



Extension of the Japan Aerospace Exploration Agency long-term Northern Hemisphere snow cover extent product beyond half a century

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Abstract. The Japan Aerospace Exploration Agency (JAXA) has developed a long-term global snow cover dataset spanning 1978 to the present using a series of satellite-borne optical sensors. As the MODerate resolution Imaging Spectroradiometers (MODISs), one of the satellite sensors that have been in use, are scheduled to cease operation between late 2026 and early 2027, data from Visible Infrared Imager and Radiometer Suite (VIIRS) and Second generation GLobal Imager (SGLI) have been incorporated since April 2018 to ensure continuity of the record. Radiometric and geometric corrections were applied to VIIRS and SGLI using overlapping observations with MODIS, enabling consistent estimation of snow cover extent (SCE) including discrimination between dry and wet snow cover. The existing snow detection algorithm was retained, while additional cloud screening was introduced for SGLI to compensate for the absence of a mid-infrared band. Validation using in-situ snow depth and surface air temperature observations demonstrated stable SCE and wet snow cover extent accuracy from 1982 to 2024. Seasonal SCE biases remained below 1%, indicating consistency with the MODIS-based product. The extended dataset reveals a significant long-term decline in Northern Hemisphere SCE, accompanied by pronounced regional and seasonal variability, while the summer wet snow cover fraction has increased. Snow cover duration has shortened significantly in western Eurasia, whereas trends in Asia and North America are weaker. Regularly updated for nearly five decades, the JAXA snow cover dataset provides a stable, consistent, and continuously extendable record for climate monitoring and long-term snow cover analysis.

1 Introduction

Snow cover alters the Earth's surface albedo and significantly impacts the radiation budget (Warren, 1982; Armstrong and Brun, 2008). It also plays a crucial role in hydrological cycles and meteorology within watersheds as a water resource (Sturm, 2015; Modi et al., 2022). Therefore, it is an essential observation target for evaluating the Earth's radiation and water budgets. Snow cover extent (SCE) is one of the Essential Climate Variables defined by the World Meteorological Organization's Global Climate Observing System, and its monitoring is primarily conducted through satellite observations (GCOS, 2022).



30 Among datasets on snow cover extent based on satellite observations, the one with the longest record is the Climate Data
Record (CDR) versions of the National Oceanic and Atmospheric Administration (NOAA)'s weekly Northern Hemisphere
SCE chart spanning from 1966 to the present (Estilow et al., 2015). According to the NOAA-CDR weekly SCE chart, SCE
tends to decrease in spring and summer, but conversely tends to increase from autumn through winter (e.g., Estilow et al.,
2015 shows the trends in all seasons for 1972–2014; Cohen et al. (2012) discussed the impacts of autumn and winter SCE
35 trends during the period of 1988–2010 on the general circulation pattern in the Northern Hemisphere). However, it has been
shown that the latter increasing trend in autumn does not align with that of other independent snow cover data, such as
ground-based in-situ snow depth observations, snow depth or mass reconstructed from meteorological reanalysis data, and
snow water equivalent retrieved from satellite passive microwave radiometer observations (e.g., Brown and Derksen (2013)
shows the trend in October for 1982–2011). While its unparalleled historical observation span is irreplaceable, it has been
40 noted that the accuracy of snow cover detection for the NOAA-CDR weekly SCE charts has shown a tendency to fluctuate
over time (Hori et al., 2017), and it does not agree with snow models driven by meteorological reanalysis data (Chereque et
al., 2025). Because the NOAA-CDR weekly SCE charts reflect the evolution of analytical techniques over time at the
operational agency, the accuracy of snow cover detection is bound to continue improving. Consequently, it is not considered
suitable for objectively assessing long-term trends in snow cover variability. If corrections are made to account for the long-
45 term bias in snow cover detection accuracy, the usefulness of the dataset is expected to increase further.

Mudryk et al. (2020) analyzed multiple observational datasets, historical trends in snow cover in the Northern Hemisphere,
and projected changes from the Coupled Model Intercomparison Project Phase 6 (CMIP6) multi-model ensemble. Their
results showed that SCE has been decreasing in most months since the early 1980s, with the greatest decline occurring
during the spring melt season. Their results also indicated that CMIP6 climate models broadly reproduce the observed
50 decline and project continued reductions in SCE under future warming.

Intergovernmental Panel on Climate Change Sixth Assessment Report (IPCC, 2023) assigns a “very high level of confidence”
to the decline in spring snow cover in the Northern Hemisphere, but assigns a “moderate level of confidence” to autumn
(October–November) trends and regional variations, noting that there is significant variability among observational datasets.
Furthermore, future challenges include maintaining and expanding high-resolution, long-term continuous satellite snow
55 cover observations, as well as filling gaps through the integration of heterogeneous data. It is therefore crucial to ensure the
continuity of satellite-based snow cover observations moving forward.

Recently, European Space Agency project Snow Climate Change Initiative has developed the first global daily snow cover
fraction dataset covering 1979–2023 (Xiao et al., 2026). By harmonizing data from 16 optical satellite sensors and applying
advanced gap-filling methods, it achieves high temporal consistency and accuracy. The open-access dataset provides a
60 valuable long-term record for climate change research. An increase in the variety of satellite data is expected to expand the
volume of comparative information available, thereby contributing to an improvement in the quality of our comprehensive
understanding of snow cover trends.



Japan Aerospace Exploration Agency (JAXA) has also developed its own long-term SCE product with the capability to discriminate between dry snow and wet snow, and has made it available since 2015 through the JAXA Satellite Monitoring
65 for Environmental Studies (JASMES) data portal (JASMES, 2025). The SCE product including wet snow cover extent (WSCE) was generated by analyzing radiance data observed from satellite-borne optical sensors using a more objective and standardized methodology. In this processing, particular emphasis was placed on standardizing the analysis method that maintains consistent accuracy of snow cover detection throughout the entire period by analyzing the data using only the five
70 wavelength bands available from the earliest Advanced Very High Resolution Radiometer (AVHRR) sensors. The analysis of the JASMES SCE products revealed that SCE in the Northern Hemisphere during the period from 1982 to 2015 is decreasing in all seasons and the snow cover duration (SCD) is rapidly shortening across Europe (Hori et al., 2017). To date, with the exception of JASMES, there have been no other examples in which the land snow cover has been classified into “wet snow” and “dry snow” and made publicly available as a long-term satellite dataset spanning several decades. Although Hori et al. (2017) did not analyze long-term trends for WSCE, it is expected that by identifying areas of wet snow
75 (snowmelt) and dry snow (non-snowmelt), this data can be used to improve the accuracy of snowmelt runoff assessments and forecasts using numerical hydrological models.

In addition, the JASMES/SCE product has been utilized in various research studies in recent years. For example, the snow cover duration derived from JASMES SCE product is used as an input for estimating the permafrost thermal state in the Northern Hemisphere (Ran et al., 2022). Kouki et al. (2023) used the JASMES SCE to verify the ERA5-Land SCE and
80 confirmed that ERA5-Land SCE showed high consistency with the satellite-derived SCE. Recently, Chereque et al. (2025) calculated snow water equivalent (SWE) in the Northern Hemisphere using a simple single-layer temperature-index snow model named “B-TIM (Brown Temperature Index Model)” (Brown et al., 2003) which uses only air temperature and precipitation as primary inputs. They used three different reanalysis data (ERA-5, MERRA-2, JRA-55) as driving data, and converted the derived SWE to SCE below a fixed threshold, and compared with two satellite SCE products (JASMES SCE
85 and the NOAA-CDR weekly chart). The SCE calculated from SWE using a fixed threshold showed a decreasing trend in autumn, which was in direct contradiction to the increasing trend indicated by the NOAA-CDR data. The results also showed that JASMES SCE could be accurately reproduced using a fixed threshold for the entire period, proving the validity of their physical model for SWE calculation and confirming that a temporal sensitivity drift (bias) exists in the NOAA data.

In this way, the utilization of the long-term JASMES SCE products analyzed through objective methods has gradually
90 expanded. However, the “MODerate resolution Imaging Spectroradiometer (MODIS)” optical sensors onboard Terra and Aqua satellites, which are used to derive the JASMES SCE, have ceased orbit control in 2020-2021 due to aging, and are scheduled to end operations between late 2026 and early 2027 (Twedt et al., 2023). Consequently, in order to extend the availability of JASMES SCE data in the future, it is necessary to incorporate data from successor sensors.

This paper aims to achieve the following objectives: (1) extend the SCE record beyond half a century by replacing the aging
95 MODIS observations with VIIRS and SGLI data; (2) re-evaluate the accuracy of the SCE and WSCE products throughout



the entire observation period using in-situ measurements, with a focus on verifying the connectivity between MODIS-based existing product and those based on the newly introduced sensors; (3) obtained DOI registration for the dataset; and (4) update the long-term trends of SCE and SCD reported in Hori et al. (2017) using the extended product.

This paper comprises six sections. Section 2 describes the satellite data and preprocessing, including inter-sensor radiance adjustment. Section 3 presents the snow cover detection methods, including wet and dry snow, accuracy assessment, and definitions of the snow cover variables. Section 4 presents the results of radiance adjustments and the analysis of SCE and WSCE together with the discussion of the accuracy and uncertainty of snow cover detection. In addition, as climatological applications of the SCE products, the climatological values and long-term trends of snow cover variables are also shown. Section 5 summarizes this paper and presents the conclusions. All figures follow the color scheme of Scientific Colour Maps Version 8.1.0 (Crameri et al., 2020) to improve accessibility for readers with color vision deficiencies.

2 Satellite data

2.1 JASMES snow cover product

JASMES snow cover products are generated from observational data collected by optical sensors aboard a series of satellites launched in succession. Specifically, these data are derived from AVHRR onboard polar orbiting weather satellites launched by NOAA, and MODIS onboard the Earth observing satellites “Terra” and “Aqua” operated by the National Aeronautics and Space Administration (NASA). For generating the snow cover products, AVHRR data were used from 1978-2000, while MODIS data have been used since 2000. However, as mentioned above, MODIS has ceased orbital control and has entered the mission termination phase. Therefore, in this study, two new types of optical sensors, the Visible Infrared Imaging Radiometer Suite (VIIRS), which is carried on the joint NASA/NOAA Suomi National Polar-orbiting Partnership (Suomi NPP) and another NOAA-20 (formerly Joint Polar Satellite System-1 (JPSS-1)), and the Second generation Global Imager (SGLI) onboard Global Change Observation Mission-Climate (GCOM-C) satellite launched by JAXA, are being introduced. The optical sensors and their spectral bands used in the SCE analysis are shown in Table 1. Even after the two MODIS sensors ceased orbital control in 2020 and 2021, the use of VIIRS (afternoon orbit) and SGLI (morning orbit) data began with the April 2018 observations in order to extend the data period to more than half a century. The observation intervals (daily, half-month, month), horizontal resolution (5 km), and output snow flag specifications remain the same as in the previous processing (Hori et al., 2017), while the spectral bands used for SCE detection have changed only for SGLI data processing (as described in the next section).



Table 1: Spectral bands of satellite-borne optical sensors used for cloud screening and snow detection (wavelength in μm). The second row indicates the satellite name and the data period used for the SCE analysis.

Sensor		AVHRR		MODIS	VIIRS	SGLI
Wavelength range						
Satellite name (Data period)	TIROS-N (1978.10-1980.1)	NOAA-7 (1981.7-1985.2)				
		NOAA-9 (1985.1-1988.11)	NOAA-16 (2001.6*)	Terra (2000.3-2024.12)	Suomi-NPP (2018.3-2025.12)	
		NOAA-11 (1988.11-1994.12)		Aqua (2002.7-2024.12)	NOAA-20 (formerly JPSS-1) (2018.3-2025.12)	GCOM-C (2018.3-2025.12)
		NOAA-14 (1995.1-2000.2)				
Visible	0.55-0.90	0.58-0.68	0.58-0.68	0.620-0.670	0.620-0.670	0.654-0.694
Near Infrared	0.725-1.10	0.725-1.00	0.725-1.00	0.841-0.876	0.841-0.876	0.849-0.889
Shortwave Infrared						1.36-1.40
						2.16-2.26
Mid-Infrared	3.55-3.93	3.55-3.93	3.55-3.93	3.66-3.84	3.66-3.84	
Thermal Infrared	10.50-11.50	10.30-11.30	10.30-11.30	10.78-11.28	10.78-11.28	10.06-11.54
	Band 4 repeated	11.50-12.50	11.50-12.50	11.77-12.27	11.77-12.27	11.26-12.74

* The data from June 2001 are used for SCE generation when MODIS data are not fully available for producing bi-monthly SCE.

130 Radiometrically and geometrically corrected VIIRS and SGLI granule scene data were resampled and projected onto a
 global geographic latitude-longitude grid (latitude: 90°N to 90° S, longitude: 0–360°) in the same manner as was done for
 AVHRR and MODIS. The pixel spacing is 0.05°, and the array resolution is 7200 × 3601 pixels, which is the geographic
 grid commonly adopted for global geophysical datasets released on the JASMES website (JASMES, 2025). The latitude and
 longitude of the center of the upper left pixel were set to 90° N and 0.0° E, respectively. For detailed product specifications,
 135 refer to Hori et al. (2017) and the JASMES website.

