

Research papers

Integrated evaluation of snow density reanalysis products in the Northern Hemisphere

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ABSTRACT

Snow density, as a key snow element, not only reflects the physical characteristics of snow cover but also plays a vital role in data assimilation, climate modeling, and hydrological cycle studies. However, systematic evaluations of snow density in reanalysis datasets are still lacking. In this study, we use 4,319 snow stations across major snow-covered regions in the Northern Hemisphere, to assess the applicability of snow density data from five widely used reanalysis datasets (ERA5-Land, GLDAS-Noah, GLDAS-CLSM, GLDAS-VIC, and JRA-3Q) during water year 2001–2023. Our results indicate that ERA5-Land and GLDAS-Noah better capture the spatial patterns and temporal variability of snow density across the study regions. Using these two datasets and in-situ observations, we analyze long-term trends of snow density in Canada, Russia, and the Western U.S. We find that, reanalysis datasets fail to reproduce the observed interannual trends. Reanalysis products tend to underestimate observed interannual changes of snow density in early winter or shift them to late winter months. Moreover, the impact of snow density biases on snow depth biases in reanalysis datasets varies by region and dataset through offsetting or amplifying snow water equivalent biases. This study provides a comprehensive evaluation of snow density accuracy in reanalysis datasets, and reveals the distinct spatiotemporal trends in snow density under global warming. Our results also highlight the divergent contribution of snow density biases to snow depth biases in reanalysis datasets across regions.

1. Introduction

Snow cover is a critical part of the cryosphere. It affects climate system by influencing the radiative processes and hydrologic cycle, and also serves as a vital freshwater resource (Brown and Goodison, 1996; Sturm et al., 2002; Barnett et al., 2005; R. Armstrong and Brun, 2008; Bookhagen and Burbank, 2010; Immerzeel et al., 2010; R. L. Armstrong et al., 2019). Snow cover also has a high albedo and low thermal conductivity, which has a significant impact on the surface energy balance (Robock, 1980; Brown, 2000; Hansen and Nazarenko, 2004). As an indicator of climate change, the spatial and temporal characteristics of the snow cover are undergoing rapid changes (Intergovernmental Panel on Climate Change (IPCC), 2022).

Snow density is a macroscopic manifestation of the microphysical characteristics of snow cover, which is significantly related to snow thermal and radiative properties (Sturm et al., 1997; Gergely et al.,

2010; Surendar et al., 2015). Snow density is also a fundamental parameter in land surface models (Koren et al., 1999; Livneh et al., 2010; Dawson et al., 2017), and plays a key role in various snow-related studies, such as avalanche forecasting (Schweizer et al., 2003), snow remote sensing applications (Hannula et al., 2016), and climate prediction (Cao et al., 2020). Furthermore, bulk snow density is commonly used to estimate snow water equivalent (SWE) from snow depth (SD) (Jonas et al., 2009; Sturm et al., 2010; McCreight and Small, 2014), thus profoundly influencing hydrological cycle studies and water resource assessment and management.

More than 98% of global seasonal snow cover occurs in the Northern Hemisphere, making it the primary focus for studies on snow variability and change. Due to variations in geographical location, topography, and landforms across different snow-covered regions, snow density exhibits significant spatial differences. Zhao et al. (2023) reported substantial variation in average snow density across the Northern Hemisphere,

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ranging from 50 to 600 kg/m³. Overall, snow density in North America is higher than that in Eurasia (Mizukami and Perica, 2008; Zhong et al., 2014; Zhao et al., 2023). Specifically, snow in the Coast Ranges along the Canada–US border exhibits the highest average density—exceeding 350 kg/m³—despite its limited spatial extent. In contrast, more widespread snow across much of the mid- to high-latitude regions of Eurasia and North America generally shows lower average densities, typically ranging from 200 to 250 kg/m³ (Zhong et al., 2014; Zhao et al., 2023). In the Northern Hemisphere, snow density in China is comparatively low, with annual mean values typically around 150 kg/m³ (H. Wang et al., 2023), which is lower than those observed in most other major snow-covered regions. In terms of temporal characteristics, a study on the former Soviet Union reported notable interannual variations in snow density (Zhong et al., 2014), whereas most other studies suggested that regional snow density exhibits little interannual variability (Bormann et al., 2013; Jonas et al., 2009; Mizukami and Perica, 2008; Peter Kershaw and McCulloch, 2007; Sturm et al., 2010). However, the lack of long-term studies leads to uncertainties in these conclusions. Regarding intra-annual variations, it is widely acknowledged that snow density gradually increases throughout the water year due to snowfall and densification processes (Brun et al., 1992; Sturm and Holmgren, 1998; Roebber et al., 2003). Nonetheless, it remains unclear whether the characteristics of the seasonal cycle of snow density have changed under climate change.

Previous researches mainly concentrate on local-scale snow density changes (Bormann et al., 2013; Mizukami and Perica, 2008; Peter Kershaw and McCulloch, 2007; Zhong et al., 2014), with few studies addressing the overall characteristics across the Northern Hemisphere. Further, due to the uneven distribution of in-situ stations and variations in the length of their records, comprehensive monitoring of snow-covered regions remains challenging (Fayad et al., 2017; Yang et al., 2019). These limitations result in substantial spatiotemporal heterogeneity in the data, thereby increasing uncertainties in the conclusions.

In recent years, reanalysis datasets have become essential data sources for studying snow variation and their responses to climate change, owing to their advantages of long temporal coverage, broad spatial extent, and homogeneity. Previous studies have evaluated the accuracy of variables such as SD, SWE, and snow cover fraction (SCF), while snow density has been largely overlooked (Bian et al., 2019; Xiao et al., 2020; Mortimer et al., 2020; Zhang et al., 2021; Kouki et al., 2023; Yan et al., 2024). In the limited studies evaluating snow density, Gao et al. (2022) found that the snow density output from ERA5 and ERA5-Land is closer to observations in China compared to that from ERA-Interim, although they still underestimate snow density and fail to accurately capture the snow densification process. Dawson et al. (2017) found that NLDAS-Noah underestimates snow density during the early snow season, while the density increases rapidly after March, deviating from SNOTEL data. However, these studies are limited to specific regions and provide only a coarse evaluation of a few reanalysis datasets, lacking a comprehensive assessment of snow density from more reanalysis datasets across the Northern Hemisphere.

In this study, we integrate observations from 4,319 snow sites across the Northern Hemisphere and use this dataset to evaluate the accuracy of snow density data in five reanalysis datasets (ERA5-Land, GLDAS-Noah, GLDAS-CLSM, GLDAS-VIC, and JRA-3Q) from water year 2001 to 2023. The evaluation covers spatial patterns, monthly variations, annual trends, and SD-dependent biases. Furthermore, we employ the best-performing reanalysis datasets and observations to analyze long-term snow density variations in Canada, Russia, and the Western United States. Finally, we discuss the impact of snow density on the accuracy of SD estimates in reanalysis datasets.

