

Dear editor and reviewer,

Thank you for your positive comments and very important recommendations to improve our manuscript. We have carefully modified the manuscript based on your suggestions and provide a response to each comment. This paper has been polished by a native English speaker. The following revise are based on two reviewers suggestions. Reviewer comments are given in black, and responses are given in blue. Below we provide a marked-up manuscript version showing the changes based on your comments. The main modifications to the manuscript are as follows:

1. The descriptions about the SVR SD retrieval algorithm were added in *Section 3.2 "Processing flow overview"* according to the reviewers' suggestions in page 9 Lines 1-12
2. The equations for analysis metric were added in *Appendix*.
3. We revised the order "extremely significant increase, significant increase, non-significant change, extremely significant decrease, and significant decrease" to "extremely significant decrease, significant decrease, non-significant change, significant increase, and extremely significant increase" in Table 5. And the figures (Fig. 8 and Fig. 11) were revised and updated according to reviewers' suggestions.

Please see below the detailed responses (in blue color).

## **REVIEWER 2#**

I reviewed the paper titled, tc-2019-33-AC1-supplement.pdf, which was a revision of the paper after the previous reviewer pointed out a calculation error.

In this study, SWE and snow depth data over North America are developed over a long period of record, 1992-2016, to evaluate spatial and temporal trends in snow mass and snow cover duration during that time. The study uses a SVR method which combines passive microwave data with other variables to estimate snow depth. They compute SWE using seasonally varying density estimates developed for different snow classes. They find overall decreasing trends in snow mass during the study period, particularly after 2002, though results vary regionally and at different rates seasonally.

The paper needs a thorough English language review. The developed data and analysis are interesting and important, but at times it is difficult to understand exactly what was done. In particular, the variation rate analyses are unclear. I suggest adding equation for this metric, and maybe all of them, to make it obvious what was done. Beyond that, my main feedback is to provide additional high-level details about the SVR method. The way the paper is written it is mandatory that the reader refers to Xiao et al. 2018 in order to understand the process. Enough detail should be given here that the reader has a high-level understanding of the SVR algorithm and the process steps involved.

Response: Thank you very much for your review of our manuscript. We appreciate your positive comments and very useful suggestions for improving the manuscript. This paper has been polished by a native English speaker. We made modification according to your suggestion. The point-by-point revisions are as follows.

We added more description about SVR snow depth retrieval method in page 9 Lines 1-12 (Section 3.2) as following:

“

We shortly described the SVR SD retrieval algorithm involved six steps (see Fig. 3): step 1 is preprocessing meteorological station SD measurement data and PM brightness temperature data; Before estimating SD using PM data, it is necessary to identify snow cover and dry snow by a set of criteria in step 2; To segregate the land cover effect on snow cover distribution (step 3) and snow properties evolution effect (step 4), SD retrieval model were established on different land cover types (forest, shrub, prairie, bare-land) and snow cover stages (snow cover accumulation, stabilization and ablation stage); in step 5, we chose SVR as retrieval function (Eq. 1) with specific kernel functions and parameters; step 6 is constructing a set of SD retrieval models trained by the suitable size and quality training samples. The more detailed descriptions of these other steps can refer to the Xiao et al paper (2018) not repeated here. Here, we provide more detailed but different descriptions for the SVR SD retrieval algorithm in several steps (Fig. 3).

“

Specific comments:

Page 6, Line 29: SSM/I is listed twice.

Response: Thanks. We have changed “SSMIS (Special Sensor Microwave Imager), SSM/I (Special Sensor Microwave Imager Sounder)” to “SSM/I (Special Sensor Microwave Imager), SSMIS (Special Sensor Microwave Imager Sounder)” in Page 3, lines 8-9.

Page 8, line 11: “SVR” hasn’t been defined in article yet.

Response: We have added the description of SVR, support vector regression in Page 4, line 20.

Page 9, lines 15-18: If only 9000 stations are valid, why were 17000 used? How were they selected? Does the map (figure 1) show all the stations, or just the ones used in this study? I would recommend only showing the stations used.

Response: Thank you very much. This sentence “Data at approximately 30000 meteorological stations were recorded of which 9000 typically are valid” have been revised to “Data at approximately 30000 meteorological stations were recorded of which more than 9000 station are currently obtainable” in Page 5, line 25. Stations with observation dates between 1992 and 2016 were selected in this work. Due to the observation time in some station of this historical dataset are very short, e.g. 1 year, 2 year, even less than one year. Hence, the station used in our work (about 17000) is greater than the number of stations currently obtainable. Figure 1 show the stations finally selected.

Page 11, line 4: “SD”, which actually is SWE” Can you explain what this means?

Response: The sentence “ “SD”, which actually is, is one of the thirteen parameters provided” was changed to “SWE, which is labeled as SD in this dataset, is one of the thirteen parameters provided” in page 7, lines 15-16.

Page 11, line 24: List of parameters (DS, A, T, G, L, D) are used in sentence but not defined until later. They should be defined when first used. I would recommend revising the sentence to something like “The snow retrieval process uses various parameters to yield snow depth (Xiao et al. 2018).

Response: Than you very much. We changed “The snow retrieval process uses DS and other

parameters (A, T, G, L, D ...) to yield snow parameters (e.g. SD, Eq. 1) (Xiao et al., 2018)” to “The snow retrieval process uses various parameters to yield snow parameters (e.g. SD, Eq. 1) (Xiao et al., 2018)” in page 8, lines 5-6

Page 13, lines 13-23: I’m not sure what is meant by layers. Do you mean layers within the snowpack? Or are you referring to observations of snow at low, medium and high depths?

Response: These three layers mean the observed snow depth is at low, medium and high depth. We changed “Firstly, the numbers of sample in the three layers, layer1 ( $0 \leq SD < 50$ ), layer2 ( $50 \leq SD < 100$ ) and layer3 ( $SD \geq 100$ ), should be concretely quantified” to “Firstly, the numbers of sample in the three layers that split up by snow depth should be concretely quantified, i.e. layer1 ( $0 \leq SD < 50$ ; low depth), layer2 ( $50 \leq SD < 100$ ; medium depth ) and layer3 ( $SD \geq 100$ ; high depth)” in page 10, lines 5-7

Page 13, line 29: the part of the sentence, “or medium-to-deep” doesn’t seem like it fits. Should this be removed?

Response: Thanks, we removed “or medium-to-depth” in this sentence in page 10, line 18.

Page 14, equation 2: units of density are wrong if you want SWE in mm. Should use a density ratio (snow density/water density) to keep units consistent. (since density of water is 1 g/cm<sup>3</sup>, values will be the same)

Response: Thanks. We have revised the original formula to  $SWE(mm) = SD(cm) \times \rho_{snow}(g/cm^3) / \rho_{water}(g/cm^3) \times 10$  in page 11, line 4, Eq. 2

Page 14, line 21. Why do you have “(decrease)” here?

Response: Thank you. The “decrease” here want to say the snow density could decrease when falling fresh snow. To avoid ambiguity, we removed “(decrease)” in this sentence in page 11 line 12.

Page 16, line 24: I think “shadow” should be “shallow”

Response: We changed “shadow” to “shallow” in page 13 line 16.

Page 17, line 26: Switch the order of “extremely significant decrease” and “significant decrease” so that the 5 grades are listed in order from largest increase to decrease. Same with Figure 8 and Table 5.

Response: Thanks. We have revised the original order to “extremely significant decrease, significant decrease, non-significant change, significant increase, and extremely significant increase” in this sentence (page 14 lines 18-20) and the description in Table 5. Meanwhile, we updated Fig. 8 and Fig. 11..

Page 18, line 25-26: Can you provide the equation for this metric: “Seasonal average SD was defined as the cumulative SD divided by the days in one snow cover season”? It’s not clear to me what is being computed.

Response: Thanks. Seasonal average SD is the average SD in one season, e.g. seasonal average SD in winter is averaging the SD in three months (December, January, February). This sentences “Seasonal average SD was defined as the cumulative SD divided by the days in one snow cover

season” can be described by the following formula.

$$SD_{average} = \frac{\sum_{i=1}^n SD_i}{n} \quad (1)$$

$n$  is the number of days in one snow cover season,  $i$  is  $i$ th day in one snow cover season. This formula have been added in Appendix.

Page 20, lines 9-11: Maximum snow mass is occurring later in the year? This is in contrast to most recent literature that is finding max SWE occurring earlier.

Response: Thank you very much. We have searched and consulted plenty of literature about snow mass or snow water equivalent. Perhaps because of the limited research data available to us, we have not found a study on the occurrence time of maximum snow mass on the hemisphere scale. More research is on the change trend of the snow mass or the maximum SWE. Our finding is consistent with other research conclusions, and it is found that the snow mass and annual maximum SWE exhibits a decreasing trend in the long-term sequence (Section 4.2).

As described in Section 4.2 and Section 3.3, snow mass is calculated by SWE multiplied by snow cover area; SWE is derived from snow depth and snow density. For this contrast trends, one possible reason is due to the temporal and spatial differences in snow depth and snow density distribution, the snow mass finally generated will also vary in different study areas, resulting in different occurrence time for maximum snow mass. Therefore, this conclusion on the hemisphere scale may be contrary to the findings of the small study area or regions. Zeng et al. (2018) found the high values of annual maximum snow water equivalent primarily occur over mountainous regions over western Conterminous United States and maximum snow water equivalent occurs later over mountains area. Moreover, with the increase in temperature, precipitation may be another reason that affects the downward trend of the maximum snow mass in March. Kumar et al. (2012) quantified the impacts of more extreme precipitation regimes (MEPR) on the maximum seasonal snow water equivalent and found that MEPR potentially alleviate the maximum seasonal snow water equivalent decrease trend. It should be noted that in our future work, we will further study the impact of extreme precipitation conditions and or climatic factors on the trend of snow mass change in the northern hemisphere.

We added the sentence “This finding needs to be further analyzed in the future work by correlation with climatic factors, such as precipitation effects (Kumar et al., 2012)” in page 17 lines 1-2.

Zeng, X., Broxton, P., & Dawson, N. (2018). Snowpack Change From 1982 to 2016 Over Conterminous United States. *Geophysical Research Letters*, 45, 12,940-912,947

Kumar, M., Wang, R., & Link, T.E. (2012). Effects of more extreme precipitation regimes on maximum seasonal snow water equivalent. *Geophysical Research Letters*, 39

Page 20, line 27 (and Table 7): it seems strange that February average snow mass rate decreases significantly, while March increases slightly. Is this snow that accumulated during each month or average snow mass at the time? Can you add text stating why you think that is? It would also be nice to see the data and how the months compare. You could create a figure like Figure 10, showing the time series for all the months in different colors.

Response: Thank you. The statement “An increasing trend appears in March with a rate of approximately 1.9068 km<sup>3</sup> yr.<sup>-1</sup> ( $P > 0.05$ ), however, relatively large decrement in fall and winter

are unable to partially be offset by the increment of March.” have been revised to “However, there are no significant trends in March and April with large interannual variations (Table 7)” in page 17 lines 16-17.

The monthly average snow mass index used here is averaging the daily snow mass in one month. So this index only describes snow cover information during this month. Figure 1 exhibits the anomalies of monthly average snow mass (from September to June) from 1992 through 2016 with respect to the monthly average of 1992–2016 across the Northern Hemisphere. Table 7 and Figures 1-F showed a significant decrease trend in February with  $R^2=0.54$ ; while in March is no significant trend with large interannual variation,  $R^2=0.009$ . In general, monthly average snow mass shows a significant decrease trends from September to June except March and April, and no trends with large interannual variability in March and April.

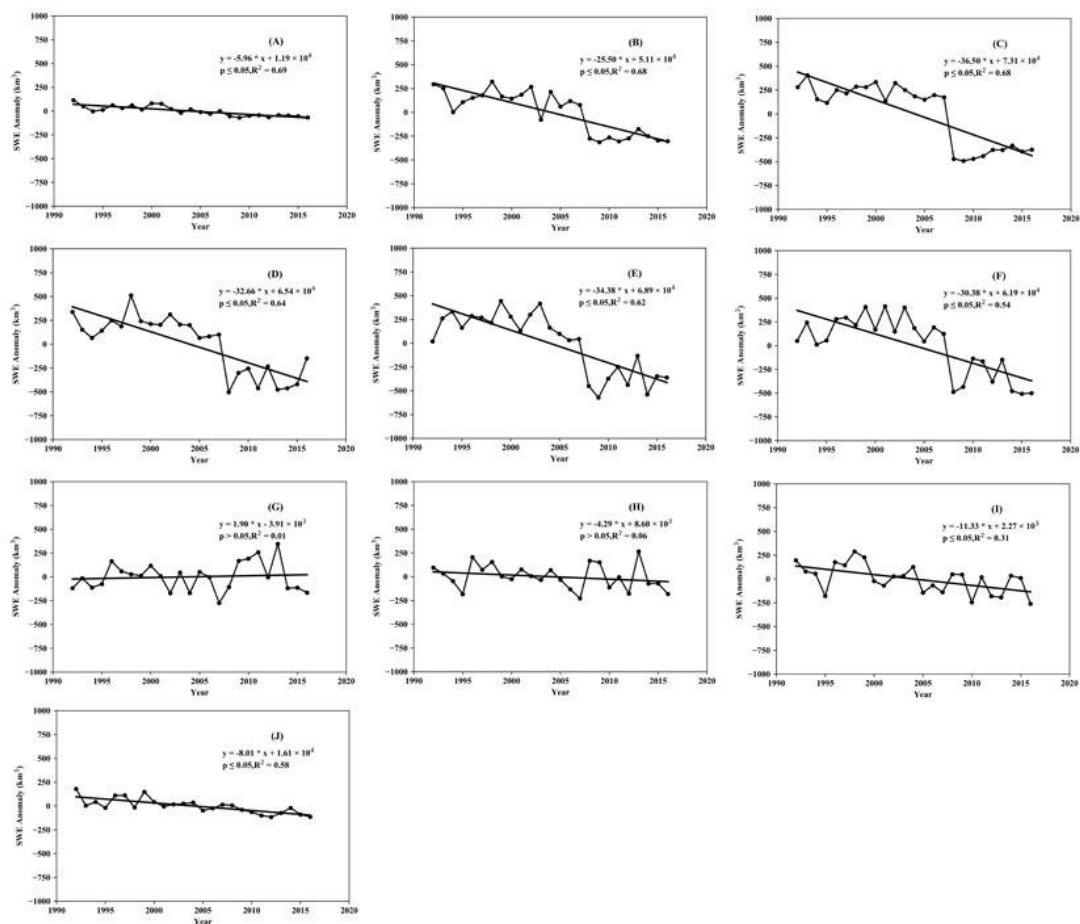


Figure. 1. The anomalies of monthly average snow mass (from September to June) from 1992 through 2016 with respect to the 1992–2016 average across the Northern Hemisphere. (A) September. (B) October. (C) November. (D) December. (E) January. (F) February. (G) March. (H) April. (I) May. (J) June.