2.2 Selection of spectral bands for VIIRS and SGLI

The snow cover detection process for the JASMES snow cover product utilizes data from five spectral bands (reflectance in
 visible to near infrared bands and brightness temperature in mid- to thermal infrared bands), the same as AVHRR. The basic
 approach remains unchanged for using data from a new satellite sensor of VIIRS. However, when using the data from the
 140 other sensor (SGLI), since SGLI lacks the mid-infrared (MIR: 3.7 μm) wavelength band (Chen et al., 2014), it was decided



to use the two additional shortwave infrared bands at 1.38 μm and 2.2 μm as substitutes as shown in Table 1. These two bands are primarily used for cloud detection instead of 3.7 μm band.

2.3 Adjustment of radiances

The sensitivity degradation observed in the reflectance of each AVHRR sensor has already been calibrated and adjusted in Hori et al. (2017) to match MODIS reflectance over the Antarctic ice sheet. Therefore, in this study, radiances and brightness temperatures of VIIRS and SGLI data were adjusted to those of MODIS for each band using a set of global data from the overlapping observation period of April 1 in 2019, enabling the calculation of SCE equivalent to those derived from MODIS as described below.

VIIRS has the same five wavelength bands as AVHRR and MODIS. Therefore, the data adjustment between sensors were performed by aligning VIIRS reflectance and brightness temperature with those of MODIS using the daily global data acquired on April 1, 2019. Since VIIRS is mounted on the afternoon-orbiting Suomi-NPP and JPSS (now renamed to NOAA-20) satellites, the data adjustments were performed only with MODIS mounted on the Aqua satellite in the same afternoon orbit.

For SGLI, the data has been adjusted for bands sharing the same wavelength range as AVHRR (the four spectral bands other than 3.7 μm) using a daily global data from the observation overlap period (April 1, 2019) with MODIS. In this case, because SGLI is mounted on the morning-orbiting GCOM-C satellite, the data adjustments were performed only with MODIS mounted on the Terra satellite in the same morning orbit. In addition, for the adjustment of the spectral bands at 2.2 μm and 1.38 μm , which serve as alternatives to 3.7 μm , reflectance at 2.2 μm was adjusted to be equivalent to that at 3.7 μm , while reflectance at 1.38 μm was independently thresholded to optimize cirrus cloud removal (see next Sect. 3.1).

3 Analysis method

3.1 Processing flow

The snow cover detection process implemented after adjusting the reflectance and brightness temperature basically followed the same processing flow described by Hori et al. (2017). However, for SGLI processing only, several additional threshold tests using the reflectance of 1.38 μm band for detecting clouds were introduced. Table 2 summarizes the cloud detection tests and thresholds used for the processing of SGLI data (bold indicates those modified or added for SGLI).



Table 2: Cloud detection tests and their thresholds for SGLI data processing.

Targets	Cloud flag switch* ¹	Threshold Tests* ²										
		Height [m]	$Ref_{0.6}$ [-]	$Ref_{0.8}$ [-]	$Ref_{3.7}$ [-]	$Ref_{0.6}-Ref_{0.8}$ [-]	$NDVI$ [-]	$NDSI$ [-]	BT_{11} [K]	$BT_{3.7}-BT_{11}$ [K]	$BT_{11}-BT_{12}$ [K]	$Refs_{1,3}$ [-]
High & Cold Land ($Height > 300m$ & $BT_{11} < 260K$)	On	<3000							≥240	>8		
	On	≥3000							≥240	>15		
	On								<240	>30		
	On				>0.1	>-0.02		<0.82				
	On	≤2000										>0.08
	On	>2000										>0.3
	Off						>0.5		>288			
	Off								>310			
	On								<260	>7.5		
	On					>-0.02			<310	>9		
Other Land	On		>0.3			>-0.02			<293	>8		
	On			>0.4		>-0.03			<293	>7.5	>-1	
	On			>0.4					<278	>18	>-1	
	On		>0.3		>0.02				<263			
	On	≤2000										>0.08
	On	>2000										>0.3
	On	≤300										>0.03
	Off						>0.5		>288			
	Off								>310			
	Off	>1000	<0.4			<-0.04			>275			
	Off					<-0.05			>300			

*1 The threshold tests for cloud detection are applied from the top of the list to the bottom for each target. If the cloudy flag switch is “on,” the pixel is set to cloudy when all of the threshold tests listed on the right hand side meet the conditions. If the switch is “off,” the pixel identified as cloudy in the previous tests is reset to clear (i.e., the decision for cloudy is cancelled).

175 *2 Ref and BT denotes the reflectance in percent and brightness temperature in Kelvin at the wavelength indicated by the subscripted number. $NDVI$ denotes the normalized difference vegetation index calculated by $NDVI = (Ref_{0.8} - Ref_{0.6}) / (Ref_{0.8} + Ref_{0.6})$. $NDSI$ denotes the normalized difference snow index calculated by $NDSI = (Ref_{0.6} - Ref_{3.7}) / (Ref_{0.6} + Ref_{3.7})$. Text in bold indicates tests or thresholds that have been modified or added for SGLI.

180 Snow cover detection was performed on a daily basis using a two-step procedure based on multiple threshold tests, including cloud identification. Processing flow and flowchart are shown in Fig. 1 (a) and Fig. 1 (b). The processing begins by projecting the radiance data along the satellite orbit onto global data with a 0.05-degree grid (shown in the square in the first row of Fig. 1 (a)). Then, a preliminary cloud and surface classification flag (PRCSF) including dry and wet snow cover was generated using reflectance (Ref) and brightness temperature (BT) data derived from radiance on a single observation day

185 (shown as “PRE-CLASSIFICATION” in the second row of Fig. 1 (a) and also shown in the upper part of the flowchart in Fig. 1 (b)).

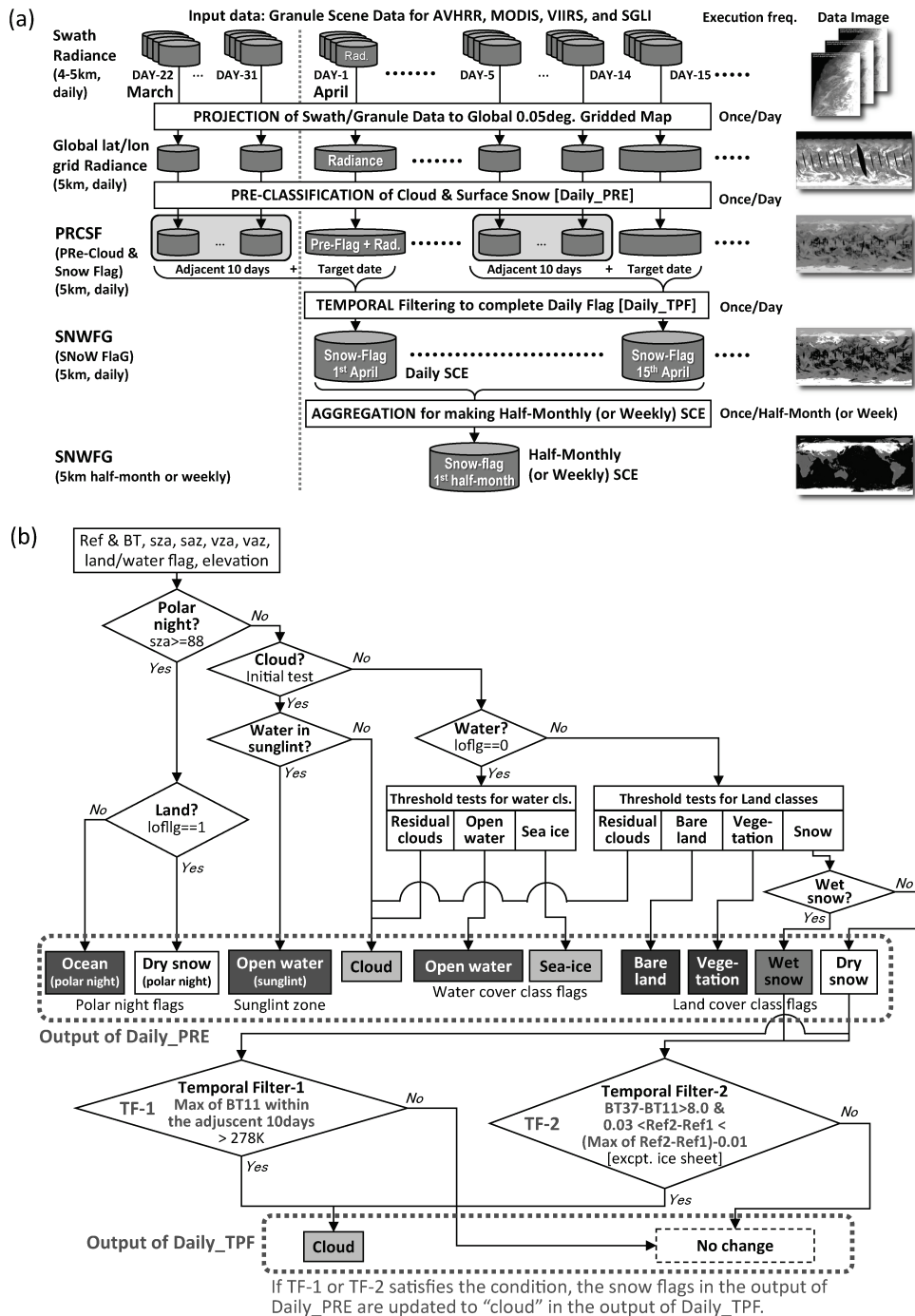


Figure 1: (a) Processing flow of satellite data and (b) Processing flowchart for cloud and land surface classification (updated from Hori et al., 2017).



Next, a temporal filtering method was applied to make the final determination of the daily surface classification flag (SNWFG) (shown as “TEMPORAL Filtering” in the third row of Fig. 1(a), and the lower part of flowchart in Fig 1 (b)). The temporal filtering method utilized not only the reflectance and brightness temperature data from a single observation day but also the average, minimum, and maximum *Ref* and *BT* values from the preceding 10 days to remove residual cloud pixels within the PRCSF. The land surface pixels in SNWFG were classified into 5 classes; bare land, vegetation, dry snow, wet snow, and residual clouds.

Finally, daily surface classification flags from SNWFG were aggregated to generate temporal composite SCE datasets covering half-month, monthly or weekly periods (the fourth row of Fig. 1 (a)). In this temporal aggregation process, the fractions of days with snow detection and wet snow detection to the number of clear weather days (i.e., valid observation day for detecting snow) during the aggregation period are calculated and stored as snow cover temporal fraction (Snowcover_Tfrac) and wet snow cover temporal fraction (Wet_Snowcover_Tfrac) for each pixel. For the details on the surface classification method, which includes initial cloud detection, followed by snow cover detection, and temporal aggregation, refer also to Hori et al. (2017), which lists the thresholds used in the individual threshold tests (Table 2 and 3 in that paper). In this paper, we will briefly describe the methods for detecting snow cover and wet snow cover in next sections (3.2, 3.3).

Based on the processing flow described above, SCE products were generated using VIIRS and SGLI for the period from Apr. 2018 to Nov. 2024, and connected to the existing products derived from AVHRR (from Nov. 1982 to Feb. 2000) and MODIS (from Mar. 2000 to Mar. 2018). To distinguish between products derived from individual sensors, we assigned “GHR” to AVHRR, “M5C” to MODIS, and “SVC” to VIIRS-SGLI based products as their respective identifiers. The origins of these IDs are as follows. “GHR” derives from the fact that the “Data-type” ID for the AVHRR GAC data released by NOAA-CLASS which serves as the input data is “GHRR.” “M5C” stands for “MODIS 5-Channel,” indicating that the product uses only the five channels of MODIS. “SVC” stands for “SGLI VIIRS Combined data”. These IDs are used as file IDs on JASMES and are also used within the information published via DOI registration. In this study, to perform accuracy comparisons, we also generated M5C products derived from MODIS for the same time period (from Apr. 2018 to Nov. 2024) as the SVC products.

3.2 Detection of snow cover

In this product, as shown in Fig. 1 (b), pixels where the solar zenith angle is 88 degrees or higher are first classified as polar night, and all land areas meeting this condition are classified as “Dry snow.” Subsequently, cloud and clear classifications are performed based on the threshold tests (Table 2 of Hori et al. (2017) and Table 2 of this study), and multiple threshold tests are then applied only to pixels classified as clear weather to classify them into the five classes including snow cover as described above based on the threshold tests (Table 3 of Hori et al. (2017)).