2. Data

2.1. In-situ data

In this study, we integrate snow density observations from 4,319 snow sites from multiple nations over the Northern Hemisphere (Table 1). In Canada, we use Canadian historical Snow Water Equivalent dataset (CanSWE, 1928–2023) (Vionnet et al., 2024), which includes manual and automated pan-Canadian observations of SWE, SD and derived bulk snow density. The dataset for Russia originates from the Russian Research Institute for Hydrometeorological Information–World Data Center, which has recorded snow density from 517 stations since 1966 through snow course surveys. For the Western United States and Alaska, the data is from 881 automated Snowpack Telemetry (SNOTEL) stations. The manual observations mostly occur every 5–10 days or biweekly, whereas the majority of automated stations maintain daily records.

Before using these in-situ data for the throughout analysis, we conduct careful quality control (QC) processes. For Russia, QC followed the criteria proposed by the National Snow and Ice Data Center (NSIDC) and previous studies (Zhong et al., 2014; Zhao et al., 2023). Specifically, SD values less than 1 cm or greater than 200 cm and SWE values greater than 400 mm are removed. Also, records with snow density below 50 kg/m³ or above 600 kg/m³ are eliminated. For SNOTEL data, we apply QC procedures similar to those used in earlier work (Mizukami and Perica, 2008; Serreze et al., 1999; Zhao et al., 2023; Dawson et al., 2016). We first examine day-to-day changes in SWE and SD. If the change in SWE (SD) between two consecutive days exceed 200 mm (50 cm), the record is considered erroneous and excluded. When a zero value of SWE (SD) appears between two consecutive nonzero days, the zero is also removed. In addition, we exclude records with snow density below 50 kg/m³ or above 700 kg/m³. Previous studies found that snow density in the Western US is relatively high, sometimes exceeding 600 kg/m³ (Mizukami and Perica, 2008), so a higher upper threshold is used compared with Russia. Snow data in Canada is already subject to rigorous QC (Brown et al., 2019), so we use them directly.

2.2. Reanalysis data

We select reanalysis datasets based on the criterion that they either provide snow density directly or include both SD and SWE outputs, from which snow density can be derived. Accordingly, the reanalysis datasets employed in this study are detailed in Table 1. Specifically, GLDAS-2 drives three land surface models (LSMs): Noah, Catchment (CLSM), and the Variable Infiltration Capacity (VIC), resulting in different snow density. Therefore, we evaluate them separately.

ERA5-Land (ERA5-L) dataset, published by the European Centre for Medium-Range Weather Forecasts (ECMWF), is generated by replaying

Table 1
Data information for this study.

Data type	Country	Number of sites	Period
In-situ data	Canada	2921	1928–2023
	Russia	517	1966–2023
	United States	881	1994–2023
Data type Reanalysis data	Dataset	Land model	Spatiotemporal resolution
	ERA5-L	HTESSEL	1950–2023, hourly, 0.1° × 0.1°
	GLDAS-2.1	Noah	2000–2023, 3 h, 0.25° × 0.25°
		CLSM	2000–2023, 3 h, 1.0° × 1.0°
		VIC	2000–2023, 3 h, 1.0° × 1.0°
	GLDAS-2.0	Noah	1948–2014, 3 h, 0.25° × 0.25°
	JRA-3Q	Improved SIB	1947–2023, 6 h/daily, 40 km

the land component of the ERA5 climate reanalysis (Muñoz-Sabater et al., 2021). ERA5-L uses the Tiled ECMWF Scheme for Surface Exchanges over Land (HTESSEL) model to simulate snow cover accumulation and melt processes with a single snow layer, and does not assimilate snow observations. In land surface snow schemes, bulk snow density reflects wind- and temperature-dependent new snow density, overburden compaction, temperature-sensitive metamorphism, and densification linked to liquid-water storage and refreezing. During snowfall, snow density is updated by mixing existing snow with new snowfall—whose density depends on near-surface temperature and wind speed—using a weighted average of the two (Dutra et al., 2010).

Version 2 of the Global Land Data Assimilation System (GLDAS-2), developed by NASA and NOAA, consists of three sub-versions: GLDAS-2.0, GLDAS-2.1, and GLDAS-2.2 (Rodell et al., 2004). GLDAS-2.0 is driven entirely by the global meteorological forcing dataset from Princeton University (Sheffield et al., 2006), whereas GLDAS-2.1 uses a combination of observational and model data. In this study, we evaluated GLDAS-2.1 in detail (GLDAS in Section 4.1, 4.2 and 4.3 refers to GLDAS-2.1). Additionally, GLDAS-Noah (v2.0) was included for long-term analysis, considering its extended time coverage and good spatial accuracy. Notably, neither GLDAS-2.0 nor GLDAS-2.1 incorporates snow observation assimilation (Bian et al., 2019).

The Japanese Reanalysis for Three Quarters of a Century (JRA-3Q; Kosaka et al., 2024) is the third long-term reanalysis product developed by the Japan Meteorological Agency (JMA). For land surface analysis, the use of an online model in JRA-3Q enables interactions between atmospheric and land surface processes. LSM in JRA-3Q is the JMA Simple Biosphere (SiB) model, which incorporates a new snow scheme with up to four layers. This scheme considers the increase in snow density due to compaction. Notably, although JRA-3Q provides a snow density variable in its snow analysis fields, this variable represents the mass density of solid components in snow rather than the bulk snow density. Therefore, in this study, bulk snow density is calculated based on available SWE and SD fields. Additionally, the SD analysis in JRA-3Q incorporates observational data assimilation, potentially impacting its performance in snow simulations (Kosaka et al., 2024).

3. Methods

3.1. Data preprocessing and study sub-regions

All reanalysis data are first remapped to a uniform $0.1^\circ \times 0.1^\circ$ grid—the highest native resolution among the datasets in this study (ERA5-L)—using nearest-neighbor interpolation. This choice ensures consistency in spatial resolution while preserving each product's native grid values without introducing smoothing or artificial sub-grid structure. For in-situ observations, which are point measurements, two options are common—nearest-grid extraction or upscaling stations to the grid cell. We adopt the latter: within each 0.1° cell, we average all QC-screened records to match the areal-mean grid value, enabling comparisons under equivalent conditions. Additionally, this approach avoids over-weighting densely clustered stations relative to sparsely sampled areas. It is particularly appropriate for snow density, whose spatial variability is smaller than that of SD or SWE. Nevertheless, residual sub-grid heterogeneity—especially in complex terrain—can still introduce representativeness uncertainty. We state this limitation explicitly and consider it in our interpretation.