1 Table 7. Variation rate and changes of monthly average snow mass during 1992-2016. The asterisk  
2 indicate that the changes are significant at 95% confidence level. The changes was calculated with  
3 respect to the average of monthly average snow mass on 25 years.

Month	Variation rate (km <sup>3</sup> /yr.)	The percentage of Changes
September	-5.96*	-63.89%
October	-25.50*	-43.99%
November	-36.50*	-26.96%
December	-32.66*	-5.00%
January	-34.38*	-9.53%
February	-30.89*	-11.91%
March	1.90	-4.30%
April	-4.29	-6.46%
May	-11.33*	-19.59%
June	-8.01*	-64.67%

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# Spatiotemporal variation of snow depth in the Northern Hemisphere from 1992 to 2016

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**Abstract:** Snow cover is an effective ~~best~~ indicator of climate change due to its ~~effect~~ impact on regional and global surface energy and, water balance, thus weather and climate, hydrological process and water resources ~~y, -climate,~~ and ecosystem as a whole ~~function~~. The overall objective of this study is to investigate changes and variations of snow depth and snow mass over the Northern Hemisphere from 1992 to 2016. We developed a long term Northern Hemisphere daily snow depth and snow water equivalent product (NHSnow) by ~~the applying~~ the application of the support vector regression (SVR) snow depth retrieval algorithm ~~to historical~~ using passive microwave ~~sensors~~ remote sensing data from 1992 to 2016. ~~The accuracies of the s~~ Snow depth products were evaluated against observed snow depth at meteorological stations along with the other two snow cover products (GlobSnow and ERA-Interim/Land) across the Northern Hemisphere. The evaluation results showed that NHSnow performs generally well with relatively high accuracy (bias: 0.59 cm, MAE: 15.12 cm and RMSE: 20.11 cm). Further analysis were ~~performed~~ conducted across the Northern Hemisphere during 1992-2016 using, ~~which used~~ snow depth, snow mass and, snow cover days as indexes. ~~Analysis-Results~~ showed that annual average snow mass ~~has had~~ a significant declining trends with a rate of about ( $-19.72 \text{ km}^3 \text{ yr}^{-1}$ ; or 13% reduction in snow mass). Although spatial variation pattern of snow depth and snow cover days exhibited slight regional differences, it generally reveals a decreasing trend over most of the Northern Hemisphere. Our work provides evidence that rapid changes in snow depth and snow ~~water equivalent~~ mass are occurring since the beginning ~~at the turn~~ of the 21<sup>st</sup> century accompanied with dramatic ~~climate, surface based~~ warming.



## 1. Introduction

Seasonal snow cover is an important component of the climate system and global water cycle that stores large amounts of freshwater and have significant ~~play major~~ impacts on the surface energy and water budget, thus weather and climate, hydrological processes and water resources, heat and mass exchange between the ground surface and the atmosphere, and ecosystem as a whole ~~climatology and water management~~ (Immerzeel et al., 2010; Zhang, 2005; Robinson and Frei, 2000; Tedesco et al., 2014).

On account of the high albedo and low heat conductivity properties of snow, snow cover may directly modulate the land surface energy balance (Flanner et al., 2011), influence on soil thermal regime (Zhang et al., 1996; Zhang, 2005), and indirectly affect atmospheric circulation (Cohen et al., 2012; Zhang et al., 2004; Li et al., 2018). Most jurisdictions in the Northern Hemisphere rely on natural water storage provided by snowpack (Diffenbaugh et al., 2013; Barnett et al., 2005), supplying water for domestic and industrial usage (Sturm, 2015; Qin et al., 2006). Accurate estimation of and reliable information on snow cover spatial and temporal change at regional and global scales is very critical for climate change monitoring, model evaluation and water resources management (Brown and Frei, 2007; Flanner et al., 2011).

Snow depth (SD) is the most useful and commonly measured parameter at national metrological and hydrological stations, numerous research sites, and sites for local and regional water resources assessment programs ~~using in situ observations~~. Given the sparseness of measurements, it is not possible to fully capture spatial variability of snow cover, especially at high altitude mountains and high latitude regions. Although ~~the in-situ observations method can obtain~~ accurate and relative reliable SD and snow water equivalent (SWE) data, it is unrealistic in mountain regions and low population zones because it is labor intensive and high costs, ~~material and financial resource intensive~~. Remote sensing is the most effective and powerful way of obtaining information of snow cover over larger areas (Foster et al., 2011). Optical remote sensing is capable of observing large areas of snow cover; however, it is unable to observe the Earth's surface under cloudy conditions (Foster et al., 2011; Che et al., 2016; Dai et al., 2017). However, microwave remote sensing has this potential and is an attractive alternative to optical remote sensing under all weather conditions and round the clock. It can also be used to estimate SD and ~~snow water equivalent (SWE)~~ due to the interaction with snowpack by providing dual polarization data at different frequencies (Chang et al., 1987; Che et al., 2008; Takala et al., 2011).



Snow cover products derived from [\(PM\)](#) passive microwave ~~(PM)~~ data have been widely applied to investigate regional and global climate change, and validate hydrological and climate models (Brown et al., 2010; Brown and Robinson, 2011; Dai et al., 2017). Progress in satellite data acquisition, as well as SD/SWE retrieval algorithm development, have led to a global improvement in snow monitoring (Qin et al., 2006; Snauffer et al., 2016). The PM brightness temperature of the SMMR (Scanning Multichannel Microwave Radiometer), SSM/I (Special Sensor Microwave Imager), AMSR-E (Advanced Microwave Scanning Radiometer for Earth Observing System), AMSR2 (Advanced Microwave Scanning Radiometer 2 on the Global Change Observation Mission – Water), [SSM/I](#) (Special Sensor Microwave Imager), [SSMIS](#) (Special Sensor Microwave Imager Sounder) and, FY-3B/C (Fengyun-3 satellite B/C) are available and several algorithms have been developed to estimate SD and SWE ~~using PM brightness temperature data~~ (Chang et al., 1987; Dai et al., 2012; Xiao et al., 2018; Pulliainen, 2006; Takala et al., 2011; Che et al., 2008; Foster et al., 1997).

Most retrieval algorithms operate on the principle that the difference in brightness temperature between 18 and 37 GHz reflects the quantity of SD and SWE (Chang et al., 1987). Over and underestimated trends are prevalent in these linear SD and SWE retrieval algorithms (Gan et al., 2013) for which there are two possible and reasonable explanations. One is that vegetation overlaying snow attenuates its microwave scatter signal and results in underestimating SD and SWE from PM data (Che et al., 2016; Vander Jagt et al., 2013). To reduce the effect of tree canopy, a forest fraction was introduced into retrieval algorithm developed to estimate SD and SWE (Foster et al., 1997; Che et al., 2008), or the retrieval algorithm was constructed based on particular land cover types (Goïta et al., 2003; Che et al., 2016; Derksen et al., 2005; Foster et al., 2009). The other explanation is that the relationship between snow properties (SD or SWE) and the PM brightness temperature is non-linear. Newer approaches (e.g. artificial neural networks, support vector regression, decision tree) have emerged using data-mining and have been explored to retrieve SD and SWE that are intended to replace traditional linear methods (Gharaei-Manesh et al., 2016; Tedesco et al., 2004; Liang et al., 2015; Forman et al., 2013; Xue and Forman, 2015). However, there ~~are~~ remain some limitations for these retrieval algorithms due to the diversity of land cover types and the spatiotemporal heterogeneity of snow physical properties.

Numerous studies have reported the changes in snow cover extent (SCE) at regional and hemispheric scales (Rupp et al., 2013; Dai et al., 2017; Derksen and Brown, 2012; Brown and Robinson, 2011; Huang et al., 2016). Huang et al. (2017) [reported](#) the impact of climate and elevation on snow cover

variation in Tibetan Plateau, including SWE, ~~snow-cover-area~~[SCE](#) and, snow cover days. Hori et al. (2017) developed a 38-year Northern Hemisphere daily ~~snow-cover-extent~~[SCE](#) product and analyzed seasonal Northern Hemisphere ~~snow-cover-extent~~[SCE](#) variation trends. In this study, SD was selected as basis for analyzing spatiotemporal change of snow cover. SD provides an additional dimension to snow cover characteristics. Barrett et al. (2015) explored intra-seasonal variability in springtime Northern Hemisphere daily SD change by the phase of the Madden–Julian oscillation. Wegmann et al. (2017) compared four long-term reanalysis datasets with Russian SD observation data. However, this study only focused on snowfall season (October and November) and snowmelt season (April). SD change trends have also been analyzed at regional scales (Ye et al., 1998;Dyer and Mote, 2006). Several studies quantified the spatial and temporal changes consistency of SWE or snow mass derived from satellite ~~data~~[and reanalysis data](#) (Mudryk et al., 2015) but these studies have focused on the limited dimension of snow cover variation. Dyer and Mote (2006) ~~used~~ a gridded dataset to study regional and temporal variability of SD trends across North America from 1960-2000 ~~–and~~ [Foster et al.](#) (2009) [reported](#) the characteristic of seasonal ~~snow-extent~~[SCE](#) and snow mass in South America ~~ferom~~ 1979 to 2006 was ~~descripted-and-reported~~.

There are, however, very limited data (station data, satellite data or otherwise) that can provide both SD and SWE on a hemispheric scale. This ~~paper-study~~ describes ~~the-an~~ approach to develop a consistent 25-year of daily SD and SWE of Northern Hemisphere utilized multi-source data. The primary objective of this study is to develop 25 years (1992-2016) hemispherical SD and SWE products (hereafter referred to as the NHSnow) with a 25 km spatial resolution using [support vector regression \(SVR\)](#) SD retrieval algorithm (Xiao et al., 2018). This paper will address the following questions: 1) How consistent are NHSnow and other sourced snow cover datasets with ~~the-in-in~~-situ SD observations? 2) What is the spatiotemporal variability of [SD and snow mass](#)~~snow-cover~~ in the Northern Hemisphere from 1992-2016? Meanwhile, it is extremely challenging to make extensive quantitative validation of SD and SWE estimates.

This paper is organized in [the following](#) five sections,~~as follows~~. [After the introduction section with literature review, the](#) Section 2 describes the data sets used in this study. The methods of data preprocessing and snow cover products generation ~~were-are~~ provided in Section 3. Next, we describe NHSnow validation against in-situ snow observation ~~records~~, ~~exhibit~~[demonstrate](#) the variability of snow cover in the Northern Hemisphere, and discuss the potential ~~effect~~[controlling](#) factors for the variations

of snow cover ~~results~~ utilized NHSnow data (Section 4). Finally, section 5 summarizes the work of this paper.

## 2 Datasets

### 2.1 Passive microwave data

~~Because~~ Cloud often appears in the snow cover regions ~~or condition~~, during and the winter season often conceals snowfall possibility ~~which make, here is~~ particularly advantageous for using passive microwave remote sensing ~~to detect SCE and SD~~. The SSM/I and SSMIS is PM radiometer onboard the United States Defense Meteorological Satellites Program (DMSP) satellite ([data](#) available from the National Snow and Ice Data Center, <http://nsidc.org/data/NSIDC-0032>). The SSM/I (F11 and F13) dataset from this platform, as well as SSMIS (F17), present with the equal-area scale earth grid (EASE-Grid) format and 25 km spatial resolution (Brodzik and Knowles, 2002; Armstrong, 2008; Wentz, 2013; Armstrong and Brodzik, 1995) (Table 1). The ~~snow cover area~~ [SCE](#) and SD derived from SSM/I (F11) and SSM/I (F13) data have high consistency rendering the calibration between these two sensors for snow cover area and SD unnecessary (Dai et al., 2015). To minimize the melt-water effect to some extent, which can change the microwave emissivity of snow, only descending orbit (nighttime) passive microwave data were used (Foster et al., 2009).

### 2.2 Ground-based data

~~Daily~~ Ground based SD ~~measurements~~ ~~observation~~ are used to construct and verify the SD retrieval model in this study from two sources ~~of daily SD observation~~. The first [dataset](#) is the Global Surface Summary of the Day (GSOD) dataset provided by National Oceanic and Atmospheric Administration (NOAA) (<https://data.noaa.gov/dataset/dataset/global-surface-summary-of-the-day-gsod>). This online dataset, which began in 1929, is derived from the Integrated Surface Hourly (ISH) dataset (Xu et al., 2016). There are fourteen daily elements in GSOD dataset, including SD measured at 0.1 inch. The missing ~~of~~ SD [measurement](#) or reported 0 on the day would be marked 999.9. Data at approximately 30000 meteorological stations were recorded of which [more than 9000 station](#) are [typically obtainable](#). In our study period and area, more than 17 000 meteorological station were selected with records from 1991 to 2016. [All meteorological sites and stations are](#) ~~and a location~~ far [away](#) from large water bodies [such as large rivers, lakes, and oceans](#).