3.3 Discrimination of dry and wet snow cover

Discrimination between dry and wet snow cover is performed using near-infrared reflectance at the wavelength of $0.8 \mu\text{m}$ ($Ref_{0.8}$) and thermal infrared BT at $11 \mu\text{m}$ (BT_{11}) according to the criteria of $Ref_{0.8} < 0.75$ and $BT_{11} > 270 \text{ K}$. The rationale for setting these criteria is based on previous studies (Hori et al., 2001; Hori et al., 2007), in which snow grain size was retrieved from the data of MODIS and Global Image (GLI, an optical sensor onboard a Japanese earth observation satellite named ADEOS-II) observations and its relationship with BT_{11} was investigated. The studies found that when the BT_{11} of the snow surface rose to 270 K or higher, the snow grain size (radius) increased drastically to $500 \mu\text{m}$ or larger (corresponding to the size of melt forms), indicating a state of snowmelt. Since $Ref_{0.8}$ of clean snow cover with grain size of larger than $500 \mu\text{m}$ is generally less than 0.75 , the conditional equations shown above are adopted for a simplified binary classification of dry and wet snow in the processing of this product. The accuracy of this binary classification is evaluated based on a conditional formula using air temperature as described below (Sect. 3.4.2).

3.4 Accuracy evaluation of snow cover detection

3.4.1 Snow cover

For the accuracy assessment of snow cover detection, in-situ snow depth (SD) data obtained from Global Historical Climate Network-Daily (GHCND) provided by NOAA/NCDC (Menne et al., 2012) and All-Russian Research Institute of Hydrometeorological Information-World Data Center (RIHMI-WDC) (Bulygina et al., 2025) were used. The GHCND dataset includes daily SD measurements from ground observation sites, whereas the RIHMI-WDC dataset includes both daily SD and snow cover percentage based on multiple observations in the vicinity of the observation sites. According to Hori et al. (2017), we used the same decision criteria for determining the existence of snow cover on the ground as follows;

Criterion 1: $SD \geq 2.5 \text{ cm}$ (1)

Criterion 2: The degree of snow coverage around the site $\geq 50 \%$ (only for RIHMI-WDC) (2)

The in-situ station data of SD were averaged weekly before comparison with the satellite data and used for the validation of the weekly aggregated SCE products based on the above criteria. Then, using the sample counts of the error matrix shown in Table 3, the SCE accuracies, that is, the overall accuracy (OA), user's accuracy (UA), and producer's accuracy (PA), were calculated. Note that the accuracy assessment was conducted using only data from locations where valid snow depth values were obtained at ground observations throughout the entire observation period (1982-2024). The followings are the equations for calculating the OA , UA , and PA :

$$OA = (n_{11} + n_{22}) / (n_{11} + n_{12} + n_{21} + n_{22}) \quad (3)$$

$$UA = n_{11} / (n_{11} + n_{12}) \quad (4)$$



$$PA = n_{11}/(n_{11} + n_{21}) \quad (5)$$

where n_{11} , n_{12} , n_{21} , n_{22} were the sample counts of the elements resulting from the comparison between the satellite and in-situ data, as defined in the error matrix of Table 3.

Table 3: Error matrix of sample counts n_{ij} . Satellite-derived classes are the rows while the in-situ station classes are the column.

Class		Reference: In-situ station		
		Snow	Non-Snow	Total
Satellite	Snow	n_{11}	n_{12}	$n_{1.}$
	Non-Snow	n_{21}	n_{22}	$n_{2.}$
	Total	$n_{.1}$	$n_{.2}$	n

3.4.2 Wet snow cover

For the accuracy assessment of wet snow detection, in-situ measured daily maximum surface air temperature ($T_{\max}$) obtained from GHCND were used. The criteria for determining the presence of wet snow cover were defined based on the weekly average of $T_{\max}$ ($T_{\max_weekly_ave}$) at each ground observation station and also on the percentage of days during the week when $T_{\max}$ exceeded 0 °C ($P_{T_{\max}>0\text{ °C}}$) using the following conditional formula;

$$\text{Criteria: } T_{\max_weekly_ave} > 0^{\circ}\text{C} \text{ and } P_{T_{\max}>0^{\circ}\text{C}} > 80\% \quad (6)$$

While it is not easy to define the conditions for the formation of wet snow based solely on air temperature, metrics such as Positive Degree Days, which accumulate the sum of above-freezing temperatures, and the number of consecutive days with temperatures at or above 0 °C are commonly used as criteria for the onset of snowmelt and also used to estimate the amount of snowmelt water in various studies (e.g., Martinec, 1975; Rango and Martinec, 1995; Ohmura, 2001; Hock, 2003; Ismail et al., 2023). Recently, Fontrodona-Bach et al. (2026) has shown that, in analyses using extensive data from the Northern Hemisphere, setting the snowmelt onset air temperature threshold at 0 °C captures 76% of snowmelt days. Therefore, using “0 °C” as the threshold to distinguish between dry snow and wet snow (the onset of snowmelt) is considered to be a simple yet highly effective approach. In addition, dry-to-wet snow transition is generally associated with several consecutive days of positive energy input or positive degree-day accumulation, which warms the snowpack toward an isothermal state and initiates meltwater percolation. Therefore, in this study, the conditions for the presence of wet snow were defined as follows.

During the one-week observation period, the average daily maximum temperature ($T_{\max_weekly_ave}$) must be 0 °C or higher, and on at least 80% of the days in that period (6 days per week) the daily maximum temperature ($T_{\max}$) must be 0 °C or higher.



285 The above criteria were used in this study for identifying the existence of the wet snow cover on the ground during the weekly aggregation period. Then, the accuracies of WSCE detection (OA , UA , PA) were calculated. As in the case of SCE, the assessment of WSCE accuracy was conducted using only data from locations where valid snow depth and air temperature values were obtained at the ground stations throughout the entire observation period (1982-2024).

3.5 Definition of snow cover variables

290 In this paper, we use JASMES snow cover products to calculate snow cover related metrics such as snow cover extent, snow cover frequency, and snow cover duration, and in Sections 4, we examine and discuss the characteristics of their long-term variations and spatial distributions, focusing primarily on the Northern Hemisphere (excluding the Antarctic region). In this section, we explain the definitions of each of these metrics.

3.5.1 Snow Cover Extent and Wet Snow Cover Extent

295 In this paper, SCE refers to the area of snow-covered land in the Northern Hemisphere, calculated based on snow cover flags (including dry and wet snow) stored in half-monthly aggregation data (weekly aggregated data were used only for validation purposes). Temporal resolution is therefore half-monthly. WSCE is calculated as the area of SCE consisting solely of wet snow cover flag. The units of SCE and WSCE are km^2 , and the temporal resolution is on a half-month basis.

3.5.2 Snow Cover Frequency

SCF (unit: %) is calculated for each pixel on a half-monthly basis and represents the proportion of years during the observation period (e.g., 22 years) in which snow cover was detected. The spatial distribution maps shown later display SCF values for both total snow cover (dry + wet snow) and wet snow cover alone, combined using color-coding (Sect. 4.5.1).

300 3.5.3 Snow Cover Duration

SCD is defined as the annual sum of the temporal fraction of snow cover calculated on a half-monthly basis, and is derived for every land pixel. The unit of SCD is months, and the temporal resolution is based on the temporal fraction of snow cover (Snowcover_Tfrac) stored in the aggregation product (half-monthly values ranging from 0 to 1).

3.5.4 Snow Melt Date

305 Snow melt date (SMD) is defined as a date (in month units) in December or later for which (1) the total duration of the past three half-months (i.e., 1.5 months) during which snow cover was present is 2.0 or longer (where 1.0 represents a half-month during which snow cover was present throughout the entire period); and (2) the total duration of snow cover over the next two half-months (1 month), including the current period, is shorter than 1.0. The temporal resolution of SMD is the same as SCD.



310 3.5.5 Snow Appearance Date

Snow appearance date (SAD) is defined as a date (in month units) in March or before where (1) the total duration of the past three half-months (i.e., 1.5 months) during which snow cover was present is 0.5 or shorter; and (2) the total duration of snow cover over the next two half-months (1 month), including the current period, is 1.5 or longer; and (3) where the difference between the total snow cover duration for the past three half-months (1.5 months) including the current period and the total snow cover duration over the next three half-months (1.5 months) is 1.0 or longer. The temporal resolution of SAD is the same as SCD.

3.6 Statistical Methods for Temporal Stability and Trend Analysis

In this paper, statistical tests were conducted to evaluate the temporal stability of SCE and WSCE detection accuracy and to determine the statistical significance of long-term trends in various snow cover variables (SCE, WSCE, SCD, SMD, and SAD). In most cases, the Mann-Kendall test was used to test the significance of trends, and the slope is represented by Sen's slope. The Theil-Sen robust linear regression method is used to calculate the regression line only when evaluating the temporal stability of the detection accuracy of SCE and WSCE.

4 Results and discussion

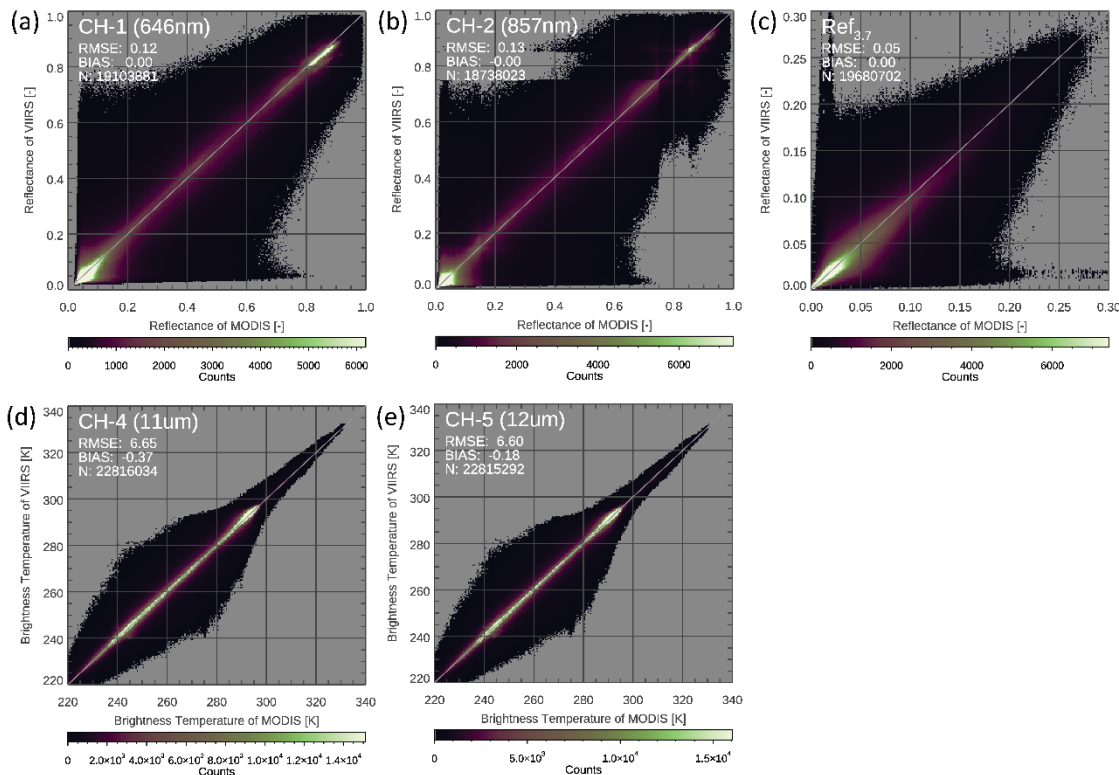
4.1 Radiance adjustments

Figures 2 and 3 show scatter plots comparing the adjusted reflectance and brightness temperature of VIIRS and SGLI with those of MODIS for five representative bands (plots for other bands not shown in Fig. 2 and Fig. 3 are included in the supplementary materials Fig. S1 and Fig. S2). Basically, VIIRS and MODIS have overlapping wavelength bands, and the reflectance and brightness temperature for both instruments are in good agreement across all bands (with the reflectance bias less than 0.5% and BT bias less than 0.4 K), allowing for conversion using simple linear formulas. As shown in Fig. 3, the reflectance and BT of SGLI also exhibit a good agreement with MODIS showing a generally linear relationship (with the reflectance bias less than 1.5% and BT bias less than 0.4 K) with the exception of the 2.2 μm band, where the reflectance values tend to be scattered (Fig. 3 (c)). Since SGLI lacks MODIS's mid-infrared 3.7 μm bands, it uses the 2.2 μm shortwave infrared band as a substitute. To compensate for this shortcoming, as mentioned earlier, we added a threshold test using the 1.38 μm band (see Sect. 3.1) to ensure the accuracy of cloud detection. Table 4 summarizes the conversion formulas used to convert from SGLI reflectance and brightness temperature values to MODIS-equivalent values.



