the updated version of ERA-Interim reanalysis data set, ERA5 reanalysis has proven to perform very well in hydrological applications and regional climate downscaling (Nogueira, 2020; Ou et al., 2020). Therefore, ERA5 (31 × 31 km²) reanalysis data set (Including pressure levels: temperature, U and V components of wind, geopotential height, relative humidity; surface variables: surface pressure, mean sea level pressure, sea surface temperature, 2-m temperature, 2-m specific humidity, 10-m U and V components of wind, soil data (soil temperature, soil moisture, and soil height), snow density and snow depth) with 6-h interval has been chosen as the initial and lateral boundary conditions. The default nudging parameters (0.3×10^{-4}) were adapted for winds, temperature, and water vapor in WRF to prevent the possible model drift and closely follow the large-scale atmospheric conditions from ERA5 (Sataloff et al., 1990). The main parameterization schemes are presented in Table 2 (T. Yang, Li, Chen, et al., 2020): the Single-Moment 6-Class (WSM-6) cloud microphysical scheme (Hong & Lim, 2006), Rapid Radiation Transfer (RRTM) longwave radiation model (Mlawer et al., 1997), Yonsei University planetary boundary layer (YSU) (Hong et al., 2006), Kain-Fritsch Cumulus Scheme (Kain, 2004), Dudhia shortwave radiation model (Dudhia, 1989), MM5 Monin-Obukhov surface layer (Monin & Obukhov, 1959), and Noah-MP Land Surface (Niu et al., 2011).

As an advanced version of the Noah LSM, the Noah-MP model provides multiple parameterization options for the simulation of land-atmosphere interaction process (Niu et al., 2011). The three-layer snow structure could effectively describe the processes of liquid water contents, snow destructive/melt metamorphism, and compaction in the snowpack. The key physical parameterization schemes in Noah-MP including (Niu et al., 2011): the CLASS (Canadian Land Surface Scheme) ground surface albedo, Jordan's scheme for precipitation partitioning between snow and rain (Jordan, 1991), thermal conductivity function considering the snow density, Monin-Obukhov surface layer drag coefficient, snow canopy interception and upload with

Figure 2. Annual variation of the monthly snow mass from D02 in the Tianshan Mountains and its subregions.

the effect of phase change, temperature and wind (Niu & Yang, 2004), the Ball-Berry vegetation stomatal resistance, the Noah semi-implicit snow/soil temperature scheme, and two-streams approximation of the radiative transfer scheme with a consideration of the canopy gap probability for the vegetation shading and scattering (R. Yang et al., 2001). The default vegetation parameters' look-up table and LC data induced large uncertainties in the climate simulations (Bonekamp et al., 2018). Previous numerical control experiments demonstrated that the performance of snow simulation in WRF/Noah-MP could be improved by updating the default vegetation parameters with remote sensing product in the TS (T. Yang, Li, Chen, et al., 2020). Therefore, the CCI-LC 2000 was selected to deliver land cover data input for both D01 and D02 in this study. In addition, the daily GLASS LAI and FVC data were used as updated real-time values in D02 for Noah-MP model. The LAI and FVC have utilized the default geographical data set for D01.

2.4. Snow Mass Calculation

March snow is the closest to the annual peak snow mass in the TS (Figure 2). In addition, as the transitional season of the snowpack, March plays a significant role in the snow accumulation and ablation (Pulliainen et al., 2020; Ye, 2019). Snow mass (gigatonnes, Gt) in the whole TS could be calculated as follows:

$$\text{Snow mass} = \sum_{i=1}^N \frac{81 \times 10^3 \times \text{SWE}_i}{10^9} \quad (1)$$

where N is the total number of WRF grid cells in the TS and SWE_i represents the March SWE estimated by WRF/Noah-MP in the i th grid cell.