To supplement data from stations that were not reporting during ~~the study~~1991 to 2016 periods, ground-based measurements of daily SD were gathered from an additional 635 Chinese meteorological stations available at the National Meteorological Information of China Meteorological Administration (Xiao et al., 2018;Zhong, 2014). These daily SD records begun in 1957 include SD (unit, cm), observation time, and geographical location information available (<http://data.cma.cn/en>).

### 2.3 Topographic and land cover data

We also used topography as an auxiliary information to estimate SD (Xiao et al., 2018). Elevation was available from ETOPO1 at a resolution of 1 arc-minute (Amante, 2009) available at (<http://www.ngdc.noaa.gov/mgg/global/>). To match the resolution of the PM brightness temperature data with 25 km spatial resolution, we resampled the ETOPO1 to 25 km resolution (Fig. 1).

To increase the accuracy of SD estimates for different land cover types, we ~~both~~-used [both the](#) MODIS land cover (MCD12Q1 V051) from 2001 to 2013 (Friedl and Sulla-Menashe, 2011;Friedl et al., 2010) and [the](#) Advanced Very High Resolution Radiometer (AVHRR) Global Land Cover classification generated by the University of Maryland Department of Geography. The MCD12Q1 International Geosphere-Biosphere Program (IGBP) classification scheme divides land surface into 17 types, which were reclassified into five classes according to Xiao et al (2018) study.

AVHRR imagery was acquired between 1981-1994 from the NOAA-15 satellite (Hansen et al., 2000) and were categorized into fourteen land cover classes at 1 km resolution. These data allowed us to adjust the proposed snow-depth retrieval algorithm by reclassifying the fourteen native land cover classes into five classes (water, forest, shrub, prairie and, bare-land) at 25 km spatial resolution (Table A.). MCD12Q1 is available at site <https://earthdata.nasa.gov/>, while AVHRR land cover data is available from <http://www.landcover.org/data/landcover/>.

### 2.4 Satellite snow cover datasets

Two kinds of snow cover datasets were utilized based on two criteria: covering the Northern Hemisphere and long-term availability. We selected GlobSnow and ERA-Interim/Land which are widely used in global and regional climate change studies (Snauffer et al., 2016;Hancock et al., 2013;Mudryk et al., 2015). These datasets were used to compare with the NHSnow SD product.

In November 2013, the European Space Agency (ESA) released the GlobSnow Version 2.0 SWE

and Snow Extent (SE) data for the Northern Hemisphere (Takala et al., 2011; Pulliainen, 2006). These data include all non-mountainous areas in the Northern Hemisphere and are available online (<http://www.globsnow.info/>). Processing includes data assimilation based on combining satellite PM remote sensing data (SMMR, SSM/I and SSMIS), spanning December 1979 to May 2016, with ground-based observation data in a data assimilation scheme to derive SWE. GlobSnow Version 2.0 (hereinafter referred as GlobSnow) provides three kinds of temporal aggregation level products with 25 km spatial resolution: daily, weekly and monthly. This dataset covers all land surface areas in a band between 35° N ~ 85° N excluding mountainous regions, glaciers and Greenland. To convert between SD and SWE using GlobSnow, the snow density is held constant at 0.24 g/cm<sup>3</sup> [which is from](#) (Sturm et al., 2010; Hancock et al., 2013; Che et al., 2016).

ERA-Interim/Land (Balsamo et al., 2015) is a global land-surface reanalysis product with data from January 1979 to December 2010 based on ERA-Interim meteorological forcing. It is produced by a land-surface model simulation using the Hydrology Tiled ECMWF Scheme of Surface Exchange over Land (HTESSEL), with meteorological forcing from ERA-Interim. Dutra et al. (2010) described the snow scheme and demonstrated the verification using field experiments. [SWE, which is labeled as SD in this dataset](#), is one of the thirteen parameters provided. We ~~should~~ converted SWE to SD using the associated snow density data. These two datasets are available online (<http://apps.ecmwf.int/datasets/data/interim-land/type=an/>). To maximize the proximity to the descending orbit time of passive microwave sensor, the data with analysis type at 6 o'clock were used in this study, and the spatial resolution of these data is 0.125 degree.

## 2.5 Snow classification data

In order to accurately estimate SWE, snow classification data were used to convert SD into SWE. Global Seasonal Snow Classification System was defined by Sturm et al. (1995) based on snow physical properties (SD, thermal conductivity, snow density snow layers, degree of wetting, etc.), and seasonal snow cover. Snow cover ~~were~~ [was](#) categorized into six snow classes (tundra, taiga, alpine, maritime, prairie, and ephemeral) plus water and ice fields (Figure 2). Snow classification data can be accessed from the National Center for Atmospheric Research (NCAR)/Earth Observing Laboratory (EOL) (<https://data.eol.ucar.edu/dataset/6808>). The snow classification dataset was developed and tested for the Northern Hemisphere at 0.5-degree spatial resolution (Sturm et al., 1995).

## 3 Methods

### 3.1 Theoretical basis

Snow distribution is affected by various factors, but not limited to, vegetation (Che et al., 2016; Vander Jagt et al., 2013), soil and air temperature (Forman and Reichle, 2015; Grippa et al., 2004; Dai et al., 2017), topography and wind (Smith and Bookhagen, 2016). [The snow retrieval process uses various parameters to yield snow parameters](#) (e.g. SD, Eq. 1) (Xiao et al., 2018).

$$[S] = g(A, T, G, L, DS, D \dots) + \varepsilon \quad (1)$$

where  $g(\cdot)$  denotes the retrieval function. DS is the digital signal from remote sensing sensor (PM, active microwave, visible spectral remote sensing etc.), A is the atmosphere (wind speed, air temperature, humidity, precipitation etc.), T is the topography (latitude, longitude, elevation, terrain slope, aspect etc.), L is the location (latitude, longitude), G is the ground (ground surface temperature, vegetation type etc.), S is the snow properties (snow grain size, density, reflectance, SD, SWE etc.), D is the day of year and  $\varepsilon$  is the residual error or uncertainty that describes the relationship between sensor signal and measured snow properties.

The SVR SD retrieval algorithm also follows the snow retrieval process (Eq. 1). We utilized ten parameters were as input parameters, including PM brightness temperature (19 GHz, 37 GHz, 85 GHz, or 91 GHz) with vertical and horizontal polarizations, geophysical location (latitude and longitude), elevation and, the measured SD. The output parameter is the estimated SD. Apart from above factors, the SVR SD retrieval algorithm also considers other influence factors, including wet snow, land cover types and day of year (Xiao et al., 2018) to improve the accuracy of estimated SD. Day of year have been converted into three snow cover stages, which mean indirectly considering snow properties evolution.

### 3.2 Processing flow overview

The SVR SD retrieval algorithm ~~first proposed~~[developed](#) by Xiao et al. (2018), which indirectly considers seasonal variation and vegetation influence in the evolution of snow properties, was used to estimate SD. In Eurasia, it was found that the SVR SD retrieval algorithm performs much superior with reduced uncertainties compared based upon the correlation coefficient (R), mean absolute error (MAE), and root mean squared error in Xiao et al. (2018) study. It should be noted that this study used daily observation in the Northern Hemisphere with exception of July and August. ~~Here, we provide more~~

~~detailed but different descriptions for the SVR SD retrieval algorithm in several steps (Fig. 3).~~ We shortly described the SVR SD retrieval algorithm involved six steps (see Fig. 3): step 1 is preprocessing meteorological station SD measurement data and PM brightness temperature data; Before estimating SD using PM data, it is necessary to identify snow cover and dry snow by a set of criteria in step 2; To segregate the land cover effect on snow cover distribution (step 3) and snow properties evolution effect (step 4), SD retrieval model were established on different land cover types (forest, shrub, prairie, bare-land) and snow cover stages (snow cover accumulation, stabilization and ablation stage); in step 5, we chose SVR as retrieval function (Eq. 1) with specific kernel functions and parameters; step 6 is constructing a set of SD retrieval models trained by the suitable size and quality training samples. The more detailed descriptions of these ~~other~~ steps can refer to the Xiao et al ~~paper~~ (2018) ~~not repeated here~~. Here, we provide more detailed but different descriptions for the SVR SD retrieval algorithm in several steps (Fig. 3).

Step 3. Due to the study period pre-dates MODIS data, we used AVHRR land cover as supplement data. MODIS and AVHRR land cover were reclassified into four classes (forest, prairie, shrub and bare-land) which were bases of constructing SD retrieval sub-model. Table A (in appendix) describes the reclassification scheme of AVHRR land cover ~~is described~~. MODIS land cover reclassification schemes were documented in Xiao et al. (2018). Because of the relative stability of land cover change, MODIS land cover in 2013 was used for each year during 2013–2016. Similarly, MODIS land cover in 2001 was used in each year during 1998–2001, and AVHRR land cover data were used ~~for 6 years from~~ (1992 through –1997).

Step 6.1 Construction of a subcontinental model. It needs to be stressed that the snow properties in the Eurasia (~~EU~~) and North America (~~NA~~) exhibit noticed discrepancy especially in snow density. (Zhong et al., 2014; Bilello, 1984). One study pointed out that mean snow density in the former Soviet Union ( $0.21 \sim 0.31 \text{ g/cm}^3$ ) was lower than the data from ~~NA~~North America ( $0.24 \sim 0.31 \text{ g/cm}^3$ ) (Bilello, 1984), and also Zhong et al. (2014) explained the possible reasons which resulting in the diversity of snow density in ~~EU~~Eurasia and ~~NA~~North America. Based on this, we separately constructed the SD retrieval models for ~~EU~~Eurasia and ~~NA~~North America.

Step 6.2 Training dataset selection is the process of removing redundant features from spatial data. The accuracy of estimated SD primarily depends on training data quality, which also demonstrate the significance of the selection rule of training samples (Xiao et al., 2018). Inputting more data than needed



1 in the training dataset to train SD retrieval model, may lead to overfitting and an estimated SD with high  
2 error. In this study, we collected an extremely large number of daily SD records over 25 years,  
3 necessitating an optimized selection rule to avoid data information redundancy.

4 The selection rule proposed in previous research (Xiao et al., 2018) was modified and then it was  
5 divided into two steps ~~in~~ here. Firstly, the numbers of sample in the three layers that split up by snow  
6 depth should be concretely quantified, i.e. layer1 ( $0 \leq SD < 50$ ; low snow), layer2 ( $50 \leq SD < 100$ ; medium  
7 depth) and layer3 ( $SD \geq 100$ ; high depth). To avoid an inflated training sample in layer2 and layer3, we  
8 set a threshold (3 000) determined by several tests (not shown). A threshold (12000) for layer1 was  
9 adopted following Xiao et al. (2018). Table 2 summarizes the section of training sample for each layer  
10 in detail. After that, the quality of training sample in each layers determined by stratified random  
11 sampling is the second step. Stratification was performed in 1 cm SD intervals. Note that, all ~~the~~  
12 ~~selected~~en operations ~~in~~ here were randomly performed.

13 Step 7. Through above steps, the daily estimated SD data in the Northern Hemisphere from January  
14 1992 to December 2016 (excluding July and August) were obtained. Owing to the nature of radiometer  
15 observations, NHSnow products are only reliable in areas with seasonal dry snow cover. Areas with  
16 sporadic wet or thin snow are not reliably detected and areas marked as snow-free may include areas  
17 with wet snow. If one pixel is detected as snow cover by the detection decision tree (Grody and Basist,  
18 1996), but is likely to be shallow ~~or medium to deep~~ snow with an estimated value of equal or less than  
19 1 cm, the SD value is set as 5 cm (Che et al., 2016; Wang et al., 2008) (Fig. 4.).

20 Step 8. In this study, Greenland and Iceland are excluded from the generation and analysis of  
21 NHSnow (NH\_SD, NH\_SWE) products due to their complex coastal topography and the difficulty in  
22 discriminating snow from ice (Fig. 4) (Brown et al., 2010). Missing data and zero-data gaps occur in the  
23 process of generating daily SD gridded products. Therefore, the following filters were applied. Daily  
24 estimated SD was averaged with a sliding 7-day window to reduce noise and compensate for missing  
25 data in the daily time series. For example, the SD estimate for 4 January is an average of the assimilated  
26 scheme output for 1 to 7 January (Takala et al., 2011; Che et al., 2016). When finished, the sliding SD  
27 method generated daily SD products for the entire Northern Hemisphere (NH\_SD; Fig. 4).