340 **Table 4: Conversion formula used to convert SGLI reflectance and brightness temperature to MODIS equivalents.**

Threshold Test Variables for MODIS	SGLI variables	Conversion formula
$Ref_{0.6}$	$Refs_{0.6}$	$Ref_{0.6} = Refs_{0.6} \times 0.73/0.80$
$Ref_{0.8}$	$Refs_{0.8}$	$Ref_{0.8} = Refs_{0.8} \times 0.75/0.80$
$Ref_{3.7}$	$Refs_{2.2}$	$Ref_{3.7} = 46.699 \times Refs_{3.7}^2 - 0.3349 \times Refs_{3.7} + 8 \times 10^{-17}$ $Refs_{3.7} = Refs_{2.2} \times 0.05/0.30$
BT_{11}	BT_{S11}	$BT_{11} = BT_{S11}$
BT_{12}	BT_{S12}	$BT_{12} = BT_{S12}$
$BT_{3.7-BT_{11}}$	$Refs_{2.2}$	$BT_{3.7-BT_{11}} = 380.95 \times Refs_{2.2}^2 - 9.5238 \times Refs_{2.2} + 2 \times 10^{-13}$



345 **Figure 2: Scatter plots between the reference reflectance and brightness temperature from Aqua/MODIS and the adjusted reflectance and brightness temperature from VIIRS, shown for the band of (a) visible, (b) near infrared, (c) mid-infrared, (d) thermal infrared of 11 μ m, and (e) thermal infrared of 12 μ m.**

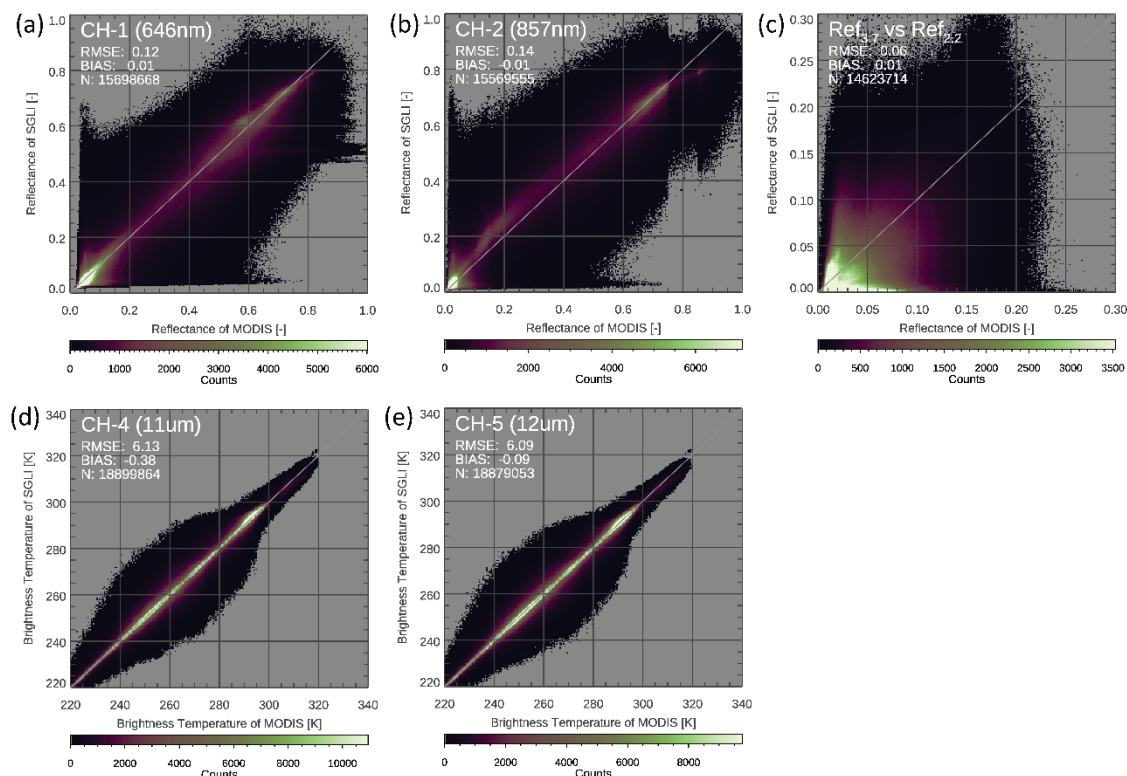


Figure 3: Scatter plots between the reference reflectance and brightness temperature from Terra/MODIS and the adjusted reflectance and brightness temperature from SGLI, shown for the band of (a) visible, (b) near infrared, (c) mid-infrared of 3.7 μm for MODIS and shortwave infrared of 2.2 μm for SGLI, (d) thermal infrared of 11 μm , and (e) thermal infrared of 12 μm .

4.2 Accuracy and uncertainty of snow cover detection

Since the seasonal and spatial variability in the accuracy of snow cover detection, the long-term stability, and the SCE error of the JASMES long-term snow cover product for the existing GHR and M5C periods have already been discussed in Hori et al. (2017), in this section, we describe the basic characteristics of the detection accuracy and uncertainty for snow cover and wet snow for the extended period covering the SVC period.

4.2.1 Snow cover

Figures 4 (a), (c), (e), and (g) show the long-term trends in OA , UA , and PA for the GHR-M5C snow cover product, while Figures 4 (b), (d), (f), and (h) show similar trends for the GHR-M5C-SVC product. All figures show data only for January, April, June, and October for the period from 1982 to 2024 (figures for other months are shown in Fig. S3 and Fig. S4). The gray dashed line indicates the fraction of ground stations where ground stations themselves detected snow cover (f_{GS}) and the



gray dotted line indicates the fraction of ground stations where the satellite detected snow cover (f_{SAT}), while the gray solid line indicates the number of ground stations (N_{GS}) used in the SCE validation.

The temporal coverage of SVC data in the GHR-M5C-SVC product is from April 2018 to November 2024, while the
 365 corresponding period for the GHR-M5C product utilizes MODIS (M5C) data. The number of ground station N_{GS} remained
 nearly constant at just under 700 (the actual number of ground stations used for validation is fixed at 700, but there are slight
 fluctuations because data are excluded when satellite pixels at a site are missing due to residual clouds, etc.). In contrast, f_{GS}
 and f_{SAT} exhibit a pattern of increasing in winter and decreasing in summer in accordance with snow cover extent. In addition,
 f_{SAT} tends to be slightly higher than f_{GS} in January and October for both GHR-M5C and GHR-M5C-SVC products, which
 370 indicates that satellites tend to overestimate snow cover in autumn and winter compared to ground stations, resulting in a
 tendency for UA (and consequently OA) to be lower than PA . The tendency for UA to be lower than PA is particularly
 pronounced in the autumn, indicating that SCE tends to be overestimated during that season. Hori et al. (2017) attempted to
 correct the SCE using the sample counts in the error matrix and indicated that, while the autumn SCE is overestimated by
 approximately $5\text{--}7 \times 10^6 \text{ km}^2$, this does not affect the long-term trend of the SCE itself. The potential SCE biases for other
 375 seasons estimated in Fig. 10 of Hori et al. (2017) are $2\text{--}3 \times 10^6 \text{ km}^2$ for winter, less than $1 \times 10^6 \text{ km}^2$, and $1 \times 10^6 \text{ km}^2$ for
 summer. Therefore, although the autumn SCE tend to be overestimated by about 20–30 percent, the long-term trend of SCE
 is considered to be valid for discussion.

The accuracy of SVC product (shown in the right column) shows values and variations equivalent to those of M5C (in the
 left column), indicating that both products possess equivalent accuracies. The accuracy of JASMES's SCE (OA , UA , PA)
 380 remains high at around 0.9 in winter and spring, and shows no significant long-term trends, maintaining stability (with the
 exception of the PA for October, which exhibits a slight negative trends). This trend has continued even during the SVC data
 period (2018–2024), when the input data transitioned from MODIS to VIIRS and SGLI. For comparison, the accuracies of
 NOAA-CDR's SCE were also plotted in Fig. S5 in which the accuracy (PA) of NOAA-CDR shows significant upward trend
 in October, November, and December, and during this period, the SCE of the NOAA-CDR exhibits an increasing trend from
 385 autumn through early winter.

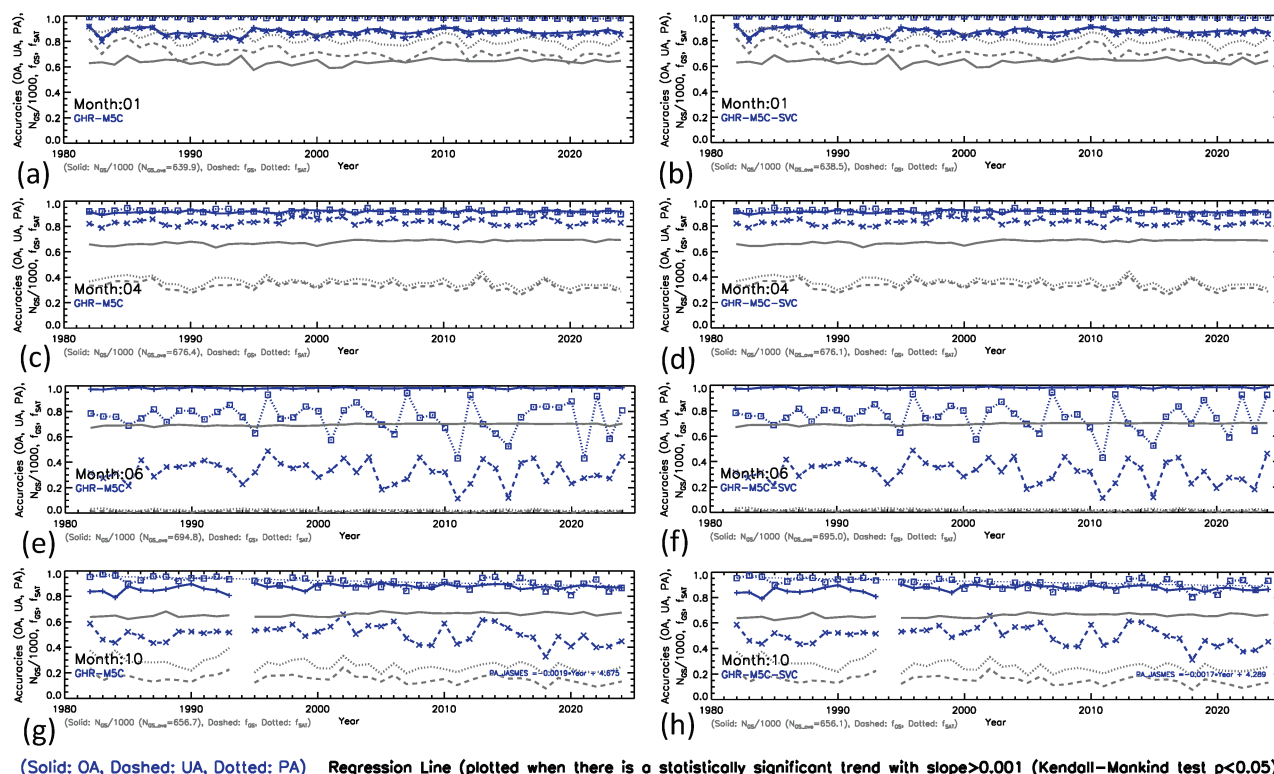


Figure 4: Long-term monthly trends in *OA*, *UA*, and *PA* for GHR-M5C snow cover product (left column) and GHR-M5C-SVC product (right column) for the period from 1982 to 2024 shown only for (a, b) January, (c, d) April, (e, f) June, and (g, h) October. Linear regression lines and equations with the slope and intercept calculated as the Theil-Sen robust line are shown only when the linear trend is statistically significant (Mann-Kendall test $p < 0.05$) and the slope is larger than $0.001 \text{ [year}^{-1}]$. Also shown are time series of the number of ground station (N_{GS}) used for the validation (gray solid line), fraction of ground stations where ground stations themselves detected snow cover (f_{GS}) (gray dashed line), and fraction of ground stations where the satellite detected snow cover (f_{SAT}) (gray dotted line).