2.5. Evaluation Method and Trend Analysis

The trend slope and its significant level of climate variables were calculated by the Sen method (Sen, 1968) and the Mann-Kendall (M-K) trend test (Kendall, 1975; Mann, 1945), respectively. The variables from the nearest grid point of the WRF output (T2, SD, precipitation, and SWE) and ERA5 data set (SD and SWE) were compared with in-situ observations (Figure 1b). In addition, WRF SCF and TWS values averaged over the entire TS were compared with MODIS and GRACE products. The performance of WRF estimation was evaluated by relevant observations using the following statistical metrics: the correlation coefficient (R), mean bias (MB), and root mean square error (RMSE).

Figure 3. Taylor diagram comparing the in situ snow depth (SD) and snow water equivalent with different simulations for the average from all stations in the Tianshan Mountains on daily and monthly time scales (a). Values closer to the reference point indicate a higher correlation and smaller differences in variance. Boxplot of the root mean square error (cm/day) (b) and mean bias (cm/day) (c) of different daily SD simulations in the sub-regions. The bottom and top edges of each box indicate the 25th and 75th percentile and the central line indicates the median.

$$R = \frac{\sum_{i=1}^N \left[\left(\text{Sim}(i) - \text{Sim}_{\text{mean}} \right) \left(\text{Obs}(i) - \text{Obs}_{\text{mean}} \right) \right]}{\sqrt{\sum_{i=1}^N \left(\text{Sim}(i) - \text{Sim}_{\text{mean}} \right)^2 \sum_{i=1}^N \left(\text{Obs}(i) - \text{Obs}_{\text{mean}} \right)^2}} \quad (2)$$

$$\text{MB} = \frac{1}{N} \sum_{i=1}^N \left(\text{Sim}(i) - \text{Obs}(i) \right) \quad (3)$$

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N \left(\text{Sim}(i) - \text{Obs}(i) \right)^2} \quad (4)$$

where N demonstrates the total number of the observed or simulated data, $\text{Sim}(i)$ and $\text{Obs}(i)$ represent the simulated and observed values at the time step i , respectively, and Sim_{mean} and Obs_{mean} illustrate the mean of the simulated and observed values, respectively.

3. Results

3.1. Performance of the Long-Time Snow Simulation

3.1.1. SD and SWE

The performance of the snow simulation in WRF/Noah-MP is shown in Figures 3–5. Generally, the SD and SWE simulations averaged from all stations in D02, which showed the highest accuracy compared to D01 and original coupling ERA5 (Figure 3a). In addition, a slight overestimation of the SD and SWE was found in D01, D02, and ERA5 compared with in situ observations (Figures 4a and 4b). Compared with ERA5 (RMSE: 3.64 cm/day and MB: 2.10 cm/day), the daily SD simulation in D01 and D02 could effectively reduce the RMSE (2.78 and 1.86 cm/day, respectively) and MB (1.32 and 0.15 cm/day, respectively). The D01,

Figure 4. Comparison of the time series observations and simulations of the monthly snow depth (a) and daily snow water equivalent (b) averages from all stations. (c) Monthly Terrestrial Water Storage anomaly estimated by D02 in comparison with GRACE. (d) Mean monthly SCF estimated by D02 in comparison with the MODIS values.

D02, and ERA5 showed a consistent spatial pattern of RMSE and MB in the SD simulations (Figures 5a–5f). Large RMSE values of SD simulations were observed in the high-altitude regions (a.s.l. >3,000 m) of TS (Figure 2b). The RMSE values in the low-altitude regions (a.s.l. < 1,500 m) of STS were significantly smaller than in the NTS and ETS (Figures 4a–4e). Similarly, large MB values of all SD simulations were displayed in the high-altitude regions of TS with a significant overestimation (Figure 3c). A widespread slight overestimation of all SD simulations prevailed in the low-altitude regions of the STS and eastern ETS. It was noted that a consistent underestimation of the SD simulation was seen in the Ili Valley and at the intersection of the NTS and ETS (Figures 4c, 4d, and 4f).