### 28 3.3 Estimation of SWE

29 SWE contains more useful information for hydrologists than SD because it represents the amount

of liquid water in the snowpack [useful for studies on surface hydrological processes and for assessing water resources](#) available to the ecosystem as the [when](#) snow melts. One way to estimate SWE [is to](#) uses SD and snow density ( $\rho_{snow}$ ) as described in Eq. 2. Northern Hemisphere SWE products were generated in this study using snow density that converts SD to SWE. (Eq. 2, Fig. 3 and 4, Step 9).

$$SWE(mm) = SD(cm) \times \rho_{snow}(g/cm^3) / \rho_{water}(g/cm^3) \times 10 \quad (2)$$

At present, the primary problem is to obtain relatively accurate snow density. In this study, dynamical calculation methods were adopted to estimate snow density. Two methods are usually used to convert SD to SWE. The first [method](#) uses a fixed value, 0.24 g/cm<sup>3</sup> (or other value), without spatiotemporal variation (Che et al., 2016; Takala et al., 2011). The second uses a temporally static by spatially variable mask of snow density to estimate SWE and are used to generate current AMSR-E SWE products (Tedesco and Narvekar, 2010). Since the snowpack are usually rather unstable, it is awfully unreasonable to set the snow density in the whole snow season to a constant. Observations show that snow density does evolve and tends to increase ~~(decrease)~~ throughout the snow season (from September to June) (Dai et al., 2012; Sturm et al., 1995). Here, daily snow density is obtained following Sturm et al. (2010) (Eq. 3). They used daily SD, day of the year (DOY), and the snow climate class (SC) to produce snowpack bulk density estimates. In this method, knowledge of SC is used to capture field environment variables (air temperature, initial density) that have a considerable effect on snow density evolution.

$$\rho(SD, DOY, SC) = (\rho_{max} - \rho_0)[1 - \exp(-k_1 \times SD - k_2 \times DOY)] + \rho_0 \quad (3)$$

where  $\rho_{max}$  is the maximum density,  $\rho_0$  is the initial density,  $k_1$  and  $k_2$  are densification parameters for SD and DOY, respectively.  $k_1$ ,  $k_2$ ,  $\rho_{max}$ ,  $\rho_0$  vary with SC (Table 3). For operational purposes in ~~our~~ [this](#) work, DOY extend to 1 September each year (Matthew Sturm, personal communication, 2018) running from -122 (1 September) to 181 (30 June). Sturm et al. (2010) didn't compute snow density for the SC ~~of as~~ ephemeral snow despite its presence in the Northern Hemisphere. According to Zhong et al. (2014) study, the snow density of ephemeral is set to an fixed value, 0.25 g/cm<sup>3</sup>. Finally, daily snow density is simulated by the Eq. 3 in the Northern Hemisphere during the 1992–2016 period.

## 4 Results and Discussion

### 4.1 Snow depth

#### 4.1.1 Validation of snow depth

Here to give insight into relative performance of SD products, we compared three sources of snow cover product (NHSnow, GlobSnow, and ERA-Interim/Land) with ground SD observations (Fig. 5-7) using three indices bias, mean absolute error (MAE) and root mean square error (RMSE). The common period (1992 - 2010) daily SD of three products (Section 2.4) were collected as validation data. This validation work primarily focus on snow cover stabilization stage (December to February). Since the snow density change slowly over a smaller range in snow cover stabilization stage (Xiao et al., 2018), using a constant value (0.24 g/cm<sup>3</sup>) for GlobSnow could introduce relative little error (Section 3.3). Subject to the unavailability of SWE station observations, the evaluation of SWE can't be carried out.

The relatively little bias (blue and green dots) between the estimated SD from three products against measured SD is located in mid and low latitude regions (< 60 °N) for these three ~~snow depth~~SD datasets (NHSnow, GlobSnow, and ERA-Interim/Land; Fig. 5). However, a large bias was found in the polar region and along the coast, such as ~~the north of Russian~~ coastal regions near the Arctic Ocean, Russian Far East, Korean peninsula, Northern Mediterranean and Northeast Canada. For NHSnow and GlobSnow, most bias is distributed near the  $\mu=0$  line with high frequency, although some bias is greater than 100 cm (or less than -100 cm) (Fig. 5b, d). Positive (negative) biases indicate mean grid cell values less (greater) than those of the respective stations SD measures. ~~Fig. 5c showed the~~ ERA-Interim/Land overestimated d snow depth in Western Siberian Plains and Eastern European Plains (around 60 °N; Fig. 5c, orange dots). As reference, a Average SD pattern of three products in February (1992-2010) were also provided in Appendix (Fig. A)

For analysis indexes, MAE and RMSE, the distribution of error points of NHSnow and GlobSnow are much the same as the distribution of its bias (Fig. 5-7). We used all evaluation records to calculate three precision indexes for three products. We found that the bias, MAE and RMSE is 0.59 cm, 15.12 cm and 20.11 cm, respectively, for NHSnow gridded product, ~~but~~ But for GlobSnow, there were more bias (1.19 cm), MAE (15.98 cm) and lower RMSE (15.48 cm) ~~for GlobSnow~~ (Table 4). This comparison (NHSnow vs. GlobSnow) showed relatively good agreement, although NHSnow over- or underestimated

the SD with larger RMSE. Overall, the performance of GlobSnow was better than the NHSnow gridded product. However, part of the validation data were also applied for GlobSnow assimilation, it is highly possible that in this case GlobSnow validation may not completely independent. The different performance for these two products may be mainly because the evolution of snow grain size by HUT (The Helsinki University of Technology) model was used to generate SWE in GlobSnow. Che et al. (2016) reported that the grain size is more important than snow density and temperature. Further, ERA-Interim/Land had the worst performance of all three products with highest bias (-5.60), MAE (18.72) and RMSE (37.77). The smallest bias is located near mid-latitude regions ( $< 50^{\circ}\text{N}$ ) and much of the bias lies at 0–100 cm for ERA-Interim/Land products (Fig. 5e, f). It must be noted that there are 89 bias records in two stations, which located in Novosibirsk Islands and Victoria Island, is much less than -300 cm (approximately -3000 cm). Large MAE and RMSE can be found in high latitude and coastal region (Fig. 5e). Unlike NHSnow and GlobSnow, ERA-Interim/Land is more likely to overestimate SD and appears to be less consistent with in situ observation across the Northern Hemisphere (Fig. 5f). Through analyzing ground observation, we can see that deep snow is distributed in high latitude areas.

While the gridded products do a fairly good job of representing smaller accumulations of SD ([shallow](#) and mid-deep snow cover), they all struggle to capture very high accumulations (deep snow) with less bias, MAE and RMSE (Fig. 5-7, Fig. A). As a result, variation in snow cover could fail to be adequately captured in areas with frequent deep snow and, thus, we should be cautious when interpreting of this validation result.

Uncertainties in these three gridded snow products caused by ground temperature and topographic factor could result in some level discrepancies between the measured and the estimated SD (Vander Jagt et al., 2013; Snauffer et al., 2016). Forests exhibit strong influence on snow distributions by canopy interception and the evolution of snow properties. The dense portions of boreal forests are widely distributed in ~~NA~~[North America](#) and northern ~~EU~~[Eurasia](#) (Friedl et al., 2010). Large bias, MAE and RMSE regions of three gridded products (Fig. 5-7) cover vast areas of tall vegetation (forests and shrub). Furthermore, the spatial inhomogeneity causes ~~one~~ [one](#) grid cells ( $\sim 25$  km) that is almost not possible to completely cover by one vegetation type (low heterogeneity). Because the estimated SD of NHSnow depends on land cover types, this discrepancy induced by surface cover heterogeneity could partly account for why NHSnow has a smaller MAE and RMSE for low vegetation (bare-land and prairie) distributed at middle and low latitudes, than the higher vegetation (shrub and forest) areas at higher

latitudes (Xiao et al., 2018).

As well, there are scale mismatches between in situ observation and the gridded products with regard to snowpack properties and their spatiotemporal representativeness (Frei et al., 2012). It is difficult to precisely validate coarse-resolution satellite observation using ground truth. Subsequently, over- or underestimates are inevitable when using a single in situ (SD or SWE) observation to test the veracity of the gridded products (Mudryk et al., 2015; Xiao et al., 2018). Snow surveys would benefit from multiple measurements at different points within one pixel (López-Moreno et al., 2011). In situ observations are highly representative when the SD varies smoothly in space, and poorly representative when the SD is spatially stepped (Che et al., 2016). However, there is almost always a lack of sufficient ground-measured data. To date, field site observations are still to be more authentic and reliable datasets than satellite observation.

As a whole, the accuracy of estimated SD in the Northern Hemisphere presented a spatial heterogeneity. Issues of scale and spatial heterogeneity of validation data notwithstanding, these comparisons conducted in our work can yield valuable insight into the performance of these products.

#### 4.1.2 Variation of snow depth

To better understand and interpret snow cover variation across the Northern Hemisphere, we conducted an analysis of SD variation using seasonal maximum SD from 1992–2016. According to the rules of variation level grading, which was divided into 5 grade (extremely significant decrease, significant decrease, non-significant change, extremely-significant increase, and extremely significant increase; Table 5), we can easily gained seasonal maximum SD variation level range 1992 to 2016. Figure 8 shows the variation pattern of seasonal maximum SD in three seasons (fall, winter and spring) with statistical significance level. In three seasons, variation trend of seasonal maximum SD exhibited a distinctly different pattern over the Northern Hemisphere since 1992. Seasonal maximum SD variation results in fall illustrated that a reduction trend account for most area of the Eurasia with the rate ranging from 0 to 1 cm yr<sup>-1</sup>. The Figure 8a shows the significant level pattern of corresponding maximum SD change trend. We can find that the area, which show extremely significant decrease in fall, are mainly located in the Russian Far East, the Qinghai-Tibet Plateau, the southern Siberian Plateau, and the northeastern region of Canada. On the contrary, Russia's Taimir Peninsula and the United States' Alaska

region shows extremely significant increase trend ( $0 \sim 1 \text{ cm yr}^{-1}$ ). In addition, the maximum SD in winter and spring also exhibited extremely significant decrease in the Qinghai-Tibet Plateau and the northeastern region of Canada (as shown in Figure 8b and 8c). The area with extremely significant decrease trend extent extend to add a Western Siberian plain region. Wang and Li (2012) used nearly 50a of daily station SD observation data to analyze the trend of maximum SD in China. The variation trend of seasonal maximum SD in the Qinghai-Tibet Plateau from Wang and Li (2012) previous study is consistent with the conclusion observed in this study (Wang and Li, 2012). There are more regions in seasonal maximum SD with extremely significant increase trend in winter and spring (green region). Furthermore, a strange phenomenon that the variations trend of seasonal maximum SD in the Russian Far East show an extremely significant decrease, while in spring, it showed an extremely significant increase it is in inverse in spring. This variation trend of maximum SD in spring analyzed using NHSnow products is consistent with the analysis results using GlobSnow products from recently published study (Wu et al., 2018). It need be pointed out that the significant increase (decrease) area is located around extremely significant increase (decrease) as shown in Figure 8. No matter which season, although the variation trend of maximum seasonal SD didn't pass the significance level test, we can draw the conclusion that the wide range of area across the Northern Hemisphere experienced pronounced change during the period 1992 to 2016.

Finally, we analyzed seasonal variation analysis of SD across the Northern Hemisphere using seasonal average SD as analysis index. Seasonal average SD was defined as the cumulative SD divided by the days in one snow cover season (refer to Eq. A in Appendix). SD variation rate fluctuated in different regions and seasons. It was generally large in the region north of  $55^\circ \text{ N}$  (Fig. 9, Fig. B and C in appendix). This fluctuation was large in winter with high of  $-0.11 \pm 0.40 \text{ cm yr}^{-1}$  than other seasons during 1992–2016 (Fig. 9d, Table 6.), which means implies that the maximum changes in average SD occurred in winter. Similar conclusion also can be easily found in the two periods 1992–2001 and 2002–2016 (Fig. B-d, C-d and Table 6). Although not all variation trends passed the significance test, most regions in the Northern Hemisphere show increasing trends during 1992–2001 (Fig. B; Table 6). The SD variation trend in the three seasons during 2002–2016 was reversed. The SD absolute variation rate during 2002–2016 is apparently greater than its rate that during 1992–2001 (Fig. C; Table 6). The last century were considered to be the warmest period.

The high fluctuation of SD variation rate especially occurred in the polar region (the Arctic and

the [Qinghai-Tibetan plateau](#)) for three seasons. ~~In the context of global climate change, we found that winter SD variation was more sensitive to climate change. The strength of this relationship is spatially complex, varying by latitude, region, and climate condition.~~

## 4.2 Snow mass

GlobSnow dataset covers all land surface areas excluding mountainous regions, glaciers and Greenland ~~as described in Section 2.4~~. From above analysis, we ~~can find~~ that ERA-Interim/Land have somewhat poor performance in SD estimation. ~~Thus, further~~ [Further](#) analysis of snow cover variation in the Northern Hemisphere used NHSnow products as analysis data. ~~The forecast for snow mass have great potential consequences on agriculture practices in many regions.~~ Snow mass ~~in here~~ is calculated by SWE multiplied by snow cover area (Qin et al., 2006). It should be noted that the snow classification tree (Grody and Basist, 1996), which have been applied in many studies (Che et al., 2008; Dai et al., 2017; Yu et al., 2012), was used to detect snow cover for NHSnow product. Liu et al. (2018) also reported that Grody's algorithm had higher positive predictive values and lower omission errors by testing snow cover mapping algorithms with the in situ SD over China. [Monthly average snow mass](#). ~~In this study,~~ Annual) [maximum](#), average ~~(maximum~~, and minimum) in one snow cover year [from September 1 through June 30](#) ~~(excluded July and August)~~ were calculated ~~as analysis indexes and also monthly average snow mass~~ in 25 years.