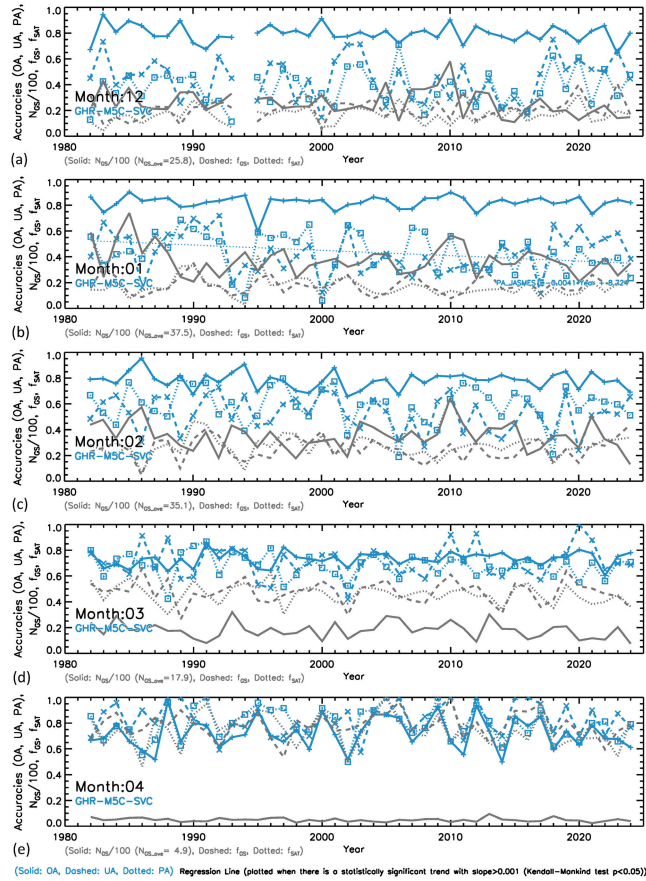


Figure 5: Long-term monthly trends in OA , UA , and PA for wet snow cover detection (based on the GHR-M5C-SVC product) shown only for (a) December, (b) January, (c) February, (d) March, and (e) April when wet snow cover extent becomes large at mid-latitude regions. Linear regression lines and equations with the slope and intercept calculated as the Theil-Sen robust line are shown only when the linear trend is statistically significant (Mann-Kendall test $p < 0.05$) and the slope is larger than $0.001 \text{ [year}^{-1}\text{]}$. Also shown are time series of the number of ground station (N_{GS}) used for the validation (gray solid line), fraction of ground stations where ground stations themselves detected wet snow cover (f_{GS}) (gray dashed line), and fraction of ground stations where the satellite detected wet snow cover (f_{SAT}) (gray dotted line).

4.2.2 Wet snow cover

Figures 5 (a) to (e) show the long-term trends of OA , UA , and PA for the wet snow cover detection of the GHR-M5C-SVC product during the period 1982–2024 shown only for December, January, February, March, and April when WSCE becomes larger at around the mid-latitude regions (figures for other months are shown in Fig. S6. The accuracy for the GHR-M5C product is almost similar to that of the GHR-M5C-SVC and figures omitted). The gray dashed and dotted lines indicate the fraction of ground stations where wet snow cover was detected by ground stations (f_{GS} for wet snow) and the satellite (f_{SAT}



410 for wet snow), respectively, while the gray solid line indicates the number of ground stations (N_{GS} for wet snow) used in the WSCE validation.

f_{SAT} for wet snow is slightly variable but without any long-term trends and nearly equivalent to f_{GS} for wet snow. The accuracy of WSCE shows that OA has remained stable at around 0.8-0.9. Furthermore, UA and PA do not exhibit the deviation observed in the SCE, and during the wet snow season in February and March, when WSCE increases in the
 415 Northern Hemisphere, the UA and PA show high values ranging from around 0.6 to 0.8. In addition, the accuracy also remains stable over the long term in any given month without any significant trends (with the exception of the January, when PA exhibits a negative trend). Although the number of ground stations for validation decreases, the high detection accuracy of WSCE persists even in April (Fig. 5 (e)). Therefore, it is expected that trends in the WSCE can be discussed during the snowmelt season in the Northern Hemisphere.

420 4.3 Connectivity between SVC and M5C products

Figure 6 (a) shows a seasonal comparison of the SCE for M5C and SVC during the overlapping period from 2018 to 2024. The SCE for SVC closely corresponds to that of M5C and follows its annual variations. Figure 6 (b) shows the difference of the SCE for SVC relative to that of M5C, expressed as a percentage. The range of the difference tends to increase during summer and autumn when the SCE is small, whereas that of the difference tends to decrease during spring and winter when
 425 the SCE is large. Calculating the average difference for the period from 2018 to 2024 reveals that it remains below 1% for all seasons (winter: -0.38%, spring: -0.86%, summer: 0.20%, and autumn: 0.14%). The difference between the SCE for M5C and those for SVC is negligible compared to the potential biases in SCE as discussed in Sec. 4.2, indicating that the SVC reproduces SCE values nearly equivalent to those of the M5C and thus can be considered that the data connection is functioning properly.

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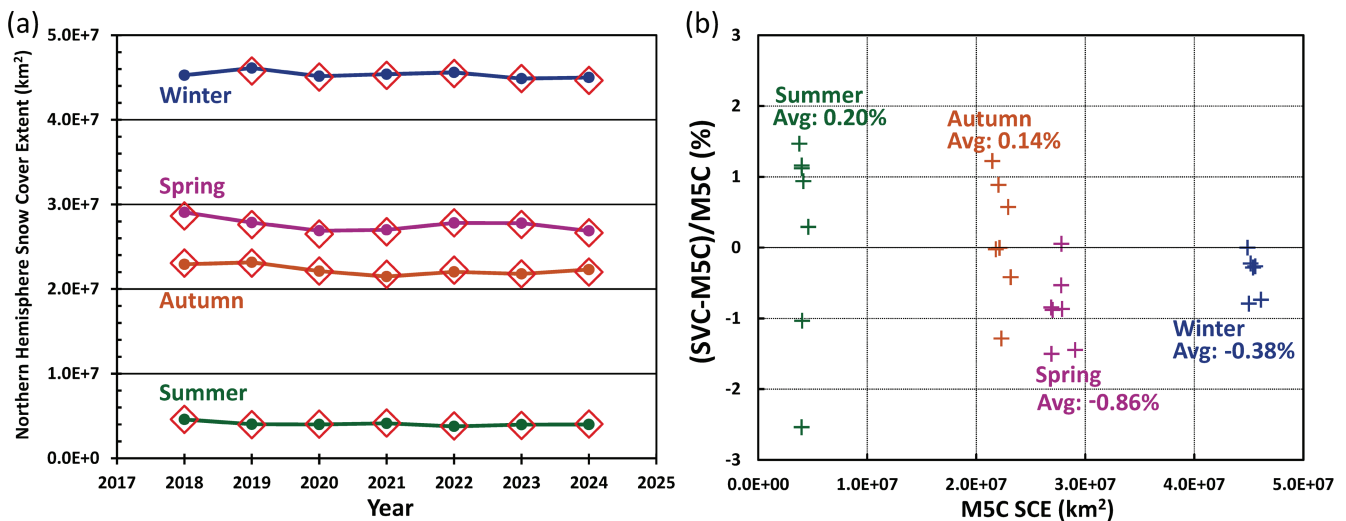


Figure 6: (a) Comparison of seasonally averaged SCE from M5C (circles with solid lines) and that from SVC (red diamonds) shown for the period from 2018 to 2024. (b) The average difference of SCE of SVC relative to that of M5C, shown by season.

435

4.4 Long-term trends in snow cover extent

4.4.1 Snow Cover Eextent

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Figure 7 shows the seasonal time-series variations in SCE for the Northern Hemisphere from 1979 to 2024. The data uses conventional GHR and M5C data through April 2018, and SVC data from April 2018 onward, which was generated by connecting and extending the SVC dataset. The solid lines representing summer and autumn in the figure indicate the presence of a statistically significant trend based on the Mann-Kendall test ($p < 0.01$), and the slopes represent the Sen's slopes. Consistent with the findings of Hori et al. (2017), it is evident that SCE in the Northern Hemisphere exhibits a negative trend, meaning it has continued to decrease across all seasons over the past 46 years.

445

However, when examining trends by dividing the period into two halves, the first and second halves, a different picture emerges. Figure 8 shows the Northern Hemisphere SCE time series divided into two periods of 1981–2002 and 2003–2024. In the first half of the period, the rate of decline in SCE was steep in every season, with indicating the significant trends in winter, spring and summer. However, in the second half, the rate of decline slowed across all seasons, and the downward trend has nearly disappeared in autumn. Considering that, as seen in Fig. 4 (h), the autumn snow cover detection rate (PA) is showing a slight negative trend, it is possible that the SCE has even begun to increase during the autumn. This suggests that the patterns of snowfall and snow accumulation in autumn have begun to differ from those in the first half of the period.

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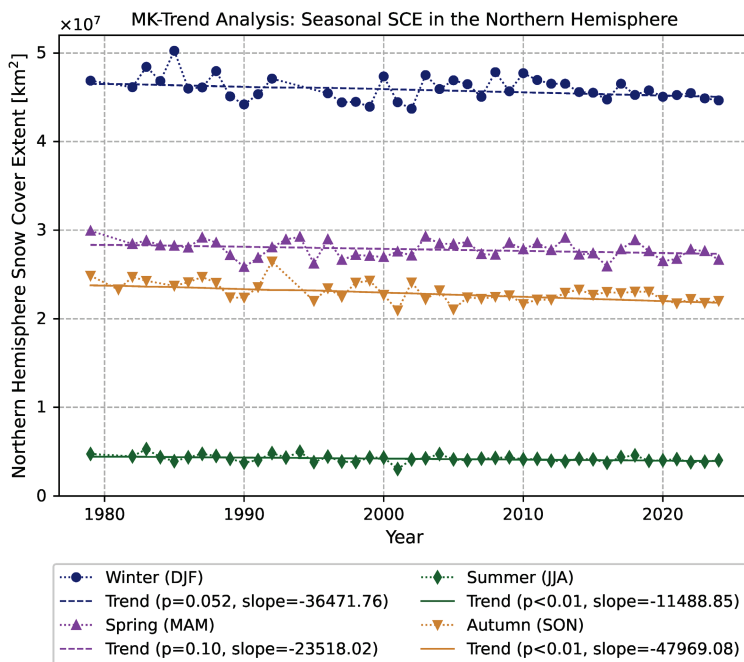


Figure 7: 46-year (1979-2024) trend of snow cover extent derived from GHR-M5C-SVC snow product (unit of slope: km²/year, indicated as Sen's slope). In the figure, statistically significant trends (Mann-Kendall test $p<0.05$) are shown as solid lines, while trends that are not statistically significant are shown as dashed lines.

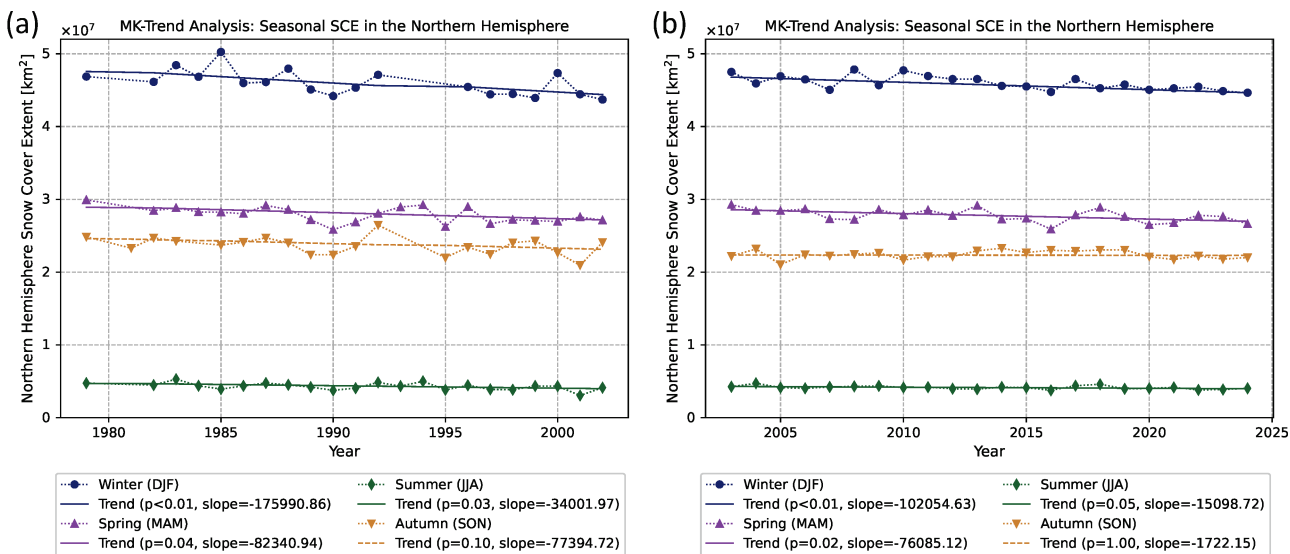


Figure 8: (a) 24-year (1979-2002) and (b) 22-year (2003-2024) trend of snow cover extent derived from GHR-M5C-SVC snow product (unit of slope: km²/year, indicated as Sen's slope). In the figure, statistically significant trends (Mann-Kendall test $p<0.05$) are shown as solid lines, while trends that are not statistically significant are shown as dashed lines.