In this study, we focus on the period from November to April within the water year (WY). These months are chosen as they align closely with the typical snow phenology characteristics of the Northern Hemisphere (Peng et al., 2013; L. Wang et al., 2025). We define WY N as the period from October 1 of year $N-1$ to September 30 of year N (e.g., WY 2023 spans October 1, 2022 to September 30, 2023). Our analysis is based on monthly mean bulk snow density derived from daily values. All in-situ datasets provide snow density directly. Among the reanalysis datasets, ERA5-L includes a density field, whereas GLDAS-2 and JRA-3Q require

derivation from SWE and SD. For consistency across products, we compute daily density for any day d as:

$$\rho_d = \frac{100 \times SWE_d}{SD_d}, \quad (1)$$

where ρ_d is the bulk snow density (kg/m^3), SWE_d is the snow water equivalent (mm), and SD_d is the snow depth (cm). For ERA5-L, we use the daily snow density product from the Copernicus Climate Data Store (aggregated from hourly fields). For GLDAS-2 (Noah, CLSM, VIC), we average native 3-hourly fields to daily SWE and SD, then compute daily density. For JRA-3Q, SWE is derived by summing the “ice content in snow” and “liquid water content in snow” from the 6-hour snow analysis field, followed by daily averaging. SD is directly obtained from the daily SD analysis field. To ensure consistent sampling, each reanalysis data is masked based on station-day availability, remaining only days when the collocated station reports valid observations. Monthly mean snow density is the arithmetic mean of these daily values. By first computing daily values, applying the station-day mask, and then performing monthly-scale averaging, this workflow ensures temporal and spatial consistency between in-situ observations and reanalysis datasets.

The study area is divided into three main sub-regions: Russia, Canada & Alaska (Alaska is included due to its geographic proximity to Canada and its high latitude), and the Western United States (WUS). Note that the available data for Alaska originates from SNOTEL and begins in the 1990s. Consequently, Alaska is excluded from the long-term time series analysis in Section 4.3.

3.2. Evaluation of snow density accuracy for reanalysis datasets

We separately evaluate the spatial and temporal accuracy of reanalysis snow density data for different regions in the Northern Hemisphere. For spatial evaluation, we calculate the multi-year average annual snow density from November to April during WY 2001–2023, comparing reanalysis data with in-situ observations. This timeframe is selected to maximize data overlap. To quantify spatial accuracy, we use the root mean square error (RMSE) and the Pearson correlation coefficient (R) as primary metrics. Additionally, Taylor diagrams (Taylor, 2001) are employed to visualize the combined information of centered RMSE, standard deviation (STDR), and R . To further evaluate the amplitude and spatial pattern of variability in the reanalysis data, we employ the Taylor Skill Score (TSS). TSS is defined as:

$$TSS = \frac{4(1+R)^4}{\left(STDR + \frac{1}{STDR}\right)^2 (1+R_0)^4}, \quad (2)$$

where R_0 is the maximum correlation attainable (i.e., 1).

For the temporal assessment, we calculate the annual mean snow density from both reanalysis datasets and in-situ observations across different regions, as well as the absolute bias of the multi-year mean of monthly snow density in reanalysis data relative to observations. These metrics are used to evaluate the performance of reanalysis datasets in representing the overall snow density across different regions on both annual and monthly timescales. To further assess the ability of reanalysis datasets to capture annual trends in snow density, we introduce a consistency index (CI) based on the Mann-Kendall test (Zhang et al., 2021; Yan et al., 2024). CI is defined as:

$$CI = \frac{N_{inc} + N_{dec} + N_{no}}{N_{tot}}, \quad (3)$$

where N_{inc} is the number of grid cells where both reanalysis and in-situ data exhibit a significant increasing trend ($P < 0.05$), N_{dec} is the number of grid cells where both datasets show a significant decreasing trend, N_{no} is the number of grid cells where neither trend is significant, and N_{tot} is the total number of grid cells. Annual trends (and CI) are evaluated only

at grid cells with at least 10 years of valid records.

3.3. Impact of snow density bias on the accuracy of SD in reanalysis datasets

In ERA5-L and GLDAS-Noah, although their SWE calculation methods and snow density parameterization schemes differ, SD is diagnosed each time step as $SD = \frac{SWE}{\rho}$ (Koren et al., 1999; Dutra et al., 2010). In other words, snow density directly determines SD in these two reanalysis datasets. Using the relationship represented in Equation (4), we can quantify the contributions of SWE and snow density biases to SD biases, providing a clearer understanding of the sources of SD deviations. Equation (4) is presented as follows:

$$\frac{SD_{re}}{SD_{obs}} = \frac{SWE_{re}}{SWE_{obs}} \frac{\rho_{re}}{\rho_{obs}}, \quad (4)$$

where the subscript “re” denotes reanalysis data, while the subscript “obs” represents in-situ observations.

Since the monthly means do not strictly satisfy the daily closure implied by Equation (4), we implement measures to guard against non-closure in our monthly ratio analysis (Fig. 11a–c). For each grid-month we compare the SD implied by monthly mean SWE and snow density ($SD^* = \frac{SWE}{\rho}$) with the native monthly mean SD, and exclude cases where their relative difference exceeds 3%. By contrast, no data are excluded in Fig. 11d–f, which use multi-year means of annual averages.

4. Results

4.1. Spatial distribution evaluation of snow density in reanalysis datasets

Snow cover is widespread across the Northern Hemisphere, with approximately 40–50% of the land surface covered by snow during winter (Bormann et al., 2013). Owing to their mid to high latitude locations, majority areas of Canada and Russia are covered by snow up to

five months each year. In the WUS, snow primarily accumulates in mountainous regions such as the Sierra Nevada, the Cascades, and the Rocky Mountains, and seasonal snow cover typically forms between November and April.

Analysis of in-situ observations reveals substantial spatial heterogeneity in snow density distribution (Fig. 1). Among the three sub-regions in the Northern Hemisphere, the highest spatially averaged snow density is observed in the WUS (291 kg/m³), followed by Canada and Alaska (243 kg/m³), and Russia (202 kg/m³). Snow density along the western coast of North America is generally high, with values exceeding 300 kg/m³ and reaching up to 449 kg/m³ at certain stations in the WUS, consistent with findings from previous studies. In Russia, snow density is generally higher in the western regions compared to the east. Notably, the lowest snow density values, ranging from 100 kg/m³ to 150 kg/m³, are observed near the border between Russia and Mongolia.

Next, we analyze the climatological snow density and its absolute bias relative to in-situ observations for the five reanalysis datasets over the same time period. Fig. 2 illustrates that while the spatial patterns of snow density differ among reanalysis datasets, they share certain similarities. Except for JRA-3Q, all datasets capture the presence of high snow density in the mountainous regions of the western North America, albeit with varying degrees of underestimation compared to observations. And all datasets depict a spatial pattern in Russia characterized by higher snow density in the west and lower values in the east.