The snow mass variation characteristic over the past 25 years were explored by interannual variation (Fig. 10) and intra-annual cycles (not show figure) of snow mass over the Northern Hemisphere. Figure 10 depicts the time series of interannual variation of annual maximum, average and minimum snow mass with respect to 1992–2016 period. The biggest value of annual maximum snow mass occurred in 1998–1999 up to 4875 km<sup>3</sup>, while the least was 3969 km<sup>3</sup> in 2007–2008. The annual maximum snow mass present particularly significant decreasing trends ( $P \leq 0.05$ ) during 1992–2016, at the rate of approximately -19.88 km<sup>3</sup> yr.<sup>-1</sup> (Fig. 10A). Trend analysis reveals that annual maximum snow mass have a 8% reduction from 1992 to 2016. Note that it present a increase variation trend by about 25.59 km<sup>3</sup> yr.<sup>-1</sup> ( $P > 0.05$ ) rate for 1992–2001. In contrast, the annual maximum snow mass exhibits a significantly decrease trends (with -34.80 km<sup>3</sup> yr.<sup>-1</sup>,  $P \leq 0.05$ ) since 2002, which would lead to a extraordinary decrease during 1992–2016. According to the static, the annual maximum snow mass usually appear in February (about 60%) and March (about 40%), and in recent several years this



occurred in March become a normal state. [This finding needs to be further analyzed in the future work by correlation with climatic factors, such as precipitation effects](#) (Kumar et al., 2012). We can find that the biggest and the least value of annual average snow mass respectively appear in 1998-1999 (~2370 km<sup>3</sup>) and 2015-2016 (~1850 km<sup>3</sup>) in Fig 10B. Likewise, in Fig 10B and 10C the annual average (minimum) snow mass exhibit a significant decrease trend in 1992-2016 period by rate -19.72 km<sup>3</sup> yr.<sup>-1</sup>,  $P > 0.05$  (-2.00 km<sup>3</sup> yr.<sup>-1</sup>,  $P \leq 0.05$ ) and 2002-2016 period at a rate of -30.70 km<sup>3</sup> yr.<sup>-1</sup>,  $P > 0.05$  (-2.2 km<sup>3</sup> yr.<sup>-1</sup>,  $P \leq 0.05$ ). For 1992-2016 period, the variation tendency of annual average (minimum) snow mass do not pass the significance level test. Moreover, the reduction for the annual average and annual minimum snow mass is 13% and 67%, respectively. Other factors, for instance, oceanic and atmospheric heat transport, sea ice season wind, and solar insolation anomalies, may have contributed to the fluctuation of snow mass (Liu and Key, 2014). Variation of snow mass across the Northern Hemisphere could well capture the variation characteristic of the Arctic sea ice extent (Tilling et al., 2015).

When analyzing long-term variation of monthly average snow mass [\(refer to Eq. B in Appendix\)](#), ten months (September to June) exhibit significant decreasing apart from March and April (Table 7). The maximum decrease rate was approximately -36.50 km<sup>3</sup> yr.<sup>-1</sup> ( $P \leq 0.05$ ) in November while the minimum decrease occurred in April at -4.29 km<sup>3</sup> yr.<sup>-1</sup> ( $P > 0.05$ ). [However, there are no significant trends in March and April with large interannual variations \(Table 7\).](#) ~~An increasing trend appears in March with a rate of approximately 1.90 km<sup>3</sup> yr.<sup>-1</sup> ( $P > 0.05$ ), however, relatively large decrement in fall and winter are unable to partially be offset by the increment of March.~~ Compared with the fall (September to November) and spring (March to June), the interannual variability of monthly average snow mass significantly decreased in winter (December to February), with average rate of less than -32 km<sup>3</sup> yr.<sup>-1</sup>. The reduction of monthly average snow mass in ten month were generated using the average pattern of each month over 1992-2016 as a reference. We found that the reduction of monthly average snow mass fluctuated ranging from -65% to -4% for each month (September to June) over 1992-2016 (Table 7). The largest and smallest reduction were about 64.67% and 4.30%, which occurred in June and March, respectively. Variation analysis of monthly average snow mass could offer a powerful evidence for annual average snow mass exhibit a significantly decreasing tendency (Table 7, Fig. 10B).

~~Over large areas, it is extremely convenient to use remote sensing to infer SWE. Albeit there are numerous ways to estimate SWE, it~~ It is very challenging to determine precise distributions of SWE at regional and global scales (Chang et al., 1987; Kongoli, 2004; Tedesco and Narvekar, 2010; Bair et al.,

2018). Snow density, which can be used to convert SWE from SD, is ~~potential~~ and key factor in accurate estimation of SWE (Sturm et al., 2010; Tedesco and Narvekar, 2010). In fact, snow density typically varies from 0.05 g/cm<sup>3</sup> for ~~fresh~~ new snow at low air temperatures to over 0.55 g/cm<sup>3</sup> for a ripened snowpack (Anderton et al., 2004; Cordisco et al., 2006). Noteworthily, this study ~~using~~ dynamic snow density to convert SD to SWE ~~is based on~~ with the assumption that snowpack occurs as a single layer (Sturm et al., 2010), ~~to capture dynamic characteristics of snow property~~. The evolution of the ephemeral snow class ~~was not~~ did not be provided by Sturm et al. (2010). The mean value (0.25 g/cm<sup>3</sup>) of snow density of ephemeral snow (Zhong et al., 2014), which means ~~that~~ without any evolution throughout the snow cover year. Meanwhile, ~~this value for ephemeral snow was set as 0.2275 g/cm<sup>3</sup> in~~ Tedesco and Jeyaratnam (2016) ~~used~~ study snow density of 0.2275 g/cm<sup>3</sup> for ephemeral snow, which is about 10% lower than the value used in this study. Snow density also exhibits great heterogeneity in vertical direction, so that a single layer of snow concept cannot fully capture the snowpack property. The density ~~at~~ of the top of snowpack (fresh snow; ~ 0.10 g/cm<sup>3</sup>) increases gradually downwards ~~from the top toward the~~ ~~bottom~~ (Dai et al., 2012). The bottom layer of snowpack is old snow undergoing compaction and grain size growth with a relatively high density (0.3~0.6 g/cm<sup>3</sup>). ~~Although our snow density description strategy does not completely describe the actual evolution in snow density, there is no better alternative.~~

#### 4.3 Snow cover days

Snow cover days (SCD) is defined as the number of days in one snow cover year in which SD is over 0 cm (Zhong, 2014). Snow cover year was defined as the period between the July 1 of a given year and the June of the following year (Xiao et al., 2018). A least-squares regression was used to analyze the variation of SCD for each pixel from 24 snow cover years, with per-pixel evaluation of significance (F-test).

We ~~exploring~~ investigated the changes and variation in SCD during 1992-2016. Most areas across the Northern Hemisphere present a prominently decreasing trend at a rate ~~ranging~~ from 0 to 5 day yr.<sup>-1</sup> (Fig. 11a). Decreasing regions are mainly distributed in ~~EU~~ Eurasia. For example, north of Russia and large parts of central Asia. The area that shows decreasing trends of SCD in ~~EU~~ Eurasia is much larger than that in ~~NA~~ North America (Fig. 11a) (Derksen and Brown, 2012). Areas that the decrease at a rate greater than 5 day yr.<sup>-1</sup> are almost all located in China, such as North of Qilian Mountain, central Tibetan Plateau, and Tianshan Mountain. Areas ~~that exhibits~~ with increasing trends, can be found in central of

1 ~~NA~~North America, Western Europe, Northwestern Mongolia, and some parts of China. Throughout the  
2 Northern Hemisphere (Fig. 11b), the decreasing trend covered most parts of the regions (~~25 through~~  
3 ~~85 °N~~) with a mean decreasing rate of approximately 1.0 day yr.<sup>-1</sup>. ~~Latitudes~~Regions around 50 °N is an  
4 exception ~~almost with no changes~~where variation is close to 0 day yr.<sup>-1</sup>. The most notable variation trend  
5 (decreasing or increasing) occurred over polar regions (Fig. 11b). This may be because there are few  
6 pixels in the polar mainland.

7 ~~SCD variation rate also were divided into 5 grade (Table 5).~~Unlike SCD variation rate patterns, the  
8 variation level pattern shows that the non-significant changes area dominates SCD variation trends across  
9 the Northern Hemisphere (Fig. 11c). Extremely significant and significant decrease appear in northwest  
10 of Hudson Bay in Canada, Kamchatka peninsula, Eastern European plains, the north of Russia, Iranian  
11 plateau, and several regions in China (the Tibet Plateau, Tianshan Mountain and Northeast China Plain).  
12 In addition, extremely significant and significant increase only occur in a limited area of ~~NA~~North  
13 ~~America~~, eastern Qinghai-Tibetan Plateau regions, and China's central and northern regions.

14 Interestingly, the opposite variation trends in SCD and SD appear in several regions. Maximum SD  
15 in spring (Fig. 8c) and annual average SD (figure not shown) show extremely significant increasing  
16 trends, whereas SCD exhibit extremely significant decreases in corresponding regions (Fig. 11c), such  
17 as Central Siberian Plateau, Greater Khingan Mountains in China, and the eastern Scandinavian  
18 Peninsula. This different variation trend of SD and SCD was also reported by Zhong et al. (2018) using  
19 ground-based data. The primary reason may be the increase of frequency of extreme snowfall in which  
20 SD could demonstrate an increasing trend. Additionally, a recent study found that the greater SWE, the  
21 faster melting rate leading to a shortened SCD in Northern Hemisphere (Wu et al., 2018).

22 Despite the similarities between the station- and satellite-derived time series, it can be demonstrated  
23 that Northern Hemisphere meteorological station data do not provide perfect large-scale variation  
24 characteristics of ground snow cover (Zhong et al., 2018). Our analyses provide further evidence  
25 supporting observations of significant decreasing trends in SCD occurring in the Northern Hemisphere.  
26 Compared to SCD derived from optical sensors snow cover product, however, the specific quantity of SCD  
27 and SCD variation rate derived from NHSnow SD data was overestimated (Wang et al., 2018; Hori et al.,  
28 2017). The SCD variation trends derived from NHSnow product ~~is about the~~almost is same as ~~one~~  
29 derived from optical snow cover product in variation pattern (Hori et al., 2017).

30 Since the optical (MODIS or AVHRR) and microwave sensors (SSM/I or AMSR-E) respond in

different parts of the electromagnetic spectrum, the estimated snow cover will ~~to~~ be somewhat vary. The shallow snow could not induce volume scattering at 37 GHz, and thus passive microwave observations often ~~give~~ provide better snow cover result at thick snow (>5 cm) (Foster et al., 2009; Wang et al., 2008). The threshold for SCD definition ~~in~~ here is 0 cm, whereas it is 1 cm or larger in other studies (Ke et al., 2016; Dyer and Mote, 2006). As well, another explanation for these discrepancy could be snow cover identification algorithm (Liu et al., 2018; Hall et al., 2002).

The microwave radiation characteristics of snow cover is similar to that of precipitation, cold desert and, frozen ground (Grody and Basist, 1996). Commission and omission errors in NHSnow product may result from coarse spatial resolution, snow characteristics and topography according to Dai et al. (2017), precipitation (Liu et al., 2018; Grody and Basist, 1996) especially over frozen ground (Tsutsui and Koike, 2012). ~~Algorithm-s~~ Several rules for NHSnow algorithm development were ~~used~~ applied to distinguish snow from precipitation, cold desert, and frozen ground (Xiao et al., 2018), it is impossible to entirely remove interference factors in each image. Additionally, the precondition of NHSnow is dry snow, which mean almost no wet snow was considered into SCD variation analysis (Singh and Gan, 2000). The poorer performance of the microwave derived products was anticipated because of documented difficulties monitoring snow cover over forested and mountainous terrain (Vander Jagt et al., 2013; Smith and Bookhagen, 2016).

## 5 Conclusions

This ~~project~~ study applied the SVR ~~SD-snow-depth~~ retrieval algorithm ~~proposed~~ developed by Xiao et al (2018), which using PM remote sensing and other auxiliary data, to ~~develop~~ generate a long term (~~from~~ January 1, 1992 to December 31, 2016) Northern Hemisphere daily SD and SWE products (NHSnow) with 25-km spatial resolution. We then analyzed the spatial and temporal change in snow cover (SD, snow mass and, SCD) across the Northern Hemisphere, and quantified the magnitude of variation of snow cover using SD and SWE extracted from NHSnow product.

In this study, we validated ~~three and compared among~~ daily gridded products (NHSnow, GlobSnow and ERA-Interim/Land) against ground truth snow-depth ~~observations~~ measurements. The results show ~~relatively~~ high estimation accuracy of SD from NHSnow, providing the relatively little bias, RMSE, and MAE ~~between the newly SD products and in situ observation. Analysis of~~ SD variations revealed that

the variation rates ranging from  $-1$  to  $1 \text{ cm yr}^{-1}$  (~~negative and positive~~) dominates the change in the Northern Hemisphere, and the maximum changes appear in winter. Additionally, the results revealed that the overall SD trends in three seasons show increasing trend during 1992–2001, however it has a decreasing trend during 2002–2016. Similar conclusions also appear in snow mass change analysis. The annual maximum, average and minimum snow mass exhibit significantly decrease trends and respectively show a 8%, 13% and 67% reduction. The monthly average snow mass has shown a decreasing trend almost in every month and the reduction range from 64.67% (June) to 4.3% (March). The annual average snow mass report well-documented significant decreasing trends ( $\sim 20 \text{ km}^3 \text{ yr}^{-1}$ ,  $P < 0.05$ ) during the study period. Regression analysis multi-year Northern Hemisphere SCD exhibits a prominent decreasing trend at a rate ranging from 0 to  $5 \text{ day yr}^{-1}$ . The area of decreasing trends of SCD in [EUEurasia](#) is much larger than in [NANorth America](#). Unlike the SCD variation rate, its variation level shows that non-significant changes areas dominate the variation pattern across the Northern Hemisphere. An abnormal and interesting phenomenon is that opposite SCD and SD variation trends appear in several regions.

While this study shed light on the spatiotemporal variability trends of snow cover across the Northern Hemisphere using 25-year NHSnow product, we cannot claim NHSnow dataset could completely capture the climate change signal in each region and season. Because of the deficiencies and limitations (e.g. overestimation, underestimation), further efforts should be made to improve the estimation accuracy and robustness of the SD inversion algorithm. Additionally, when more reliable and numerous data become available, we will do more comprehensive validation over higher latitudes and mountainous regions (Dai et al., 2017). Meanwhile, the validation analysis also should be carried out in complex terrain and different land cover types (Tennant et al., 2017; Snauffer et al., 2016). It is recommended that future work focus on the climatic effects and climatological causes in snow cover changes to comprehensively understand the associated snow cover change mechanisms against a climate change background (Huang et al., 2017; Flanner et al., 2011; Cohen et al., 2012).