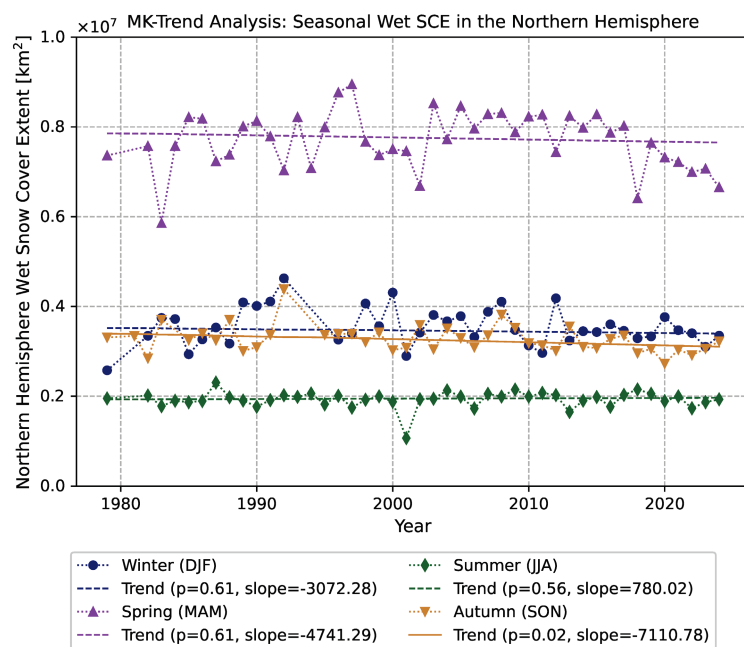


4.4.2 Wet Snow Cover Extent

Figure 9 shows the seasonal time-series variations of WSCE in the Northern Hemisphere. Although no clear signs of long-term variation are observed in WSCE, it is noted that WSCE reaches its maximum of around 8000000 km² in spring, remains roughly the same at around 3200000 km² in winter and autumn, and is at its minimum of around 2000000 km² in summer.

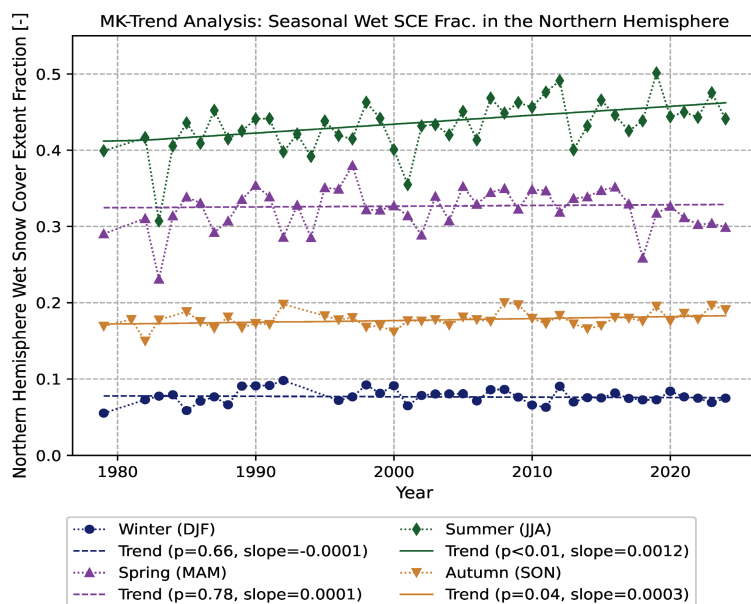
465 Figure 10 shows the variation in the ratio of WSCE to total SCE. While the area of WSCE itself is smallest in summer, its fraction relative to SCE is largest in summer. Next, comes spring, when the WSCE is at its largest, followed by autumn and winter, where the fraction of WSCE decreases as air temperature decreases.

Furthermore, an examination of the long-term trend in the WSCE fraction suggests that the summer fraction has been increasing in recent years. This is because, as shown in Fig. 7, while the SCE in summer exhibits a significant decreasing trend, no long-term trend is observed for WSCE (Fig. 9). In other words, this suggests that although the SCE is continuing to decrease, a constant proportion of wet snow cover persists throughout the summer under advancing global warming. A slight (but significant with $p < 0.05$) increase trend can also be found in autumn. This is also because the decline in SCE during the autumn exceeds the rate of decline in WSCE.



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Figure 9: 46-year (1979–2024) trend of wet snow cover extent derived from GHR-M5C-SVC snow product (unit of slope: km²/year, indicated as Sen's slope). In the figure, statistically significant trends (Mann-Kendall test $p < 0.05$) are shown as solid lines, while trends that are not statistically significant are shown as dashed lines.



480 **Figure 10: 46-year (1979–2024) trend of wet snow cover fraction derived from GHR-M5C-SVC snow product (unit of slope: /year, indicated as Sen’s slope). In the figure, statistically significant trends (Mann-Kendall test $p < 0.05$) are shown as solid lines, while trends that are not statistically significant are shown as dashed lines.**

4.5 Climatological applications of the SCE and WSCE products

485 As for the potential applications of the long-term JASMES SCE product presented in this paper, we will present case studies of applied analyses, such as the climatological values and long-term trends for the snow cover variables defined in Sect. 3.5, in the following sections.

4.5.1 Snow Cover Frequency

490 Maps for the long-term average of frequency distribution of snow cover and wet snow cover for late April (April 16 to 30) during the periods 1981–2002 and 2003–2024 are shown in Fig. 11 (a) and Fig. 11 (b) (maps for other half-month periods are shown in Fig. S7 and Fig. S8). As shown in the legend in the figures, areas with higher frequency of snow cover appear brighter, while areas with higher frequency of wet snow cover appear bluer. During both two periods, extensive areas of wet snow cover were observed in high-latitude regions of the Northern Hemisphere in late April, revealing that during this time (late April), the wet snow cover had expanded northward from the southern boundary of the continental snow cover.

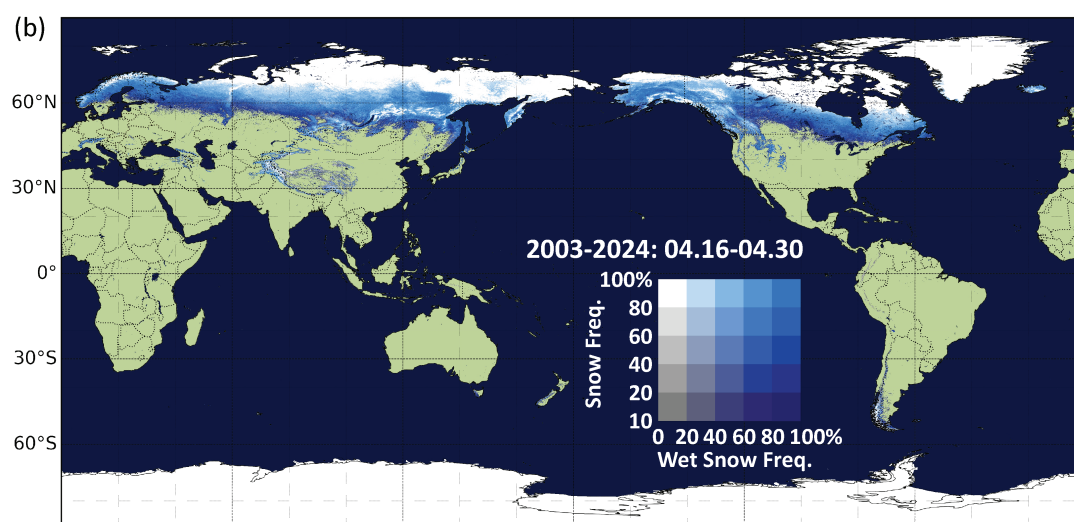
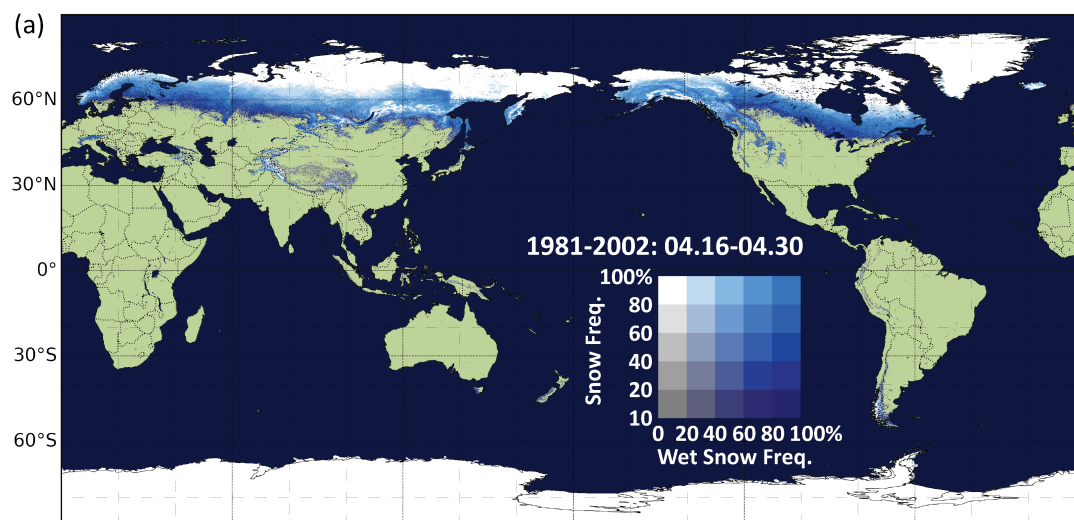
495 Figure 11 (c) is a composite image where SCF for 1981–2002 is colored in orange tones and that for 2003–2024 in blue tones shown only for late April (maps for other half-month periods are shown in Fig. S9), making the difference in frequency between the two periods clear (areas with no difference in frequency between the two periods appear gray to white). This



figure shows that, near the southern edge of snow cover, SCF was high in Europe and western Russia during the first period from 1981 to 2002 (shown in light orange, indicating that SCF decreased by 50-90% between the two periods), whereas during the latter period from 2003 to 2024, SCF was high in North America (primarily on the northeaster side of the Canadian Rockies) (shown in blue, indicating an increase in SCF of 50% or more). These results indicate that snow cover on continents does not uniformly decrease in frequency as global warming progresses, but rather exhibits different responses depending on the continent.

Figure 11 (d) shows a color composite image highlighting differences in wet snow cover frequency (WSCF) between the two periods shown only for late April (maps for other half-month periods are shown in Fig. S10). It displays only areas where SCF exceeded 40% in both periods, coloring areas with high WSCF frequency in the earlier period “purple” and areas with high frequency in the later period “dark green”. In snow covered regions, the WSCF extending southward increased in the latter period across the Eurasian continent and all of Alaska (shown in green tones, indicating that WSCF increased by 30-90% between the two periods), whereas it was higher in the earlier period in North America (excluding Alaska) (shown in purple tones, indicating a decrease in WSCF of 20-70%). These results are consistent with the fluctuations in SCF shown in Fig. 11 (c). That is, in Eurasian continent and Alaska, SCF decreased (while WSCF increased) due to a rise in temperatures during the latter period. In North America, however, temperatures fell, and SCF increased (while WSCF decreased).

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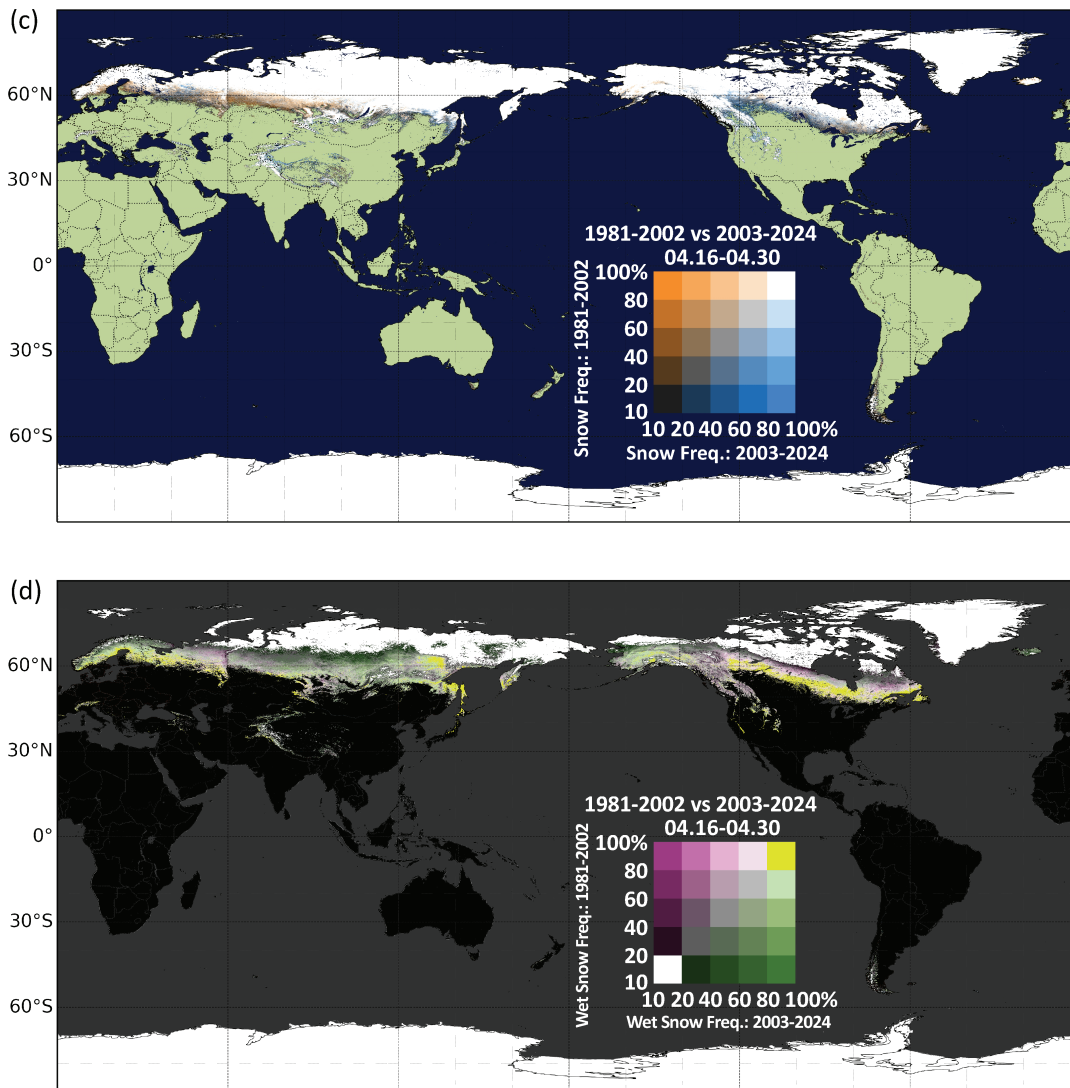