3.1.2. TWS and SCF

The monthly TWS anomaly and SCF from WRF/Noah-MP estimation in the TS were evaluated using the GRACE TWS and MODIS SCF products during the cold season (Figures 4c, 4d, 6a, and 6b). The monthly

Figure 5. Spatial distribution of the root mean square error (RMSE) (left panels, cm/day) and mean bias (MB) (right panels, cm/day) between the daily estimated snow depth (ERA5 (a and b), D01(c and d), and D02 (e and f)) and the observations.

TWS anomaly from WRF/Noah-MP demonstrated a good shape as compared with GRACE TWS (Figure 4c). Although the TWS simulation showed a general overestimation in WRF/Noah-MP (Table 3), a significant underestimation was noticed after 2012/2013. Compared with MODIS, the monthly SCF illustrated high accuracy in WRF/Noah-MP estimation of the TS, but an overestimation was also seen during the cold season

Figure 6. Spatial distribution of the (a) estimated snow cover fraction (SCF) and (b) MODIS SCF during the cold season.

Table 3
The Correlation Coefficient, MB, and RMSE of the Monthly TWS Anomaly and SCF Between the D02 and Satellite Observations (GRACE and MODIS) in the TS During the Cold Season

	R	MB (mm or %/month)	RMSE (mm or %/month)
TWS	0.43 ^a	21.70 mm	51.10 mm
SCF	0.98 ^a	11.28%	14.42%

Abbreviations: MB, mean bias; RMSE, root mean square error; SCF, snow cover fraction; TS, Tianshan Mountains; TWS, Terrestrial Water Storage.

^aSignificant at the 0.01 level.

(Figure 4d and Table 3). The snow-covered area in WRF/Noah-MP was significantly larger than that in MODIS observations, especially over the Tarim Basin (Figures 6a and 6b). The high SCF (exceeding 90%) area additionally enlarged in the high-mountain regions.

3.2. Spatiotemporal Variability of Snow Mass and SCF

3.2.1. Spatiotemporal Variability of the Maximum SD and SWE

The spatial distribution of the maximum SD and SWE in the TS during the cold season is shown in Figure 7. Generally, it shows large SD and SWE values in the high-altitude region but small values in the low-altitude regions. The SD and SWE values in the WTS and NTS were larger than those in the ETS and STS, respectively (Figures 7a–7c). The maximum SD values exceeded 80 cm in the WTS and high-altitude regions of the Ili Valley, whose maximum SWE values reached 250 mm, correspondingly. Most TS regions experienced a rise in the maximum SWE except the low-altitude regions of the STS and WTS (Figure 7d). In particular, a significant augmentation of the maximum SWE was noticed in the ETS and Pamir regions.

3.3. Spatiotemporal Variability of Snow Mass

The patterns and trends of the mean March snow mass estimated by WRF/Noah-MP across the TS are presented in Figure 8. The estimation indicated that March snow mass in the TS amounted to 97.85 (± 16.60) Gt (mean SWE 112.21 mm) with a negligible trend during 1982–2018 (Figure 8a). The mean March snow mass in the WTS (64.29 ± 11.40 Gt) was significantly larger than that in the NTS (21.45 ± 5.09 Gt), ETS (2.75 ± 0.8 Gt), and STS (9.36 ± 1.64 Gt) (Figure 7c). In addition, March snow mass consistently exhibited

Figure 7. Climatology of the estimated maximum snow depth (SD) (a), observed SD (b), and estimated maximum snow water equivalent (SWE) (c) during the cold season. Trend of the maximum SWE (d). The black dots in the figure indicate significant trends (significance level at 0.05).

Figure 8. Variation of March snow mass (a) and elevation variation in the decadal trend for March snow water equivalent (SWE) (b). Climatology of March SWE (c) and its trend (d) in the Tianshan Mountains. The black dots in (c) and (d) indicate significant trends (significance level at 0.05).

insignificant changes in all TS subregions during the past 36 years. However, March SWE showed an opposite trend between the high-altitude and low-altitude regions (Figures 8b and 8d). March SWE almost showed a decrease in the low-altitude regions (below 2,500 m a.s.l.) of the TS (Figure 8b), and the significantly decreasing values prevailed in the STS (Figure 8d). In contrast, March SWE experienced a rising trend in the high-altitude regions (over 3,000 m a.s.l.), especially in the near Pamir regions. Notably, the highest elevation zone with a decreasing March SWE could reach 3,000–3,500 m a.s.l. in the STS, which was higher than other sub-regions (between 2,500 and 3,000 m a.s.l.).