The multi-year mean snow density is computed to evaluate the correlation and RMSE between reanalysis and in-situ data. The results indicate that all reanalysis datasets exhibit the best performance in Russia. Among them, GLDAS-VIC achieves the highest correlation coefficient (0.80). However, it also has the largest RMSE (80.4 kg/m³) due to a general overestimation of snow density in Russia. The second-best performance is observed in Canada and Alaska. In contrast, the WUS generally exhibits the largest RMSE across all reanalysis datasets due to consistent underestimation. Except for GLDAS-Noah with a correlation coefficient of 0.74, the correlation between reanalysis and in-situ data shows relatively weak. Across all study regions, GLDAS-CLSM show

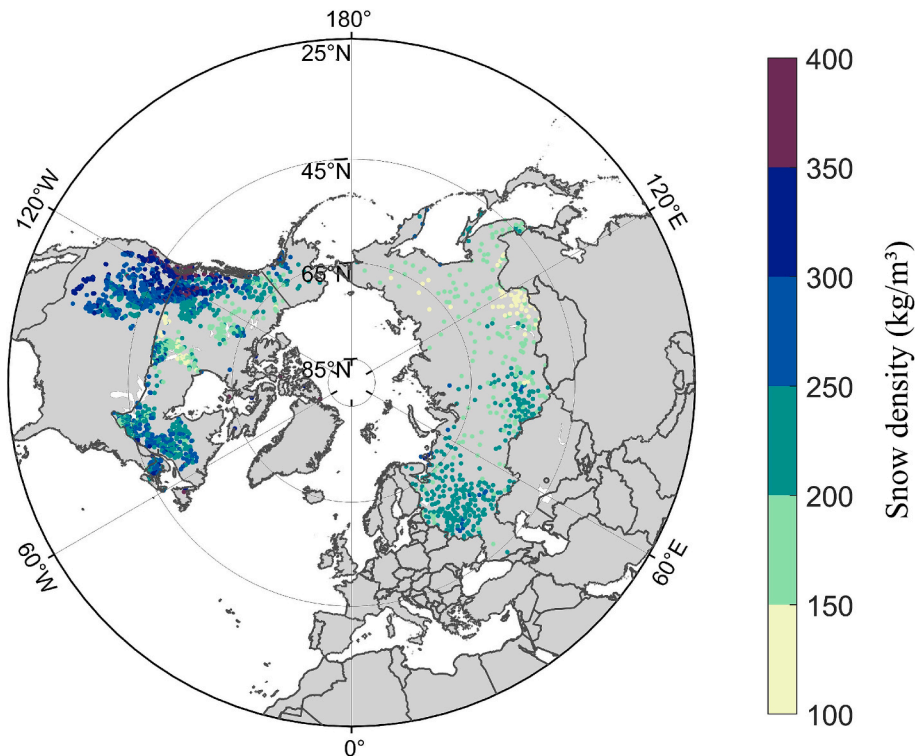


Fig. 1. Spatial distribution of climatological averaged snow density during WY 2001–2023 from in-situ data over the study region in the Northern Hemisphere. Dots mark the grid cells corresponding to station locations, and their colors indicate the climatological snow density values.

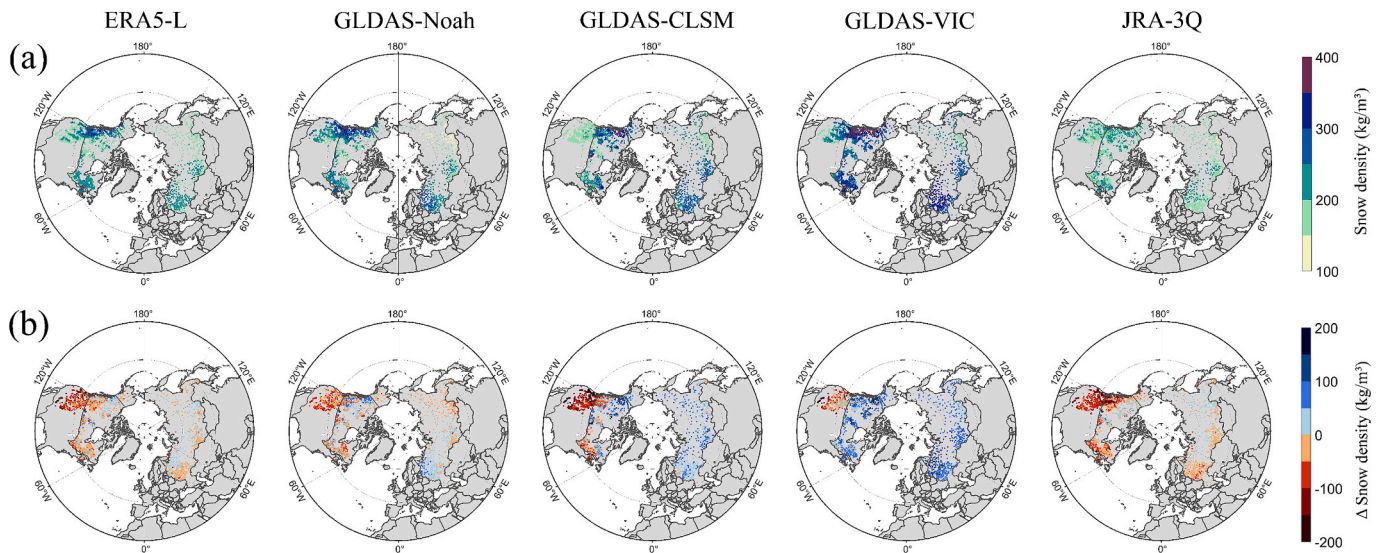


Fig. 2. Spatial distribution of averaged snow density from reanalysis datasets and its bias compared to observations. (a) Spatial distribution of averaged snow density during WY 2001–2023 from five analysis datasets over the Northern Hemisphere. (b) Biases in snow density of five reanalysis datasets relative to the in-situ data. The dots represent the centers of the corresponding grid cells.

negative correlation coefficients, indicating poor spatial accuracy. Overall, ERA5-L and GLDAS-Noah perform better, consistently demonstrating higher correlation coefficients and lower RMSE values across all three sub-regions as well as the entire study area (Fig. 3).

Further, the Taylor diagrams in Fig. 4 indicate that ERA5-L and GLDAS-Noah exhibit the highest TSS across the entire study area, with values of 0.35 and 0.46, respectively. It is noteworthy that GLDAS-VIC also demonstrates relatively high TSS, even ranking among the top-performing datasets in Canada and Alaska (TSS is 0.46) and in Russia (TSS is 0.60). This can be attributed to the fact that the Taylor diagram evaluates centered RMSE, which removes the influence of mean bias (Taylor, 2001). Although GLDAS-VIC generally overestimates snow density, it captures anomalies relative to the mean with reasonably high accuracy, showing good agreement with in-situ observations in terms of spatial variability.