Figure 11: Upper: Spatial distribution map showing the frequency of snow cover and wet snow cover during the second half of April (periods: (a) 1981-2002, (b) 2003-2024, compiled over 22 years). Lower: (c) Spatial distribution map showing the frequency of snow cover during the second half of April from 1981 to 2002 and from 2003 to 2024. The data for each period are color-composited in orange and blue, respectively (areas with identical frequency across both periods show a gray-to-white gradient), and (d) Spatial distribution map showing the frequency of wet snow cover during the second half of April from 1981 to 2002 and from 2003 to 2024. The data for each period are color-composited in purple and dark green, respectively (areas with identical frequency across both periods show shades from gray to yellow). Areas with snow cover frequency $\geq 40\%$ in both periods are depicted.



4.5.2 Snow Cover Duration

Figures 12 (a) to (c) shows the climatological maps of SCD for a 44-year period (1981-2024, but excluding 1993-1994 due to the lack of valid AVHRR data), a 22-year period (1981-2002, excluding 1993-1994), and 22-year (2003-2024), respectively. Figure 12 (d) shows map of the difference in SCD between the second and first periods (i.e., SCD (2003-2024) – SCD (1981-2002)). Examining the climatological distribution of SCD in the Northern Hemisphere, SCD tends to be longer up to 12 months at high latitudes, while it tends to be shorter, less than one month, at low latitudes. Compared to the SCD in the first period, the SCD in the second period tends to be shorter in Western Eurasia (the reddish area in Fig. 12 (d)) and longer in inland Asia and North America (the bluish areas). In particular, the north-south contrast in the high-mountain regions of Asia is consistent with the findings of Yao et al. (2022), who discuss the water balance imbalance in the Asian Water Tower (AWT) surrounding the Tibetan Plateau.

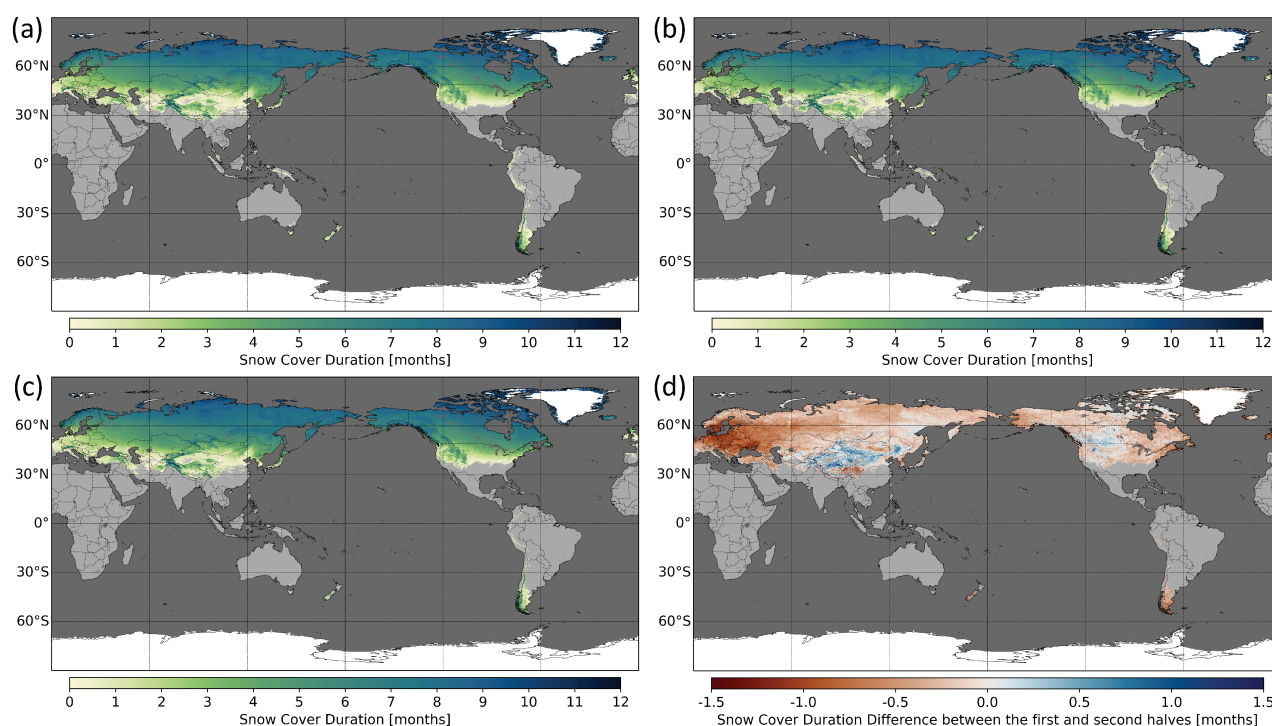


Figure 12: (a) Spatial distribution of 44-year average of SCD for M5C+SVC (1981-2024, excluding 1993-94, 1994-95), (b) Spatial distribution of 22-year average of SCD for M5C+SVC (1981-2002, excluding 1993-94, 1994-95), (c) Spatial distribution of 22-year average of SCD for M5C+SVC (2003-2024), and (d) Spatial distribution of difference between the 1st and 2nd periods of SCD for M5C+SVC.



4.5.3 Snow Melt Date

Figures 13 (a) to (c) shows the climatological map of SMD for a 44-year period (1981-2024, excluding 1993-1994), a 22-year period (1981-2002, excluding 1993-1994), and 22-year (2003-2024), respectively, and Fig. 13 (d) shows map of the difference in SMD between the second and first periods (i.e., SMD (2003-2024) – SMD (1981-2002)). Spatial distribution of SMD climatology shows that SMD in the Northern Hemisphere tends to lag behind until June to July at high latitudes, while it tends to lead by around December to January at low latitudes. In South America, particularly near the southern tips of Chile and Argentina, SMD occurs around September. Compared to SMD in the first period, as in the case with the SCD case, SMD in the second period tends to occur earlier in western Eurasia while occurring later in inland Asia and North America; this is thought to contribute to some extent to the slight attenuation of the negative SCE trend in the Northern Hemisphere during spring shown in Fig. 8.

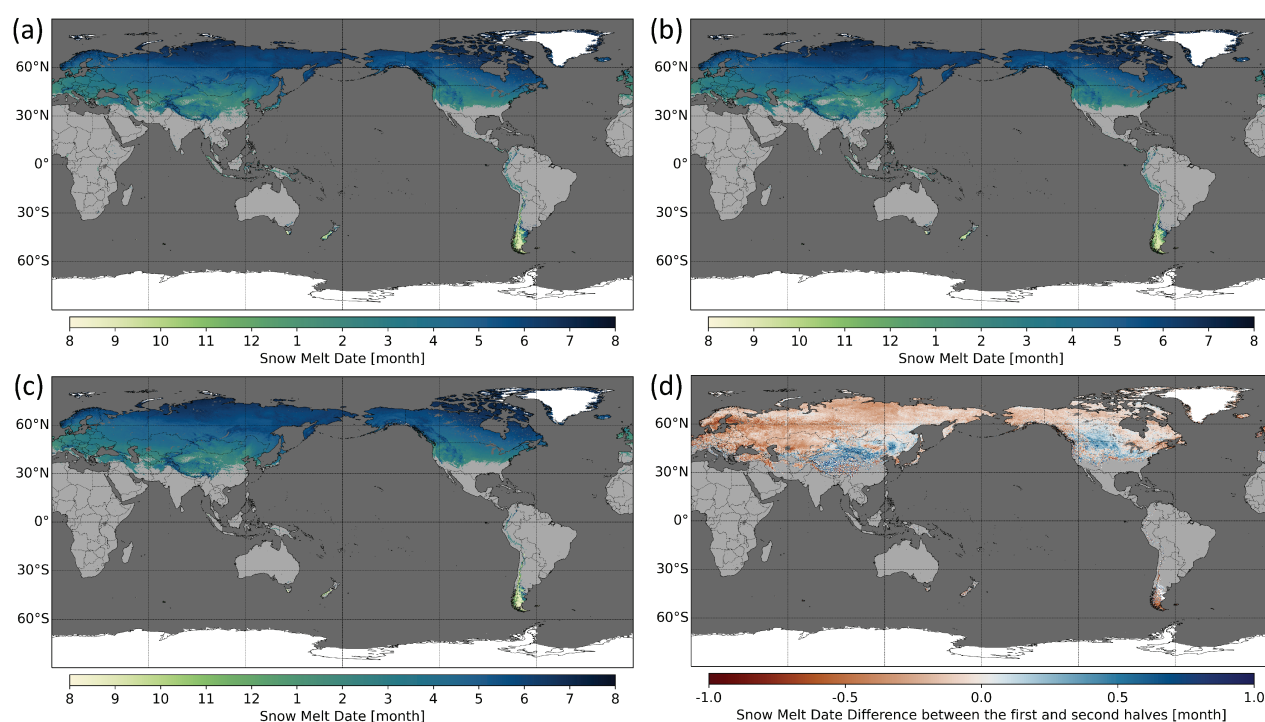


Figure 13: (a) Spatial distribution of 44-year average of SMD for M5C+SVC (1981-2024, excluding 1993-94, 1994-95), (b) Spatial distribution of 22-year average of SMD for M5C+SVC (1981-2002, excluding 1993-94, 1994-95), (c) Spatial distribution of 22-year average of SMD for M5C+SVC (2003-2024), (d) Spatial distribution of difference between the 1st and 2nd periods of SMD for M5C+SVC.



565 4.5.4 Snow Appearance Date

Figures 14 (a) to (c) shows climatological map of SAD for a 44-year period (1981-2024, excluding 1993-1994), a 22-year period (1981-2002, excluding 1993-1994), and 22-year (2003-2024), respectively, and Fig. 14 (d) shows map of the SAD difference between the second and first periods (i.e., SAD (2003-2024) – SAD (1981-2002), note that the color in the color map is mirrored compared to Fig. 12(d) and Fig. 13 (d)). Spatial distribution of SAD climatology shows that SAD in the Northern Hemisphere tends to lead by around September to October at high latitudes, while it tends to lag behind until December to January (nearly the same timing as the SMD) at low latitudes. In South America, at the southern tips of Chile and Argentina, SAD occurs around May. Compared to SAD in the first-period, the second-period SAD occurs later in western Eurasia, coinciding with the earlier onset of SMD. Therefore, it is evident that the shortening of the SCD in western Eurasia seen in Fig. 12 (d) is influenced not only by the earlier onset of the SMD but also by the delay in the SAD.