3.4. Spatiotemporal Variability of SCF

The variation of SCF in the transition season is sensitive to temperature. The spatial distribution of mean SCF changes during the cold season, November, and March from 1982 to 2018 is displayed in Figure 9. The SCF experienced a decreasing trend during the cold season, especially in March, showing a significant decrease (Figure 9a and Table 4). The decreasing rate of mean SCF in November was smaller than that in March, but larger than that in the cold season. The trend of mean SCF during the cold season and November showed a similar distribution pattern (Figures 9b–9d). The significantly decreasing values of SCF during the cold season and November were sporadically found in the eastern STS and the high-altitude regions of the Ili Valley. Additionally, the low-altitude regions of the WTS also demonstrated a significant decrease in mean SCF during the cold season. By contrast, a significantly large decrease in March SCF was found in the low-altitude regions of the TS, particularly for the ETS and STS, the decreasing rate of March SCF exceeded 6% per decade.

4. Discussion

4.1. Influencing Factors of the Snow Simulation Performance in WRF/Noah-MP

The snow model performance is highly sensitive to the accuracy of the meteorological forcing data in a mountainous environment (Terzago et al., 2020). The high quality of the simulated precipitation and

Figure 9. Variations of (a) the mean snow cover fraction (SCF) in the Tianshan Mountains. Spatial trends of (b) the cold season, (c) November, and (d) March in mean SCF. The black dots in the figure indicate significant trends (significance level at 0.05).

temperature could reduce the uncertainty of the snow simulation in the RCM LSMs (Liu et al., 2019; Wrzesien et al., 2019), especially in the mountainous regions without reliable in-situ precipitation observations (Gao et al., 2020). Reasonable precipitation could be reproduced by WRF dynamical downscaling in the complex terrain with a fine spatial resolution (S. Chen et al., 2019). Thus, compared with the original ERA5 data set and D01, the RMSE of the daily SD in D02 was reduced significantly by 95.74% and 49.12%, respectively (Figure 3). The coarse-resolution global reanalysis products and GlobSnow passive microwave SWE series' products failed to reveal the subgrid snow characteristics of the alpine regions (Bormann et al., 2018; Dozier et al., 2016). Previous studies reported that the near-surface air temperature in ERA5 reduced the cold bias compared with ERA-Interim (Hersbach et al., 2020; C. Wang et al., 2019), but a general cold bias could still be noticed in the dynamic downscaling results over the TS (Figures 10a and 10c), particularly in the STS. In addition, an underestimation of the total precipitation during the cold season prevailed in the intersection between the NTS and ETS, and the low-altitude regions of the WTS and STS (Figures 9b and 9d), but overestimated values were seen in the high-altitude regions, which were consistent with the performance from WRF downscaling in the surrounding Qinghai-Tibet Plateau and the original ERA5 data set (Gao et al., 2018, 2020; Norris et al., 2018; Ou et al., 2020; X. Wang et al., 2020). Hence, an underestimation of the total precipitation caused a negative SD bias in the Ili Valley and at the intersection between the NTS and ETS (Figure 5c). Notably, smaller SD bias values in D02 were found in the Ili Valley and the northern slope of the TS as compared with ERA-Interim dynamic downscaling results because more precipitation was produced throughout ERA5 dynamical downscaling in these regions (S. Chen et al., 2019; T. Yang, Li, Chen, et al., 2020). Moreover, more precipitation contributed to a reduction of the negative snow mass bias in the global mountainous area (Wrzesien et al., 2019). In contrast, the large SD and SCF deviation in the high-altitude region was mainly caused by the severely wet bias associated with a cold bias (Figure 5e). A severe overestimation of ERA5 and ERA5-land SD was also reported over the Tibetan Plateau (Orsolini et al., 2019). Previous studies demonstrated that the relatively sophisticated cloud microphysics