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2 XDA20100313).

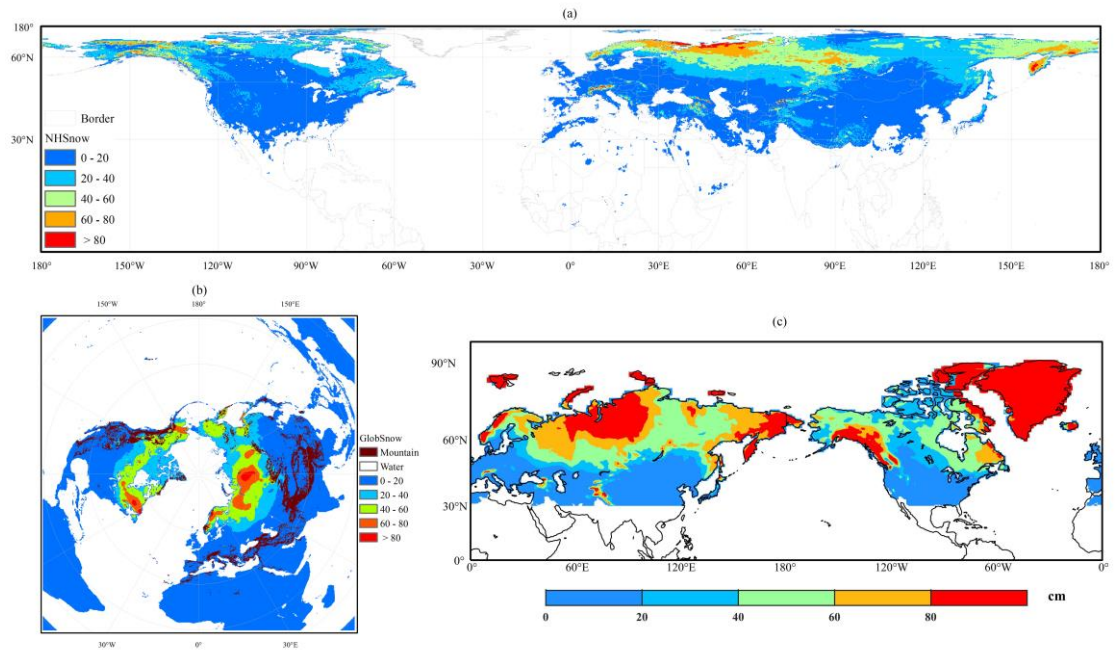
### 3 Appendix

$$SD_{average} = \frac{\sum_{i=1}^n SD_i}{n} \quad (A)$$

$$SM_{average} = \frac{\sum_{i=1}^n SM_i}{n} \quad (B)$$

4 Where  $n$  is the number of days in one specific period of time (one month, or snow cover year/season),  
5  $i$  is  $i$ th day in one specific period of time (one month, or snow cover year/season). SD is snow depth.  
6 SM is snow mass.

7

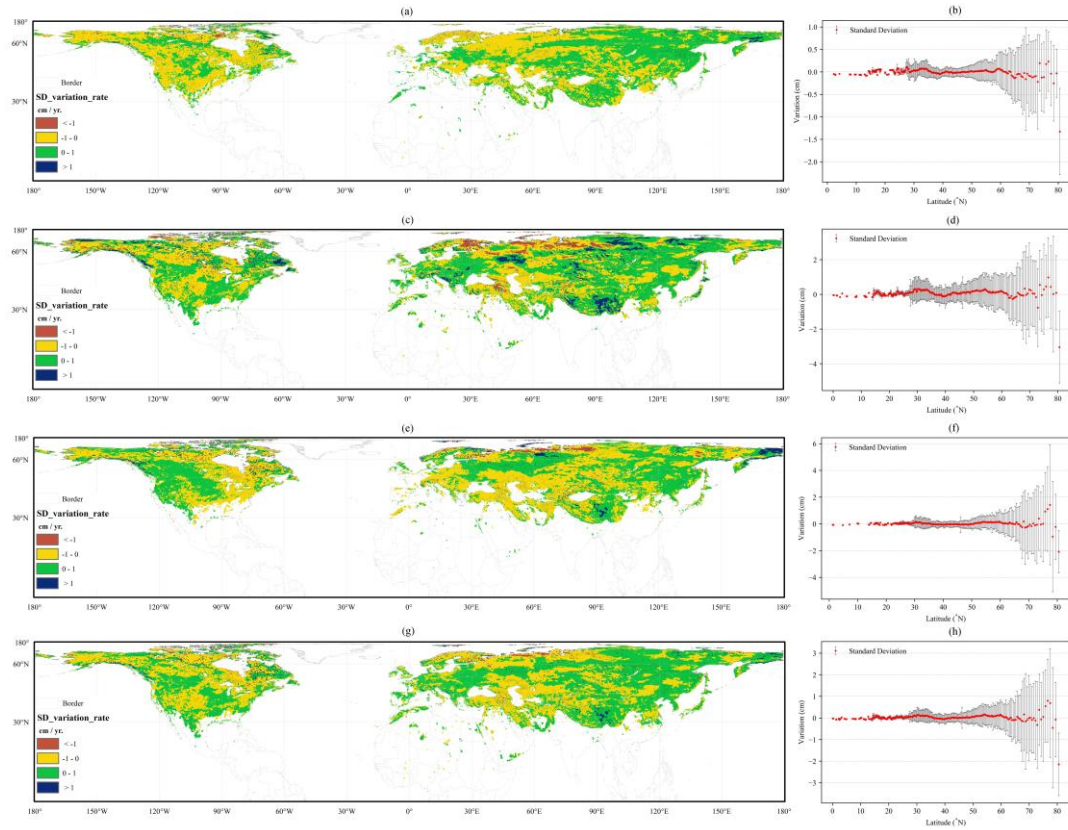


8

9 Figure A. Monthly average snow depth climatology of three products in February during 1992-2010: a)

10 NHSnow; b) GlobSnow, c) ERA-Interim/Land

11



1  
2 Figure B. The variation rate pattern of annual average (season) SD over the Northern Hemisphere for  
3 three snow cover season, fall (a, b; September to November), winter (c, d; December to February),  
4 spring (e, f; March to June) from 1992-2001. Black dots in (a, c, e, g) indicate that the changes are  
5 significant at 95% confidence level (CL). The zonal distribution in (b, d, f, h) are mapped at 0.25  
6 degree resolution in latitude. The error bars in (b, d, f, h) is one times of standard deviation.



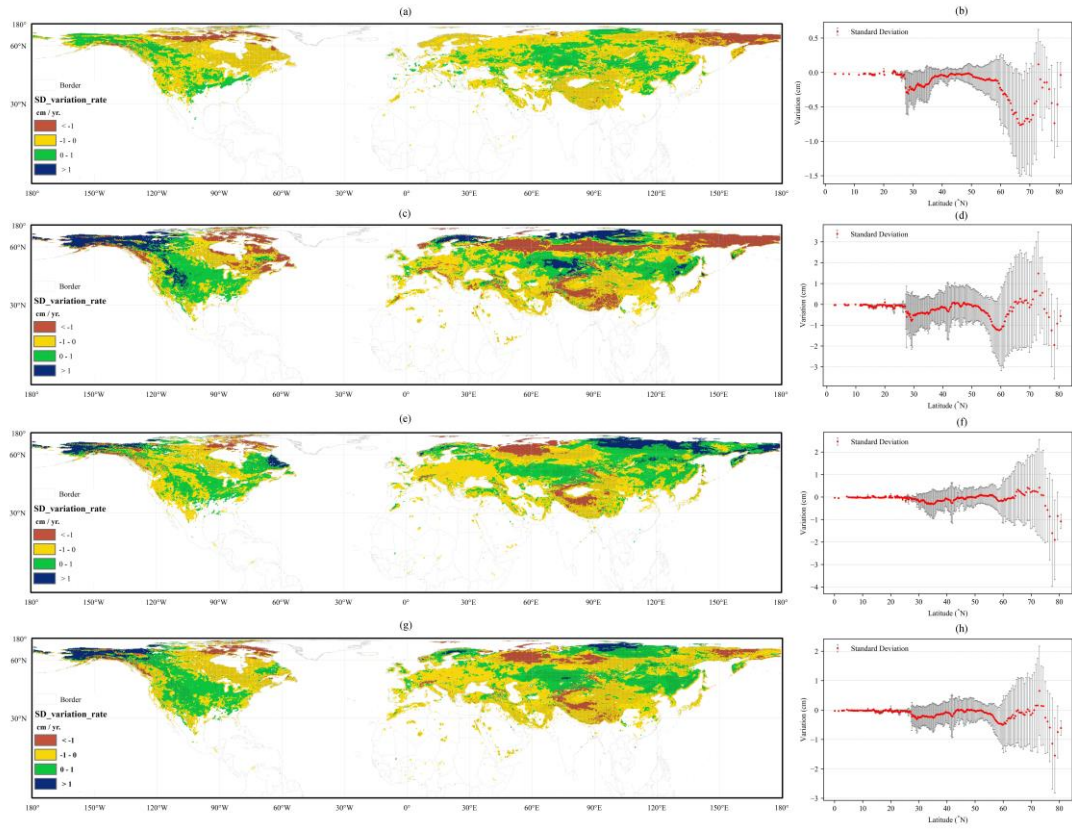


Figure C. The variation rate pattern of annual (season) average SD over the Northern Hemisphere for three snow cover season, fall (a, b; September to November), winter (c, d; December to February), spring (e, f; March to June) from 2002-2016. Black dots in (a, c, e, g) indicate that the changes are significant at 95% confidence level (CL). The zonal distribution in (b, d, f, h) are mapped at 0.25 degree resolution in latitude. The error bars in (b, d, f, h) is one times of standard deviation.

1

Table A. AVHRR Global Land Cover classification and reclassification schemes

Value	Classification Label	Reclassification Label
0	Water	Water
1	Evergreen needle leaf forest	Forest
2	Evergreen broad leaf forest	
3	Deciduous needle leaf forest	
4	Deciduous broad leaf forest	
5	Mixed forest	
6	Woodland	
7	Wooded grassland	Prairie (Grassland)
10	Grassland	
8	Closed shrub land	Shrub
9	Open shrub land	
11	Cropland	Bare-land
12	Bare ground	
13	Urban and built	

2

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## List of Tables and Figures

Table 1 Detail description for SSM/ and SSMIS sensors. H and V denotes horizontal and vertical polarization, respectively.

Satellite	SSM/I		SSMIS
Platform	F 11	F 13	F 17
Temporal coverage	1991.12-1995.5	1995.5-2008.6	2006.12 -
Channels (GHz)	19 H, V; 22 V; 37 H, V; 85 H, V		19 H, V; 22 V; 37 H, V; 91 H, V

Table 2. Training sample filter rules

Layer ID	Filter rules
Layer2.	<p>If <math>\text{Number}_{total}(\text{layer2}) \leq 3000</math></p> $\text{Number}_{training}(\text{layer2}) = (\text{Number}_{total}(\text{layer2}))/2$ <p>Else <math>\text{Number}_{training}(\text{layer2}) = 3000</math></p>
Layer3.	<p>If <math>\text{Number}_{total}(\text{layer3}) \leq 3000</math></p> $\text{Number}_{training}(\text{layer3}) = (\text{Number}_{total}(\text{layer3}))/2$ <p>Else <math>\text{Number}_{training}(\text{layer3}) = 3000</math></p>
Layer1.	<p>If <math>\text{Number}_{training}(\text{layer2}) &gt; 2000</math> or <math>\text{Number}_{training}(\text{layer3}) &gt; 1000</math></p> $\text{Number}_{training}(\text{layer1}) = 15000 - \text{Number}_{training}(\text{layer2}) - \text{Number}_{training}(\text{layer3})$ <p>Else <math>\text{Number}_{training}(\text{layer1}) = 12000</math></p>

Table 3 Snow density estimation model parameters

Snow class	$\rho_{max}$	$\rho_0$	$k_1$	$k_2$	References
Alpine	0.5975	0.2237	0.0012	0.0038	Sturm et al. (2010)
Maritime	0.5979	0.2578	0.0010	0.0038	
Prairie	0.5940	0.2332	0.0016	0.0031	
Tundra	0.3630	0.2425	0.0029	0.0049	
Taiga	0.2170	0.2170	0	0	
Ephemeral	0.2500	0.2500	0	0	Zhong et al. (2014)

Table 4. The evaluated indexes (bias, MAE, RMSE; unit: cm) for three gridded SD products (NHSnow, GlobSnow, ERA-Interim/Land).