In summary, ERA5-L and GLDAS-Noah generally demonstrate better performance in terms of spatial accuracy, exhibiting higher spatial correlations with in-situ observations and smaller biases. At sub-regional scale, all reanalysis datasets show relatively poor performance in representing snow density over the WUS, while their performance is best in Russia and moderate in Canada and Alaska, highlighting the spatial heterogeneity in the accuracy of reanalysis products.

4.2. Temporal variability evaluation of snow density in reanalysis datasets

Following the assessment of spatial accuracy, we further examine the ability of these reanalysis datasets to characterize temporal variability in snow density.

Based on spatially averaged multi-year means (Fig. 5a), ERA5-L and GLDAS-Noah are closer to the observations in Canada and Alaska, with overall underestimations of about 7 and 10 kg/m³, respectively. In Russia, GLDAS-Noah outperforms the other reanalysis, showing only a slight overestimation of 2 kg/m³; ERA5-L also agrees well, with a mean bias of -7 kg/m³. In the WUS, GLDAS-VIC shows the best agreement among all products despite its overestimations elsewhere, with a regional mean bias of -40 kg/m³. The other reanalysis datasets substantially underestimate snow density in this region, and GLDAS-CLSM performs worst, with a relative error up to 45% (-117 kg m⁻³). Over the full study domain, JRA-3Q exhibits the largest deviations (-56 kg/m³), whereas GLDAS-Noah performs best (-18 kg/m³).

Further analysis reveals that the biases vary across months. In Canada and Alaska, the underestimation in ERA5-L, GLDAS-Noah, and GLDAS-CLSM is most pronounced in November, December, and January. In Russia, the errors in ERA5-L remain relatively small throughout the months, showing overestimation in November and April and underestimation occurs in other months. GLDAS-Noah also shows relatively smaller biases from November to March but has a notable overestimation of 76 kg/m³ in April. In contrast, GLDAS-CLSM consistently overestimates snow density, with the magnitude of overestimation increasing as the WY progresses (Fig. 5b).

Comparing the temporal trends, ERA5-L and GLDAS-Noah show the highest CI values of 0.92 and 0.88, respectively (Fig. 6g). As shown in Fig. 6a, observed snow density exhibit no significant trend in most grid cells (about 92%), while those with a significant increasing trend are primarily located in the mountainous regions of Western North America, and those with a significant decreasing trend are found in Russia. ERA5-L fails to capture this pattern effectively, instead classifying more grid cells as having no trend (Fig. 6b). Meanwhile, GLDAS-Noah misrepresents the increasing trend in Western North America as decreasing trend, and underestimates the number of grid cells with a decreasing trend in Russia (Fig. 6c). This suggests that all reanalysis datasets in this study fail to accurately reproduce the interannual trends of snow density.

In summary, ERA5-L, GLDAS-Noah, and GLDAS-CLSM demonstrate better performance in representing regionally averaged snow density at both annual and monthly scales. Although ERA5-L and GLDAS-Noah perform better than the other reanalysis datasets in capturing interannual trends, they still fail to accurately reproduce the observed long-term changes. This underscores the limitations of current reanalysis products in representing the temporal variability of snow density.

4.3. Dependence of snow density bias on SD

After the spatial and temporal evaluations, we further examine whether reanalysis snow density biases vary with SD. Fig. 7 summarizes the distribution of monthly snow density biases under different observed SD conditions (0–10, 10–20, 20–40, 40–80, ≥80 cm) for each product. A clear depth dependence emerges in ERA5-L and GLDAS-Noah, where the spread of biases is widest in the shallowest bin (0–10 cm) but becomes progressively narrower as SD increases, indicating improved stability of density estimates in deeper snowpacks. GLDAS-VIC and JRA-3Q also