Table 4
The Decadal Variation of SCF (%) in the TS and Its Subregions

	WTS	NTS	ETS	STS	TS
Cold season	−0.94	−0.24	−0.16	−0.86	−0.53
November	−1.37	−0.29	0.48	0.98	−0.12
March	−2.70	−1.84	−2.86	−4.90 ^a	−2.91 ^a

Abbreviations: ETS, Eastern TS; NTS, Northern TS; SCF, snow cover fraction; STS, Southern TS; TS, Tianshan Mountains; WTS, Western TS.

^aSignificant at the 0.05 level.

Figure 10. Spatial distribution of the mean bias between the simulations and in-situ observations in (a) the mean monthly temperature ($^{\circ}\text{C}/\text{month}$) and (b) total cold season precipitation ($\text{mm}/\text{cold season}$). Boxplot of the (c) mean monthly temperature bias and (d) total cold season precipitation bias in the different subregions. The bottom and top edges of each box indicate the 25th and 75th percentile and the central line indicates the median.

schemes, such as the Thompson microphysics scheme, performed well in the snowfall estimation on a complex terrain (Norris et al., 2015). Due to limited computing time resources, the WSM6 microphysics scheme might bring a large deviation in the snowfall simulation (Fernández-González et al., 2015). Although some underestimated precipitation values were found in the STS, a large cold bias was beneficial to reserve the snow and to prolong the snow cover duration (Figures 4 and 6). However, more ground snow could increase the surface albedo and aggravate the cold bias, especially in the thin snow area (W. Wang et al., 2020) (Figure 10a).

The physical schemes and model parameterizations have a significant influence on the snow process, particularly during the snowmelt season (You, Huang, Gu, et al., 2020). The crucial snowpack physics including the snow albedo scheme, liquid water evolution in the multiple snow layers, snow density function based on the thermal conductive, turbulent flux and the moisture exchange between the canopy and snow surface, and so on in Noah-MP (Niu et al., 2011) could effectively overcome the limitation of wet snow and forest snow in the passive microwave sensor (Dong, 2018; Dozier et al., 2016), reducing snow mass underestimation (Wrzesien et al., 2019). The near-surface air temperature threshold is often selected as the rain-snow partitioning scheme in the most LSMs and hydrological models, but it underestimates the snowfall in the arid regions (Y. H. Wang et al., 2019). Nevertheless, the fresh snow density is a function of the air temperature based on field investigation in relatively humid regions (Hedstrom & Pomeroy, 1998), but a lower one was observed in the dry TS (X. Chen et al., 2011). The uncertainties mentioned above might cause a larger SD underestimation in the Ili Valley and at the intersection between the ETS and NTS (Figure 5f). The fixed fresh snow albedo parameters in most ground surface albedo schemes are designed for thick snow, but the CLASS scheme (fixed as 0.84) in the thin snow region, such as the lowland of the STS, overestimated the actual ground surface snow albedo which caused a severe cold bias and SD overestimation (W. Wang et al., 2020). The surface albedo overestimation could be reduced by optimizing SCF parameterizations and updated the vegetation parameters in the Tibetan Plateau (Y. Jiang et al., 2020). Previous studies suggested that light-absorbing impurities on the snow surfaces might increase the absorption of shortwave radiation and accelerate the snowmelt (Barnett et al., 2005; Sarangi et al., 2020). The growing

Table 5

Pearson's R Values for the Correlations Between March Snow Mass, SCF and the Melted Snow and March T2 and Total Precipitation in the TS During the Cold Season

	March snow mass	March SCF	March melted snow
March T2	−0.22	−0.91 ^a	0.49 ^a
Cold precipitation	0.78 ^a	−0.05	0.28