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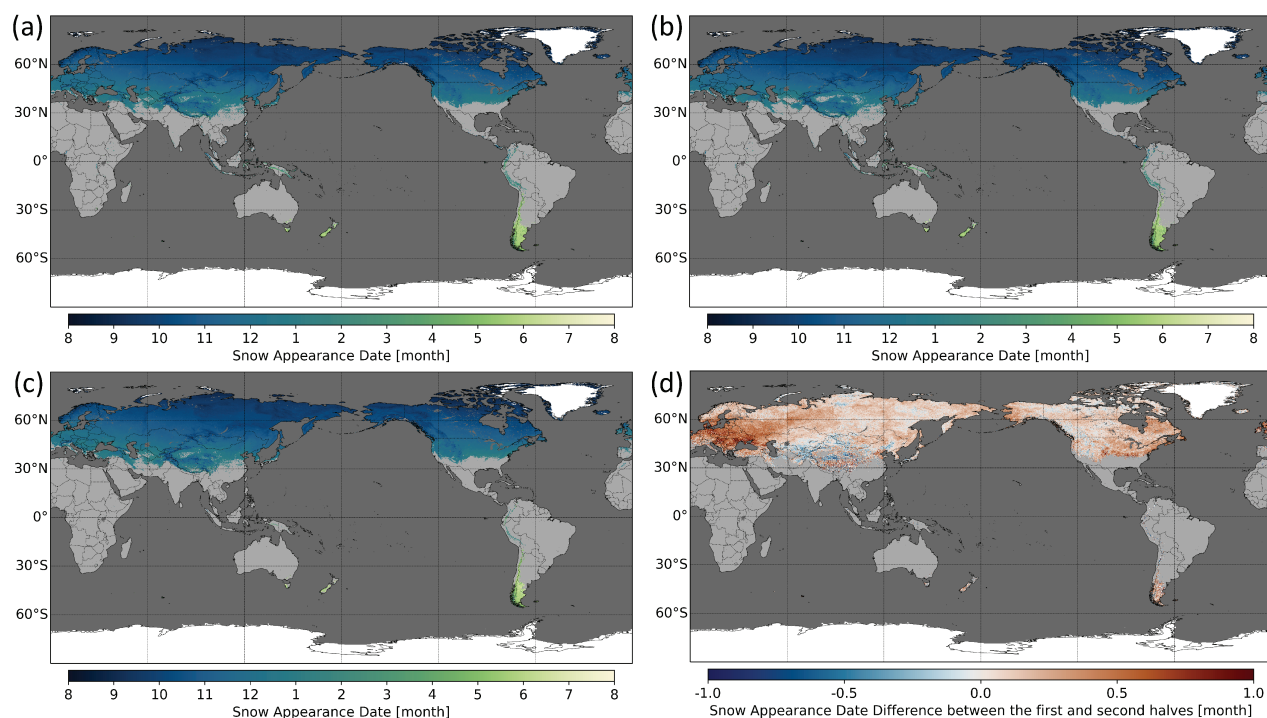


Figure 14: (a) Spatial distribution of 44-year average of SAD for M5C+SVC (1981-2024, excluding 1993-94, 1994-95), (b) Spatial distribution of 22-year average of SAD for M5C+SVC (1981-2002, excluding 1993-94, 1994-95), (c) Spatial distribution of 22-year average of SAD for M5C+SVC (2003-2024), (d) Spatial distribution of difference between the 1st and 2nd periods of SAD for M5C+SVC (Note that the color in the color map is mirrored compared to Fig. 12(d) and Fig. 13 (d)).

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4.5.5 Long-term trends of SCD, SMD, and SAD

Figures 15, 16, and 17 are maps showing the long-term trends in SCD, SMD, and SAD, respectively, over a 44-year period (1981-2024). As can be inferred from the discussion of the two-period difference in SCD (Fig. 12 (d)), a significant trend toward shortening is observed in western Eurasia, while weak lengthening trends can be seen in the interior of Asia and North America. The shortening of SCD in western Eurasia is consistent with the analysis by Hori et al. (2017), indicating that this trend has continued even when data from 2015 onwards are included. Examining the trends in SMD and SAD reveals that, as also mentioned in the previous section, the significant shortening of SCD in western Eurasia is influenced by both the earlier onset of SMD and the delay in SAD. On the other hand, the positive trends in SCD in Asia and North America shown in Fig. 15 have low statistical significance, and the trends in SMD and SAD are also weak and unclear (though they change somewhat when the statistical period is altered (figure omitted)).

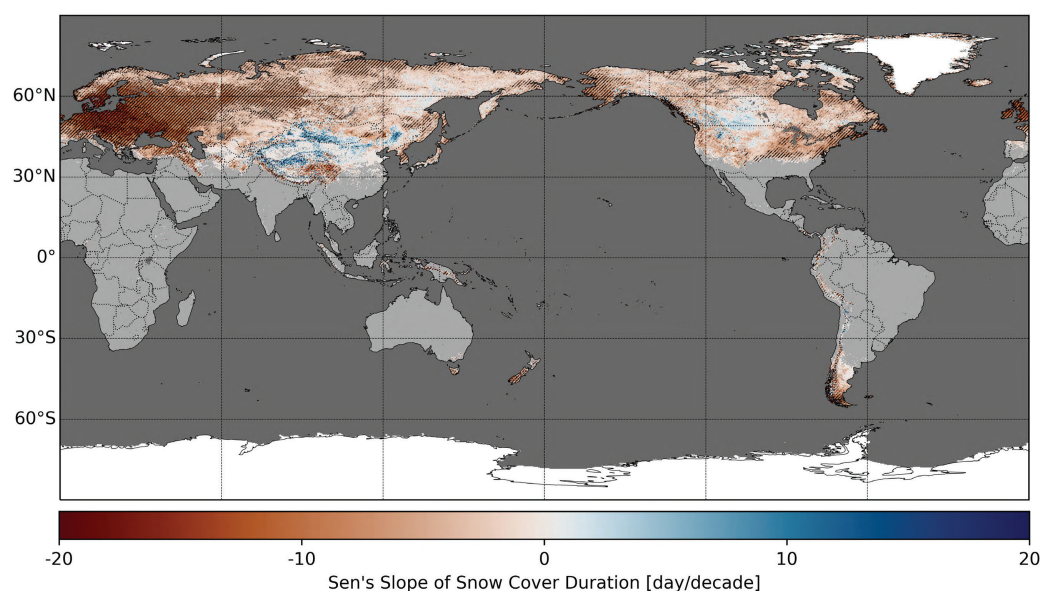


Figure 15: Spatial distribution of 44-year (1981-2024) trend of SCD (day/decade, indicated as Sen's slope) derived using the long-term GHR-M5C-SVC based snow cover product. The shaded areas indicate statistically significant regions (Mann-Kendall test $p < 0.05$).

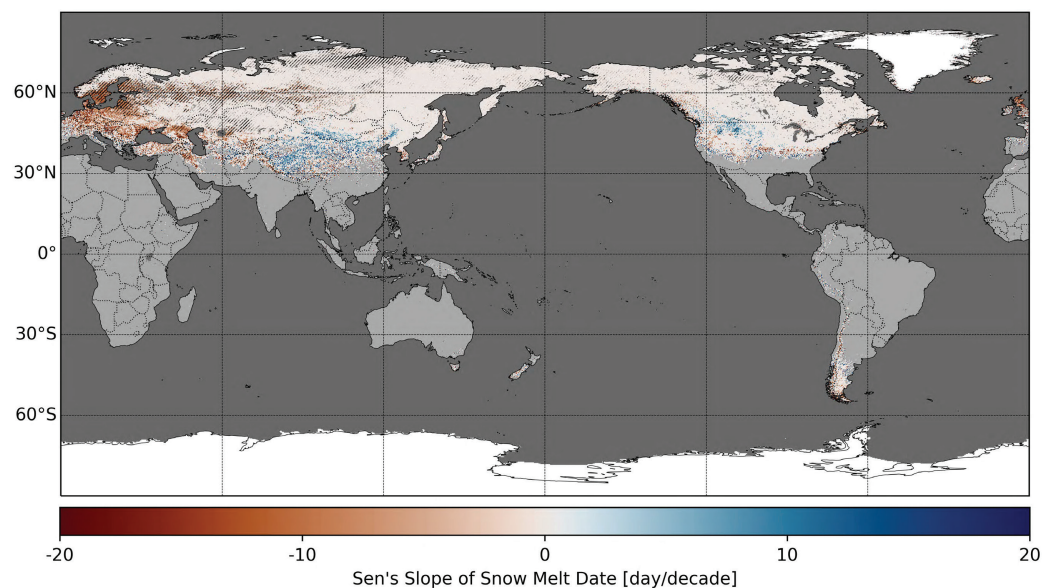


Figure 16: Spatial distribution of 44-year (1981-2024) trend of SMD (day/decade, indicated as Sen's slope) derived using the long-term GHR-M5C-SVC based snow cover product. The shaded areas indicate statistically significant regions (Mann-Kendall test $p < 0.05$).

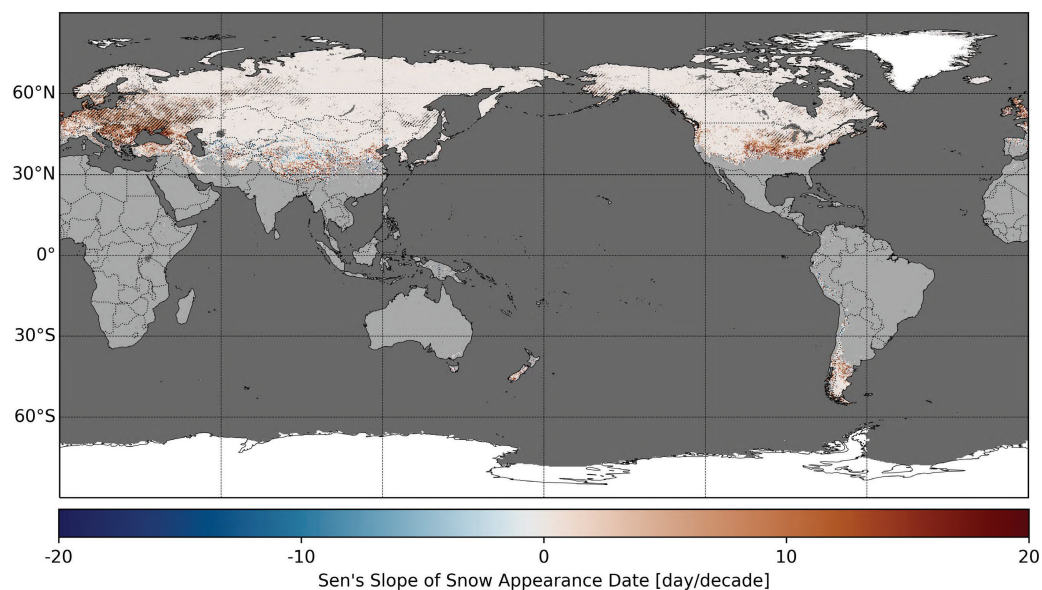


Figure 17: Spatial distribution of 44-year (1981-2024) trend of SAD (day/decade, indicated as Sen's slope) derived using the long-term GHR-M5C-SVC based snow cover product. The shaded areas indicate statistically significant regions (Mann-Kendall test $p < 0.05$) (Note that the color in the color map is mirrored compared to Fig. 15 and Fig. 16).



5 Summary and Conclusions

This study extends the JASMES global snow cover product by replacing MODIS with the successor optical sensors VIIRS and SGLI while preserving consistency with the historical AVHRR–MODIS record. Cross-sensor radiometric calibration and sensor-specific cloud detection algorithms were developed to ensure seamless continuity of snow cover detection, allowing VIIRS–SGLI products to reproduce MODIS-derived snow cover with comparable accuracy. Validation against in-situ observations confirms that the long-term performance of the JASMES snow cover and wet snow cover products remain stable across sensor transitions. The resulting dataset provides a continuous daily global snow cover record from 1979 to 2024 for robust analyses of long-term changes in snow cover extent, duration, and wet snow occurrence. Daily, half-monthly, and monthly snow cover extent products are publicly available as DOI-registered datasets through JAXA, ensuring long-term accessibility and reproducibility. The incorporation of VIIRS and SGLI establishes the basis for the continued production of JASMES as a consistent satellite-derived snow cover climate data record extending beyond four decades toward a half-century time series.

620 Data availability

The JASMES Northern Hemisphere snow cover extent dataset presented in this paper is publicly available from the JAXA Satellite Monitoring for Environmental Studies (JASMES) website (product name: snwcfrr_JXAM5_M5C, product ID: SNWFG). The dataset provides daily, half-monthly, and monthly snow cover extent products on a 0.05° latitude–longitude grid covering the Northern Hemisphere from 1978 to the present. All products are distributed in HDF4 format together with metadata and user documentation. There are no restrictions on the use of these data; however, registration with the JASMES user registration system is required to download the files. For daily, half-monthly, and monthly datasets, detailed information regarding user registration and usage constraints is available on the pages linked to the individual DOIs listed below;

625 <https://doi.org/10.57746/EO.01jcyddbzbqjvsrh2anaqebprjv> (JAXA, 2026a),
<https://doi.org/10.57746/EO.01jcyddr5vq45k72a6kbq88sdg> (JAXA, 2026b),
630 <https://doi.org/10.57746/EO.01jcyddyzsxdcvmf6vy9v147b> (JAXA, 2026c).

Author contributions

MH designed the study, processed the data related to the results presented in Sect. 4, and prepared the original draft of the manuscript. MN, RS, and TA evaluated the analysis results. RS acquired, processed, and curated the satellite data. MH, MN, and TA acquired and managed the research funding. All authors discussed the results, reviewed the manuscript, and approved the final version.

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Competing interests

The authors declare that they have no conflict of interest.

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Stewardship System (CLASS). The NOAA/NCDC weekly snow cover extent data (EASE-Grid 2.0 version) were provided
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645 generation of scientific results. All AI-assisted content was reviewed and revised by the authors, who take full responsibility
for the final content of the manuscript.

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