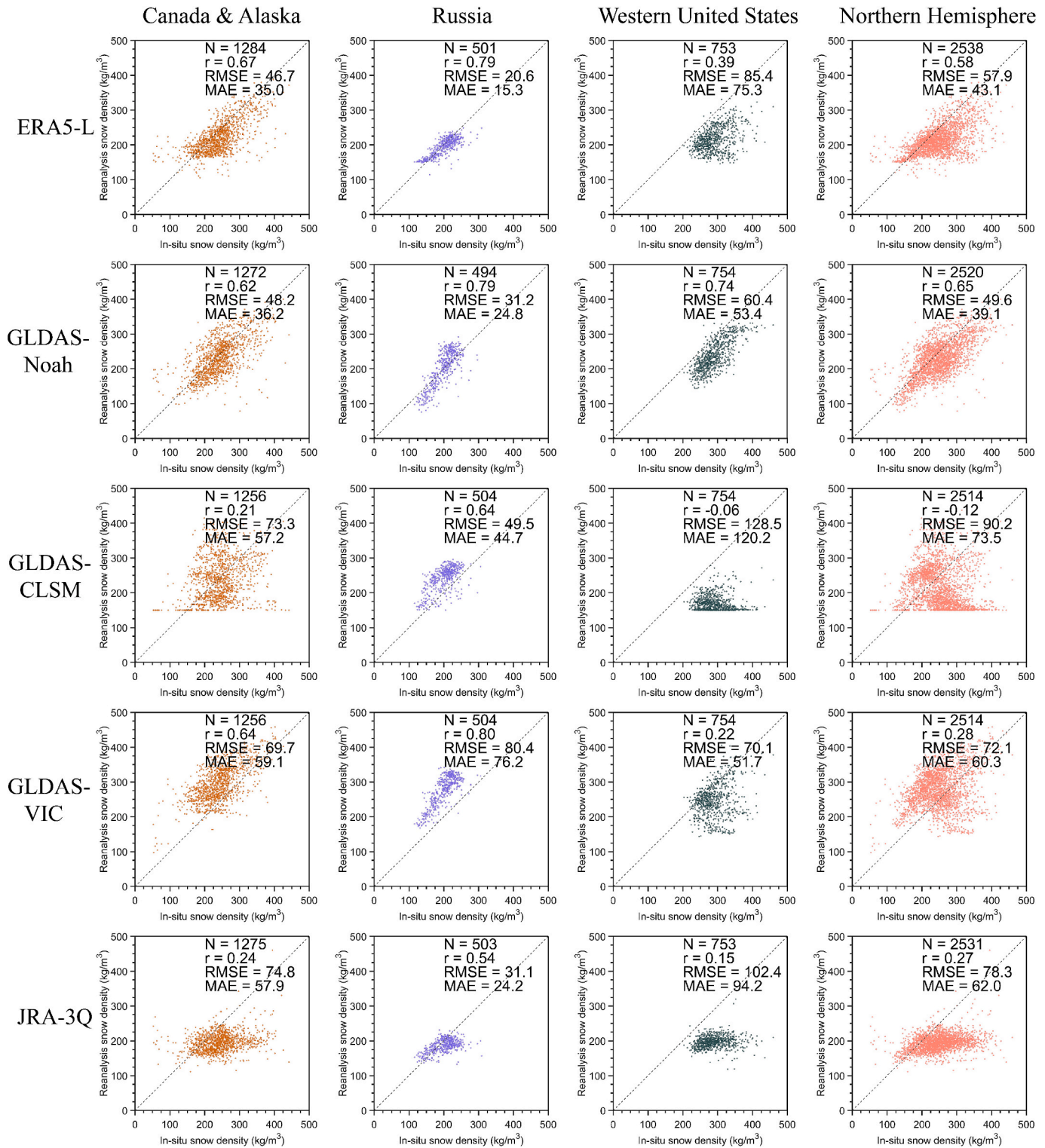


Fig. 3. Spatial comparison of multi-year average snow density between reanalysis datasets and in-situ observations. The first three columns represent results for different study sub-regions, while the last column shows the results for the entire study region in the Northern Hemisphere. The dots indicate the multi-year mean snow density at each grid cell from in-situ observations and reanalysis datasets, enabling point-by-point comparison during WY 2001–2023. “N” denotes the number of grid cells included in the comparison, “r” represents the correlation coefficient, “RMSE” stands for root mean square error, and “MAE” refers to mean absolute error.

show a broadly similar narrowing pattern, although the contraction of bias spread is less pronounced than in ERA5-L and GLDAS-Noah. In contrast, GLDAS-CLSM exhibits little sensitivity to SD, with comparable spread across all bins.

Across reanalysis products, SD dependence primarily manifests in

the range of snow density biases rather than a trend of median or mean values monotonically converging to zero. In fact, except for GLDAS-VIC, reanalysis datasets tend to systematically underestimate snow density in the deepest SD bin (≥ 80 cm). This feature is likely related to the large number of the WUS stations reporting SD exceeding 80 cm where

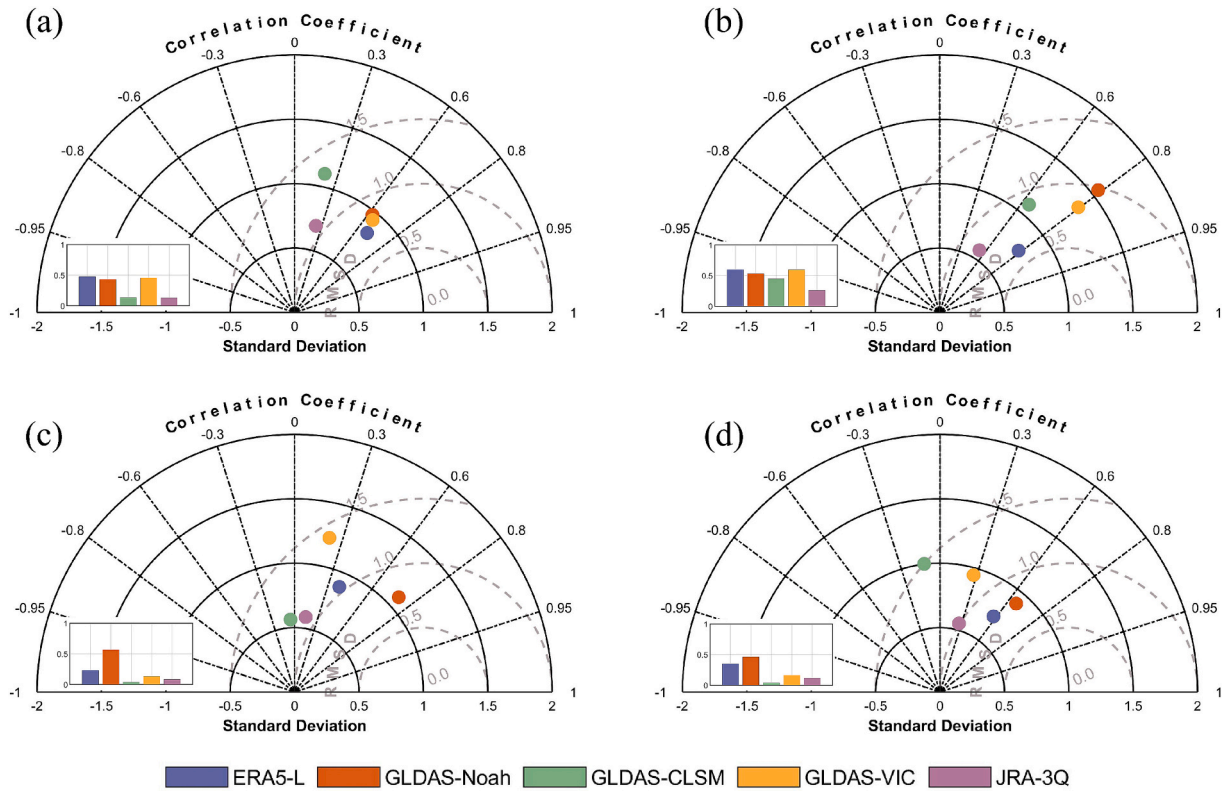


Fig. 4. Taylor diagram illustrating the correlation coefficient, centered RMSE, and standard deviation between reanalysis and in-situ multi-year mean snow density. (a)–(d) for Canada and Alaska, Russia, the WUS, and the entire study area in the Northern Hemisphere, respectively. The histograms in the lower-left corner of each panel show the TSS of the five reanalysis datasets.