Abbreviations: SCF, snow cover fraction; TS, Tianshan Mountains.
^aSignificant at the 0.01 level.

aerosol contamination could change the surface albedo and enhance the snowmelt process (Kang et al., 2020). The solar zenith angle, canopy cover, cloud, and snow contamination could cause the LAI uncertainties in the mountains which has a significant influence on the snow-related water-heat process simulation (Fang et al., 2019). Meanwhile, the inconsistency of the long-time series LAI product might contribute to the trend uncertainty (C. Jiang et al., 2017). Furthermore, the blowing snow causes the redistribution of the snowpack and increases the snow sublimation in dry air condition (Orsolini et al., 2019). In case these processes are lacking in Noah-MP, the latter could intensify the overestimation of snow in the high-altitude regions of the TS and around the Tarim Basin (Figure 5f). The soil texture data set in WRF/Noah-MP exists in large uncertainty due to the coarse resolution and lack of sufficient field investigation (J. Li,

Chen, et al., 2018), which could trigger a large deviation in the land surface energy flux simulation (Y. Jiang et al., 2020). Although WRF reproduced well the topographic precipitation with a 9-km spatial resolution, numerous studies revealed that a finer resolution could effectively decline the precipitation overestimation and snow simulation uncertainty on a complex terrain (Bonekamp et al., 2018; Y. Wang et al., 2020).

The quality of the observational data might also be a source of uncertainty in the model evaluation step (Kumar et al., 2019). Due to the wind flow, the undercatch of the snowfall in the gauge observations might contribute to excessive model precipitation in the alpine areas (Bonekamp et al., 2018). The constant human disruption such as the sensor upgrade, urban growth, and station relocation might further cause measurement errors, expanding the deviation in the model evaluation (Fiebrich et al., 2010). Due to the spatial heterogeneity on a complex terrain, a pointed-scale in-situ observation did not appear to be a robust method to evaluate the snowpack evolution in a whole grid cell (81 km²), and the performance was up to its representativeness (Kumar et al., 2019; Wrzesien et al., 2018). The process of regridding MODIS SCF to a coarse resolution might contribute to the overestimation (Bian et al., 2019). The groundwater, lakes, glaciers, and soil moisture contents are also included in the GRACE TWS (Wrzesien et al., 2018). Although the GRACE TWS anomalies were used for comparison with the TWS anomalies of WRF/Noah-MP (Figure 4c), it could not reveal that all TWS changes were caused by the snow accumulation and melting. Moreover, the gain factor, spatial resolution, and systematic errors of the GRACE products might result in uncertainty on the assessed result (Landerer & Swenson, 2012). It was not clear that the performance of the snow simulation occurred in the WTS and high-altitude regions, because most in-situ snow observations are located in the lowland of the Chinese TS area.

4.2. Impact of the Climatic Factors on the Snow Variability

Variations in precipitation, surface air temperature, and atmospheric circulation regulate the snow anomalies (Cohen & Jones, 2011; Zhong et al., 2018). Overall, March snow mass showed a negligible trend in the TS (Figure 3a). The passive microwave remote sensing similarly revealed a low-frequency variation of snow mass in the High Mountain Asia and Eurasia, but this was opposite with a significant decline in North America (Pulliainen et al., 2020; Smith & Bookhagen, 2018). It was noted that a change in the cold season precipitation was a dominant factor leading to a variability in March snow mass (Table 5). Snow was more sensitive to precipitation than the temperature during the cold season in a dry-cold climate, which was consistent with the high latitude of Eurasia and Central Asia (Notarnicola, 2020; Smith & Bookhagen, 2018; Zhong et al., 2018). The precipitation showed a consistent increase during the cold season, particularly in the ETS and high-altitude regions of the WTS and NTS (Figure 11c). In addition, a significant increase in snowfall was also reported based on the data from in-situ observations and climate model simulations (Guo & Li, 2015; de Kok et al., 2020). Anthropogenic aerosols also enhanced the latent heat exchange, forming more clouds and precipitation (Kang et al., 2020; Zhao et al., 2020). Meanwhile, the increased oasis expansion could increase the precipitation (P. Cai et al., 2019; Piao et al., 2020). Thus, it was beneficial to augment the maximum snow mass in these regions (Smith & Bookhagen, 2018) (Figure 7d). In particular, a significant SWE increasing trend was identified in the regions near Pamir and the ETS during winter (Smith & Bookhagen, 2018). Moreover, the heavy snowfall events happened frequently (T. Yang, Li, Liu, et al., 2020), which might cause a sharp rise in SD (Zhong et al., 2018). Previous studies demonstrated that