Products	Bias	MAE	RMSE
NHSnow	0.59	15.12	20.11
GlobSnow	1.19	15.98	15.48
ERA-Interim/Land	-5.60	18.72	37.77

Table 5. Rules of variation level grading

Variation rate	P value	Variation level
rate $\leq 0$	$p \leq 0.01$	extremely significant <a href="#">decrease</a>
rate $\leq 0$	$0.01 < p \leq 0.05$	significant <a href="#">decrease</a>
-	$P > 0.05$	non-significant change
rate $\geq 0$	<a href="#">0.01 &lt; p ≤ 0.05</a>	significant <a href="#">increase</a>
rate $\geq 0$	<a href="#">p ≤ 0.01</a>	<a href="#">extremely</a> significant <a href="#">increase</a>

Table 6. Mean variation rate of average SD (cm yr.<sup>-1</sup>) over the Northern Hemisphere for three common period (1992-2016, 1992-2001, 2002-1996) and snow cover seasons (fall, winter, spring). Std. means standard deviation

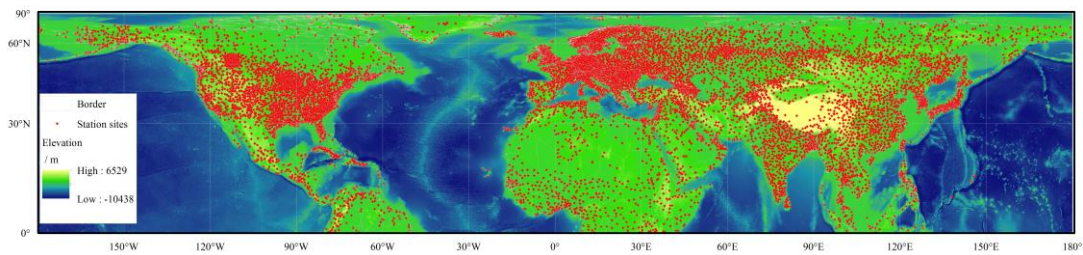
Season	1992-2016 (Mean $\pm$ 1 Std.)	1992-2001 (Mean $\pm$ 1 Std.)	2002-2016 (Mean $\pm$ 1 Std.)
Fall	-0.08 $\pm$ 0.11	-0.01 $\pm$ 0.19	-0.15 $\pm$ 0.22
Winter	-0.11 $\pm$ 0.40	0.06 $\pm$ 0.62	-0.22 $\pm$ 0.75
Spring	-0.04 $\pm$ 0.25	0.02 $\pm$ 0.51	-0.07 $\pm$ 0.41
Year	-0.06 $\pm$ 0.20	0.02 $\pm$ 0.35	-0.11 $\pm$ 0.34

Table 7. Variation rate and changes of monthly average snow mass during 1992-2016. The asterisk indicate that the changes are significant at 95% confidence level. [The changes was calculated with respect to the average of monthly average snow mass on 25 years.](#)

Month	Variation rate (km <sup>3</sup> /yr.)	<del>%The percentage of Change in the mean of monthly average snow mass</del>
September	-5.96*	-63.89%
October	-25.50*	-43.99%
November	-36.50*	-26.96%
December	-32.66*	-5.00%
January	-34.38*	-9.53%
February	-30.89*	-11.91%
March	1.90	-4.30%
April	-4.29	-6.46%
May	-11.33*	-19.59%
June	-8.01*	-64.67%

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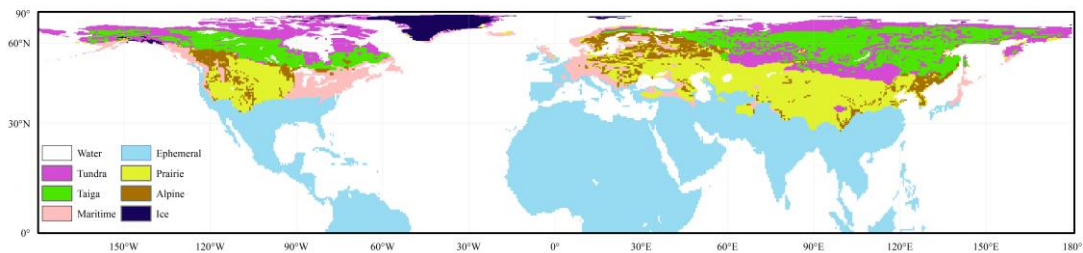
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4 Figure 1. Distribution of Meteorological stations overlaid on ETOPO1 in the Northern Hemisphere.

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Figure 2. Snow Class distribution in the Northern Hemisphere

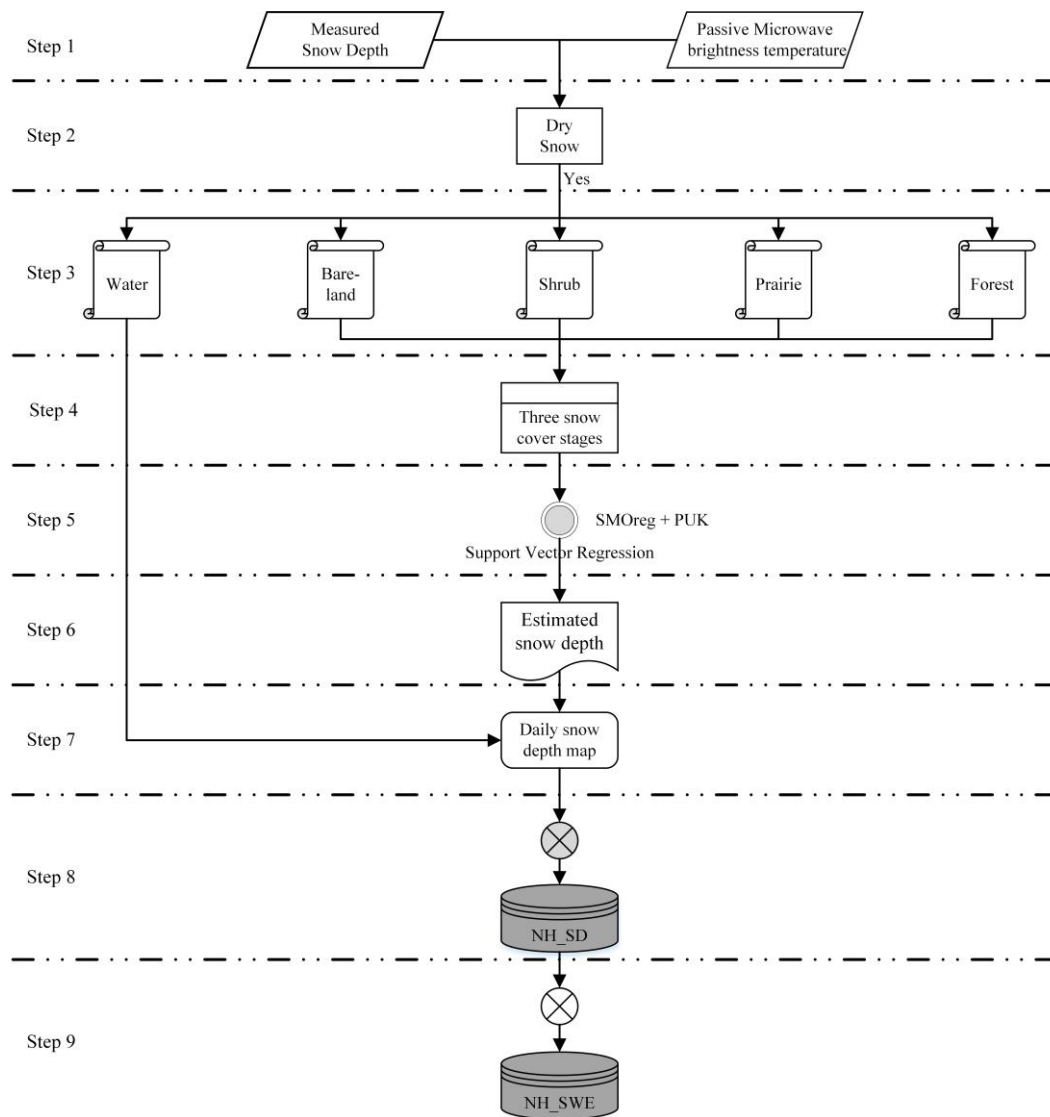


Figure 3. Process flowchart diagram for developing Northern Hemisphere daily snow depth and snow water equivalent data

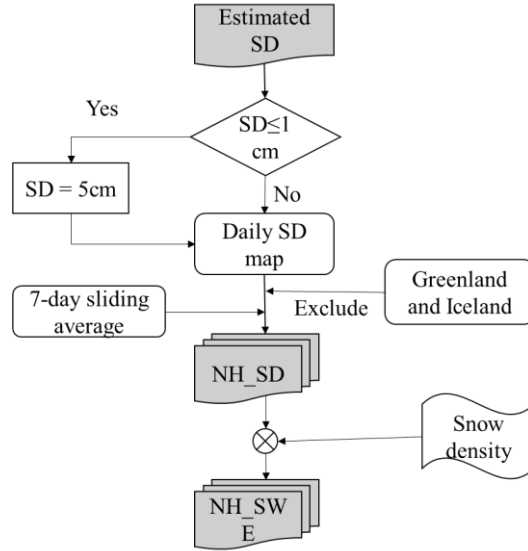


Figure 4. Flowchart diagram of the generation of NHSnow products.

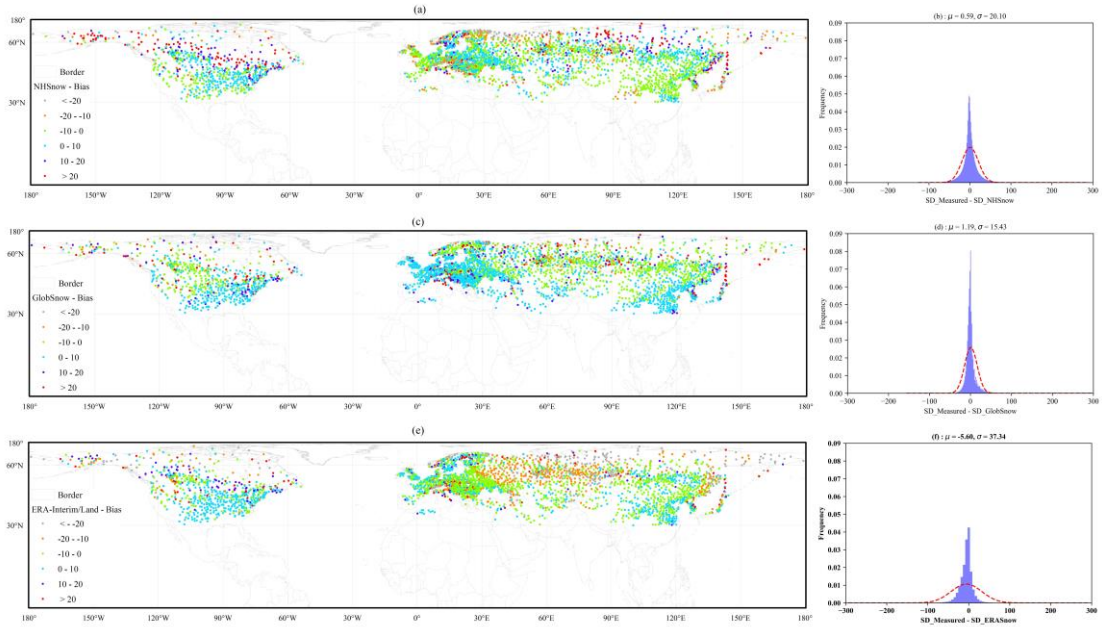
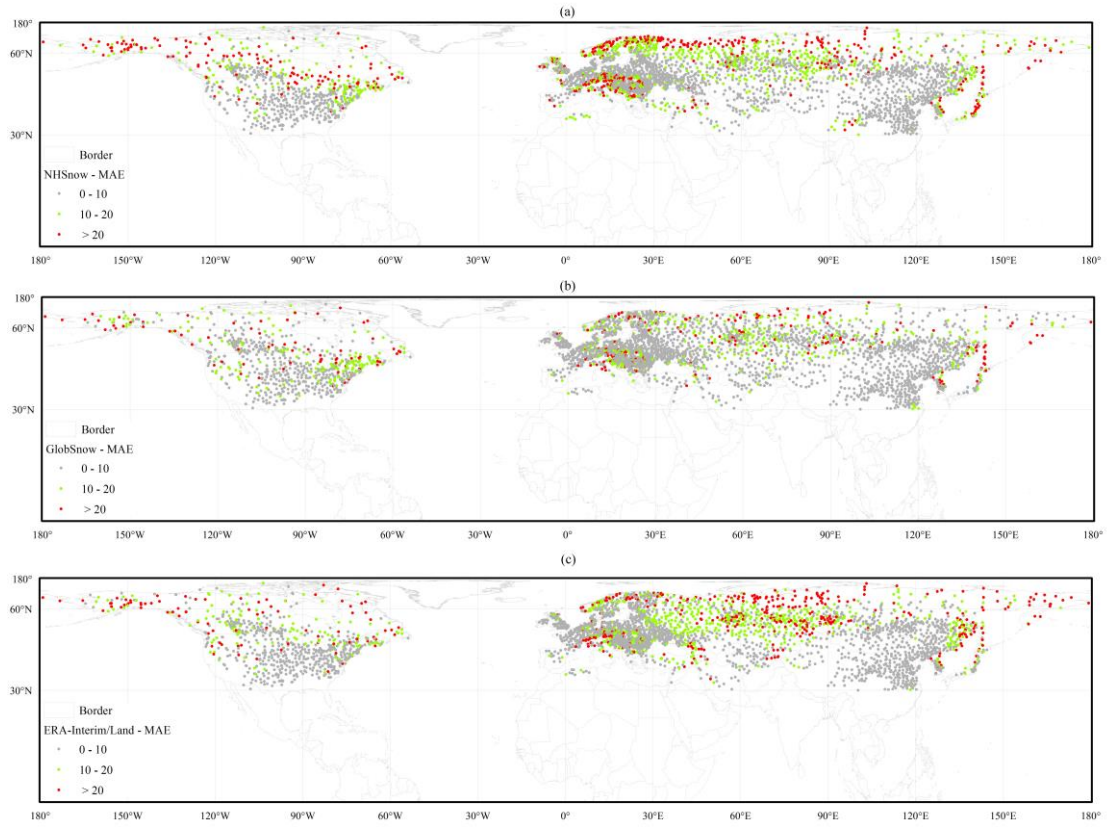
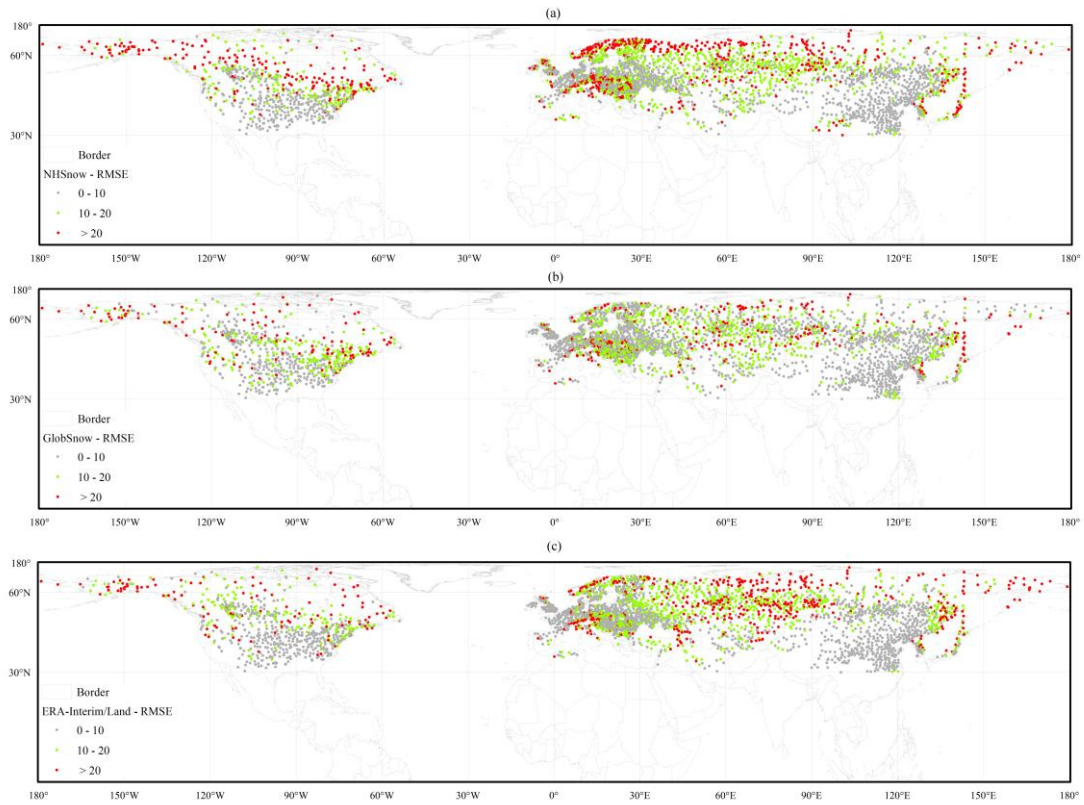