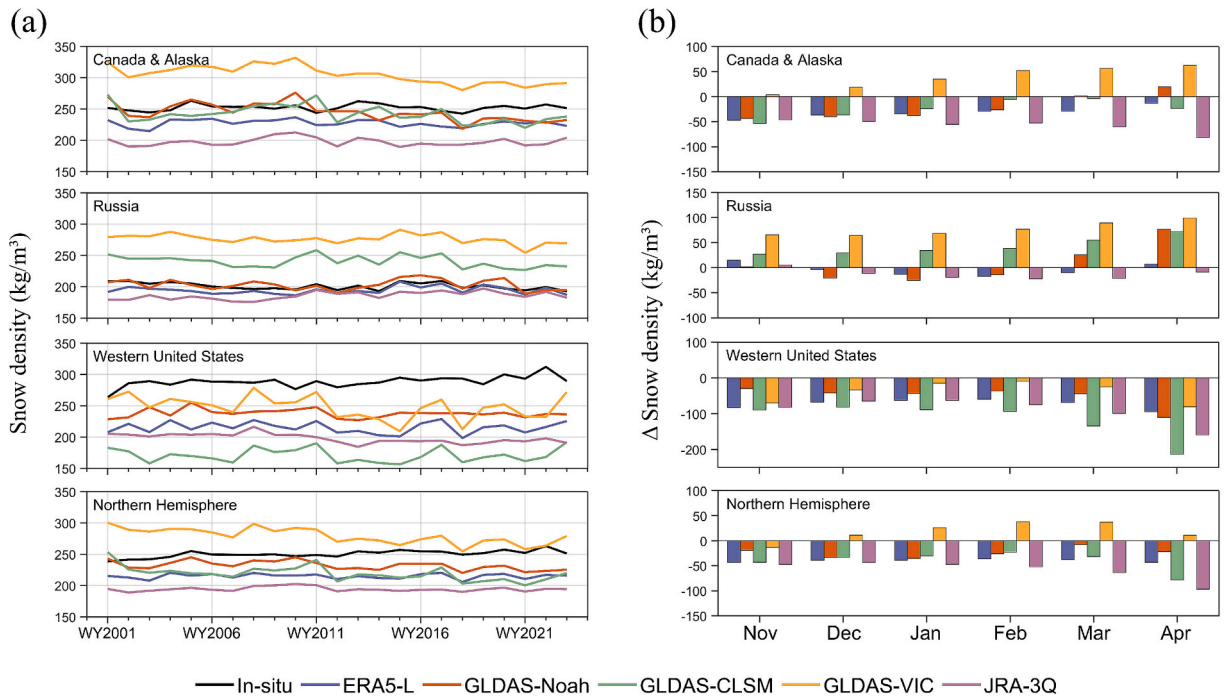


Fig. 5. Temporal comparison of snow density between reanalysis datasets and in-situ observations at annual and monthly scales. (a) Interannual variations in snow density from in-situ observations and five reanalysis datasets during WY 2001–2023. (b) Biases in the multi-year mean monthly snow density of reanalysis datasets relative to in-situ observations.

reanalysis consistently underestimate snow density. Overall, SD primarily modulates the variability of the biases, while systematic

underestimation remains pronounced under extremely deep snow conditions.

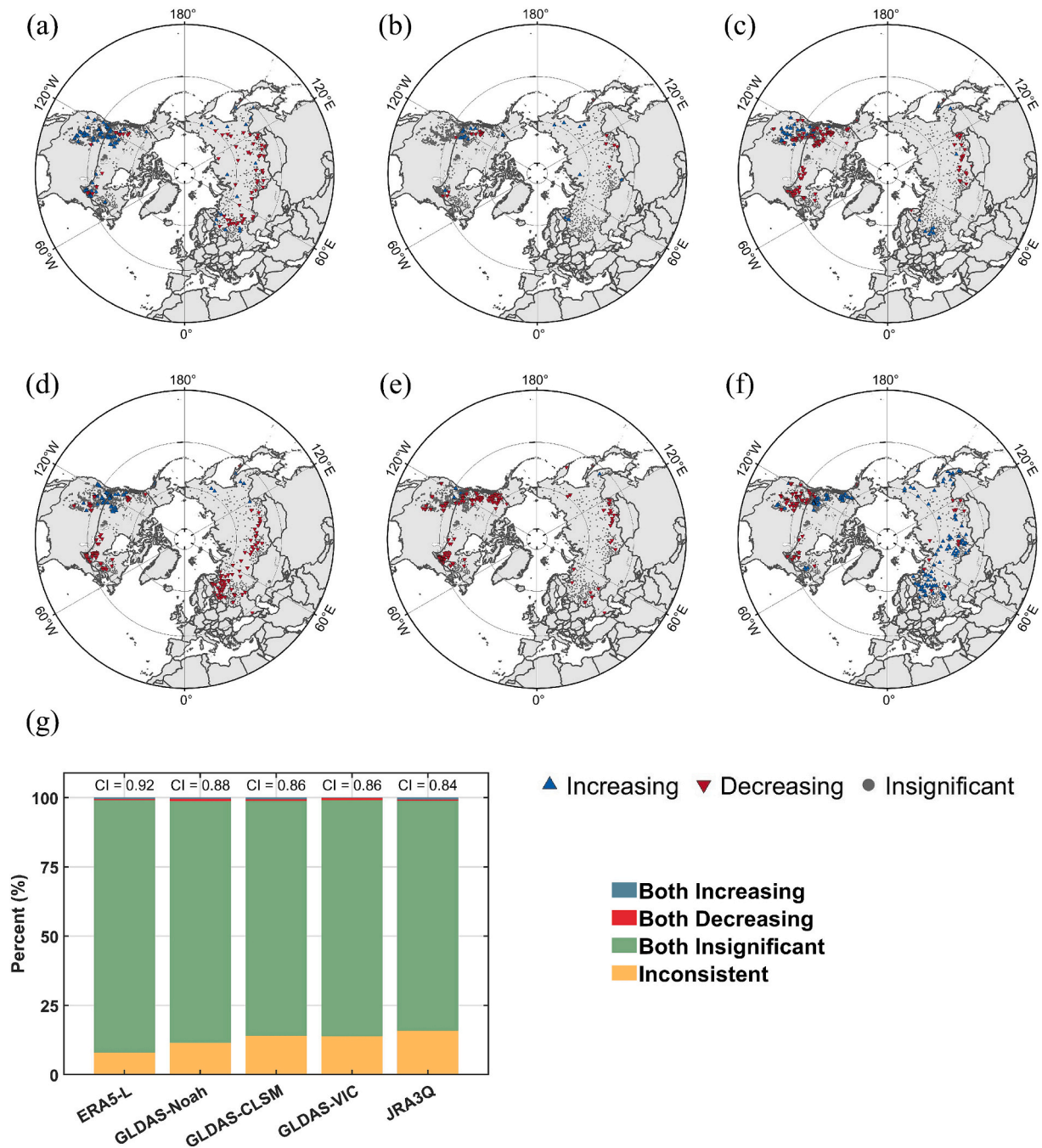


Fig. 6. Comparison of interannual snow density trends at each grid cell between five reanalysis datasets and in-situ observations during WY 2001–2023. (a)–(f) show the temporal trends derived from (a) in-situ observations, (b) ERA5-L, (c) GLDAS-Noah, (d) GLDAS-CLSM, (e) GLDAS-VIC, and (f) JRA-3Q. (g) The consistency indexes (CI) of the five reanalysis datasets, calculated by comparing their trends with those observed in in-situ data.

4.4. Analysis of long-term variability in snow density

Based on the above results, we select the two best-performing reanalysis datasets (ERA5-L and GLDAS-Noah) and combine them with in-situ data for analysis. Due to the limited temporal coverage of GLDAS-Noah (v2.1), which begins in 2000, it poses challenges for long-term analysis. Therefore, we evaluated the applicability of GLDAS-Noah (v2.0), noting that the only difference between v2.1 and v2.0 lies in the meteorological forcing. As shown in Fig. 8, GLDAS-Noah (v2.0) still exhibits good spatial accuracy across the entire study domain during WY 2001–2014, with a correlation coefficient of 0.71 and an RMSE of 53.2 kg/m³ compared to observations. To obtain more comprehensive results, GLDAS-Noah (v2.0) is also included in the following analyses.