Figure 11. Cold season (left panels) and March trends (right panels) regarding the mean temperature (a and b), total precipitation (c and d), and melted snow (e and f). The black dots in the figure indicate that the trends are significant (significance level at 0.05).

the maximum SD experienced a significant increase in the Ili Valley and ETS (Q. Li et al., 2019; T. Yang, Li, Liu, et al., 2020). This is however not reflected in March snow mass map (Figure 8d) because the maximum snow mass was detected in the ETS during February (Figure 2). The air temperature experienced an insignificant increase in the TS during the cold season, but exhibited a significantly rapid rise in March (Figure 11) as well as the days with a daily air temperature $>0^{\circ}\text{C}$ (1.5 days per decade, $P < 0.05$). However, the air temperature measured far below 0°C in the high-altitude regions, in which the warming trend had no obvious impact on the snowmelt (Notarnicola, 2020). In contrast, the largely increasing March temperature could accelerate the snowmelt rate in the low-altitude regions (Figure 8b), causing more melted snow and reducing SCF (Figure 11f). The snow variation that more snowmelt in the low-altitude regions and augmentation of snow mass in the high-altitude regions was consistent with findings of Gao et al. (2018) in the Tibetan Plateau. The heavy warming was strongly related to the rapid snow melting in most areas of the Northern Hemisphere in spring (Notarnicola, 2020). Nevertheless, the significantly increasing March precipitation values were seen in the TS except for the STS (Figures 11d), which might augment snow mass and offset the snowmelt caused by the rising temperature. Furthermore, more precipitation in the snow-rain

transitional season also resulted in the reduction of the snowfall verse precipitation ratio and the increased probability of rain-on-snow events (Musselman et al., 2018), which could bring more energy to the snow surface and enhance the snowmelt, advancing the snow end date and shortening the snow cover duration (Mazurkiewicz et al., 2008). This might be another reason for the significant reduction of March SCF in the low-altitude TS regions (Figure 9d). Previous studies illustrated that the advanced snow end day was found in the lowland of the TS based on the meteorological and remote sensing observations (Q. Li et al., 2019; Notarnicola, 2020). Some evidences revealed that the variations of the El Niño–Southern Oscillation (ENSO), westerlies circulation index, and North Atlantic/Arctic Oscillation (NAO, AO) have a substantial influence on the regional cold season climate as well as snow (Gerlitz et al., 2019). The strengthened midlatitude westerlies enhance winter precipitation in the uplifted regions of the TS (Mölg et al., 2014). In addition, the interactions between the different atmospheric circulations might form heterogeneous snow trends (Smith & Bookhagen, 2018).