Figure 5. Bias of each meteorological station and histogram of biases for three products: a), b) NHSnow; c), d) GlobSnow; e), f) ERA-Interim/Land. The red dashed line in right column figures are the fitted normal distribution curve



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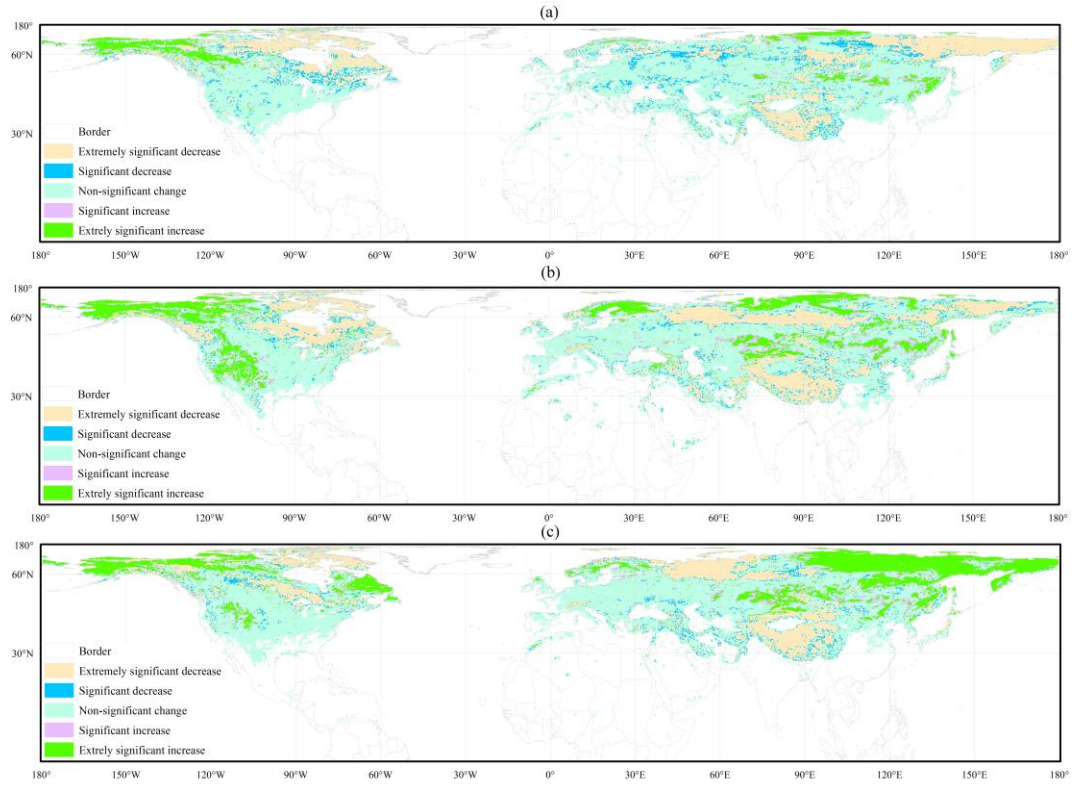
2 Figure 6. MAE of each meteorological station for three products: a) NHSnow, b) GlobSnow, c) ERA-  
3 Interim/Land.



4



1 Figure 7. RMSE of each meteorological station for three products: a) NHSnow, b) GlobSnow, c) ERA-  
 2 Interim/Land.  
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4  
 5 Figure 8. The variation rate pattern of season maximum SD with statistical significances over the  
 6 Northern Hemisphere for three snow cover season, fall (a; September to November), winter (b;  
 7 December to February), spring (c; March to June) from 1992-2016.



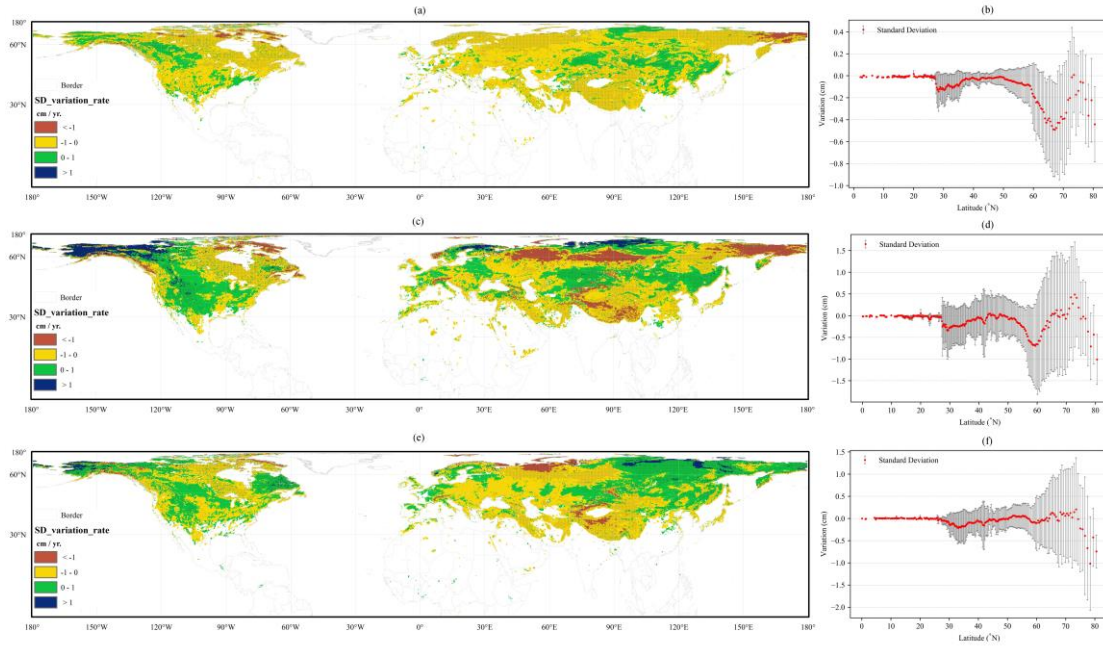
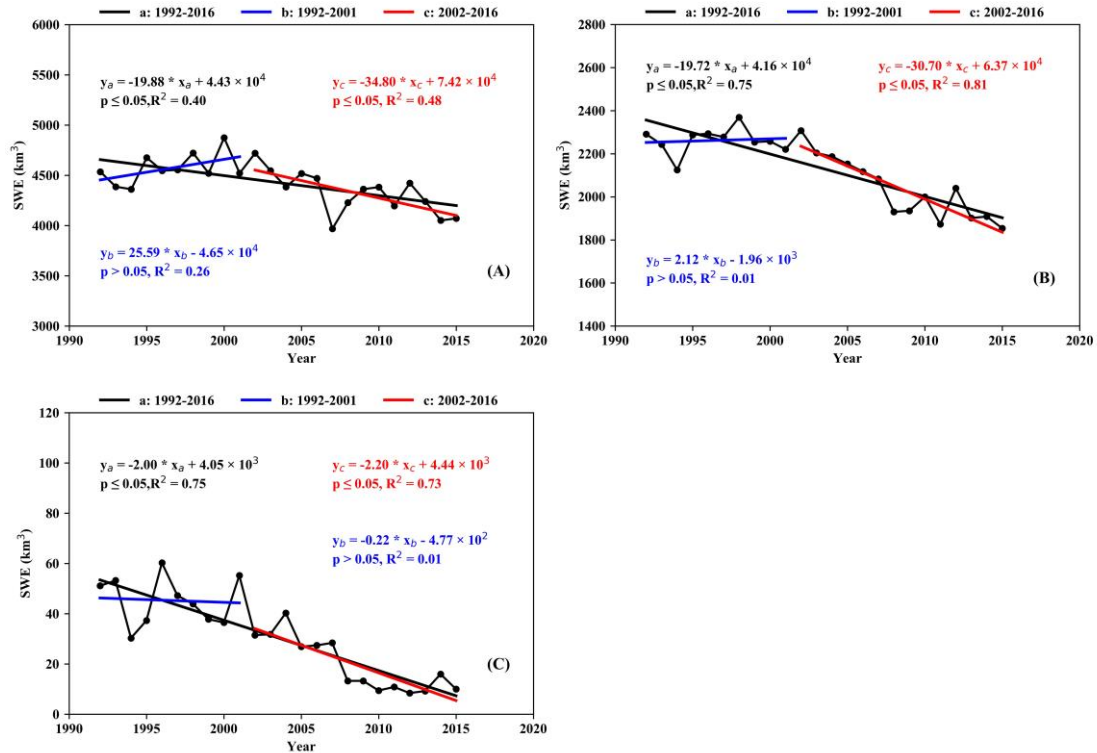
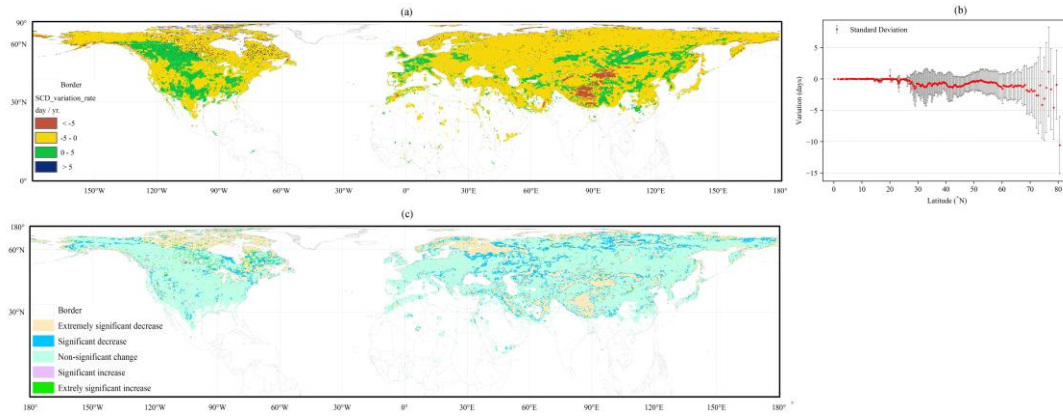


Figure 9. The variation rate pattern of season average SD over the Northern Hemisphere for three snow cover season, fall (a, b; September to November), winter (c, d; December to February), spring (e, f; March to June) from 1992-2016. Black dots in (a, c, e) indicate that the changes are significant at 95% confidence level (CL). The zonal distribution in (b, d, f) are mapped at 0.25 degree resolution in latitude. The error bars in (b, d, f) is one times of standard deviation.



1 Figure 10. Interannual variation of annual maximum snow mass (A), annual average snow mass (B)  
 2 and annual minimum snow mass (C) over the Northern Hemisphere for three period 1992-2016 (black  
 3 line), 1992-2001 (blue line), and 2002-2016 (red line). Trends estimates were computed from least  
 4 squares. P is the confidence level for the coefficient estimates;  $R^2$  is the goodness of fit coefficient.



5  
 6 Figure 11. The variation rate pattern of SCD (a) and their statistical significances (c) over the Northern  
 7 Hemisphere from 1992-2016. The zonal distribution in (b) are mapped at 0.25 degree resolution in  
 8 latitude. The error bars in (b) is one times of standard deviation.