4.3. Implications and Limitations

The change in snow has an important influence on the regional climate, water resources, and ecosystems (Huning & AghaKouchak, 2020). The increased melted snow and SCF decline could reduce the ground surface albedo and increase the soil moisture content (Blankinship et al., 2014), consequently, exacerbating the warming trend. The thick snow could warm the soil surface, but the decreased snow mass would lessen the warming effect in rich snow regions and vice versa (Zhang, 2005). The increased peak SWE in the high-altitude regions may contribute to the increase in glacier mass, but a dramatic warming accelerated the glacier mass loss in the TS (Farinotti et al., 2015; Luo et al., 2013). In addition, more melted snow during the cold season (Figures 11c) could lead to an earlier spring peak runoff and increase the risk of flooding in the snow-dominated river basin (Stewart, 2010). The shift in runoff regime might also cause a mismatch between the crop water requirements and the irrigation supply and trigger a crisis of regional water resources shortage (Qin et al., 2020). The decline in March SCF suggested that rapid snowmelt took place during a shorter period, which easily triggered wet snow avalanches (Hao et al., 2018). Indeed, the ongoing climate warming during early spring is beneficial to snow wetting and enhances the snow avalanche risk in mountainous areas (Ballesteros-Cánovas et al., 2018). Snow mass also plays a key role in the desert vegetation growth such as ephemeral plants through a consistent soil moisture regulation until summer (Peng et al., 2010). The growth of the alpine vegetation is similarly highly sensitive to the change in snow cover (Tomaszewska et al., 2020).

Limited by the forcing data period, the variability of snow mass in this study was described during a relatively short time period. A point-scale in-situ historical snow depth reconstruction was performed based on the corrected reanalysis data (Q. Li, Yang, et al., 2018). Machine learning provided a reasonable approach so as to estimate the historical snow depth in a grid cell (J. Yang, Jiang, Luo, et al., 2020). In addition, the bias-correction method could significantly reduce snow estimation uncertainty (Pulliainen et al., 2020). However, the scarcity of the surface observations gives rise to a big challenge in data assimilation and a comprehensive assessment of the snow process, especially in the altitudes exceeding 3,000 m a.s.l. Thus, the future study should enhance the intensive snow course observations and data assimilation in the RCM LSMs using a finer spatial resolution. X. Wang et al. (2020) attempted to use SD from the JRA-55 data set to initialize WRF/Noah, which partly reduced the cold bias in the High Mountains Asia. In the future study, we could replace SCF with MODIS SCF as WRF/Noah-MP initialization for a short period of simulation. Furthermore, the accurate meteorological forcing data sets, more realistic remote sensing geographical data sets, comprehensive snow process, and an optimal combination group of parameterization schemes should also be taken into consideration in the RCM LSMs so as to reduce the snow simulation uncertainties.

5. Conclusions

This study evaluated the performance of the snow simulation from 1982 to 2018 in WRF/Noah-MP, which was forced by ERA5 reanalysis data, real-time updated LAI and green vegetation fraction, and investigated the variability of March snow mass and SCF in the Tianshan Mountains. The main findings of this study are described below:

1. Snow mass estimation from WRF/Noah-MP showed a high accuracy with a slight overestimation (2.84 mm/day). Compared with the raw ERA5 data set (RMSE: 3.64 cm/day and MB: 2.10 cm/day), the RMSE and MB of the daily snow depth from WRF D02 were reduced to 1.86 cm/day and 0.15 cm/day, respectively, which performs closer to those from in-situ observation. However, a large uncertainty in snow estimation existed in the high-altitude regions of the Tianshan Mountains.
2. March snow mass (97.85 ± 16.60 Gt) represented the annual maximum snow storage in the whole Tianshan Mountains. Although a widespread increase in the peak SWE was found during the cold season, March snow mass exhibited a negligible trend. The increased precipitation in the high-altitude regions contributed to the extensive snow mass, which could offset snow mass loss in the low-altitude regions of the Tianshan Mountains. Additionally, March SCF significantly declined, particularly in the Southern Tianshan Mountains.
3. The total precipitation during the cold season controlled March snow mass variations as compared with the air temperature. In contrast, the significantly rising air temperature caused March SCF reduction.

Data Availability Statement

The ERA5 data set as the initial and lateral boundary conditions for WRF model were downloaded from the European Centre for Medium-Range Weather Forecasts (ECMWF) (<https://cds.climate.copernicus.eu/cdsapp#!/home>). The CCI-LC was provided by the European Space Agency (ESA) Climate Change Initiative (CCI) project (<https://www.esa-landcover-cci.org/>). The LAI and FVC were obtained from the Global Land Surface Satellite (GLASS) products (<http://glass.umd.edu/index.html>).

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