Considering the sparse or unstable coverage of station in the early years—which may affect the spatial representativeness for full-period analyses—we first partition the records based on the annual count of valid station-collocated grid cells and select periods with relatively stable coverage within each sub-region. Conditional on this station-stability criterion, we then choose the longest overlapping time window across the reanalysis products to maximize both temporal extent and overlap. Consequently, the trend analyses are reported over the maximum overlapping WY range that satisfies the station-coverage requirement.

According to the selection approach described above, the Canada analysis spans WY 1986–2014 (Fig. 9a). Over this period, in-situ observations show a non-significant decline of -2.41 kg/m³ per decade (p

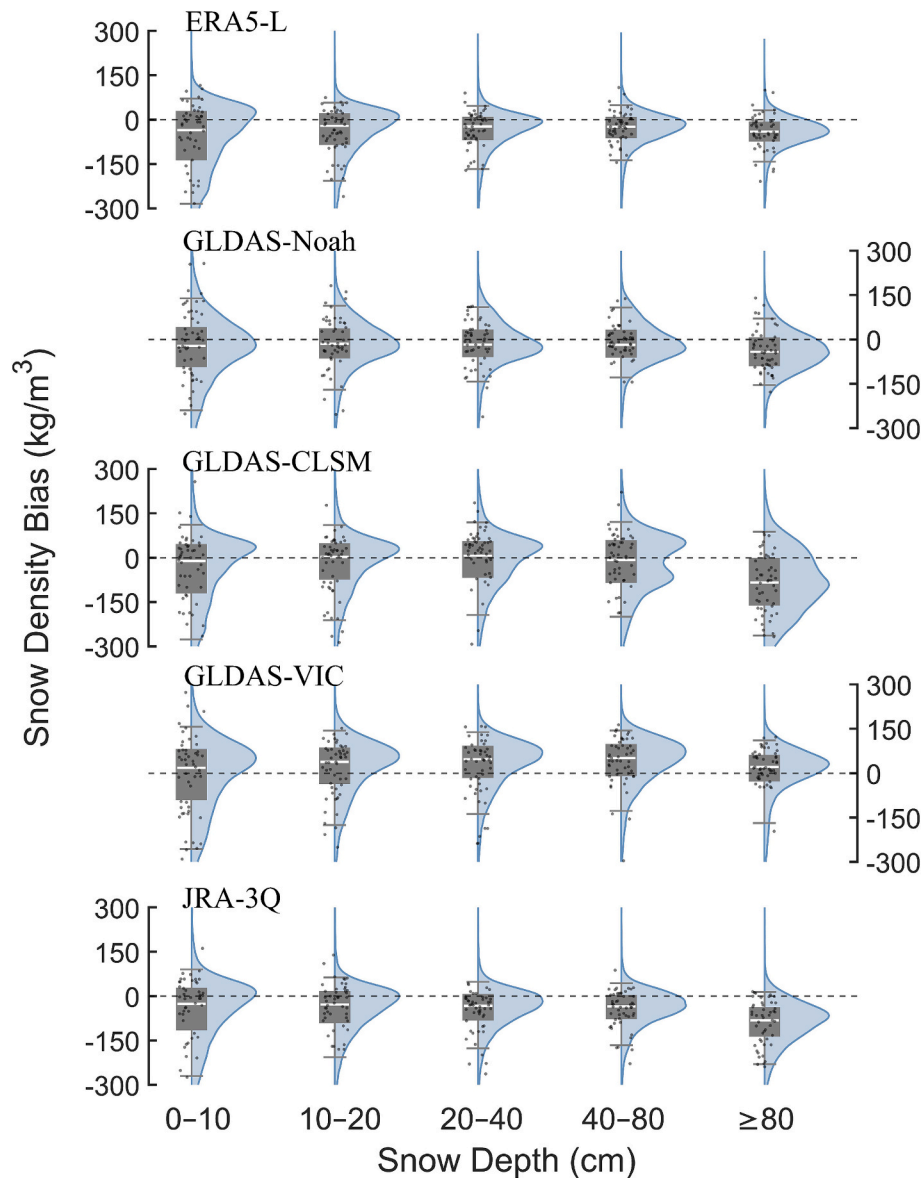


Fig. 7. Snow density bias (reanalysis data minus in-situ data, kg/m^3) as a function of SD bins (0–10, 10–20, 20–40, 40–80, and ≥ 80 cm) for ERA5-L, GLDAS-Noah, GLDAS-CLSM, GLDAS-VIC, and JRA-3Q during WY 2001–2023. Half violins (blue shading) show the probability density distribution, boxplots (gray) indicate the interquartile range with median (white line) and whiskers at the 5th–95th percentiles, dots represent randomly sampled individual values, and the dashed line denotes zero bias. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

$= 0.18$). ERA5-L shows essentially no trend (0.03 kg/m^3 per decade; $p = 0.99$), while GLDAS-Noah (v2.0) also exhibits a non-significant decline (-2.20 kg/m^3 per decade; $p = 0.45$). In Russia (WY 1967–2014; Fig. 9b), the observed snow density decreases significantly at -4.19 kg/m^3 per decade ($p < 0.01$). However, ERA5-L does not capture this trend (-0.34 kg/m^3 per decade; $p = 0.59$), and GLDAS-Noah (v2.0) shows an opposite, significantly increasing trend of 3.20 kg/m^3 per decade ($p < 0.01$). In the WUS (WY 2004–2023; Fig. 9c), in-situ observations increase significantly at 6.85 kg/m^3 per decade ($p < 0.05$), whereas ERA5-L and GLDAS-Noah (v2.1) both show no significant decreasing trend. These results are consistent with Fig. 6 and underscore notable regional differences in trend detection across products.

Further, we examine whether the interannual variations in annual mean snow density align with the interannual trends computed separately for each month. In Fig. 10, Canada shows the strongest interannual variability in November, with an apparent regime shift around WY 1996. This shift is also visible in ERA5-L and GLDAS-Noah (v2.0). For December and January, in-situ anomalies exhibit a slight interannual

increase amid fluctuations, followed by minor interannual decreases in February and March. Among the reanalysis datasets, ERA5-L shows limited variability, whereas GLDAS-Noah (both v2.0 and v2.1) amplifies changes in February–April. For Russia, in-situ data show a significant interannual decrease in November–January that is not captured by reanalysis data. Moreover, GLDAS-Noah (v2.0) indicates an interannual increase in February–April that is unsupported by observations. In the WUS, observations show interannual increases mainly in November, December, and April, with the strongest signal in November. ERA5-L markedly damps the November–December interannual variability, while GLDAS-Noah (v2.1) both weakens the November increase and erroneously depicts interannual decreases in March–April. Overall, across subregions, the observed monthly interannual variability is concentrated in early winter (November–January), whereas reanalysis data tend to underrepresent this early winter signal and, in some cases, exaggerate or misrepresent changes in the late winter (February–April), contributing to discrepancies in inferred trends.

In conclusion, long-term analysis reveals distinct regional patterns in

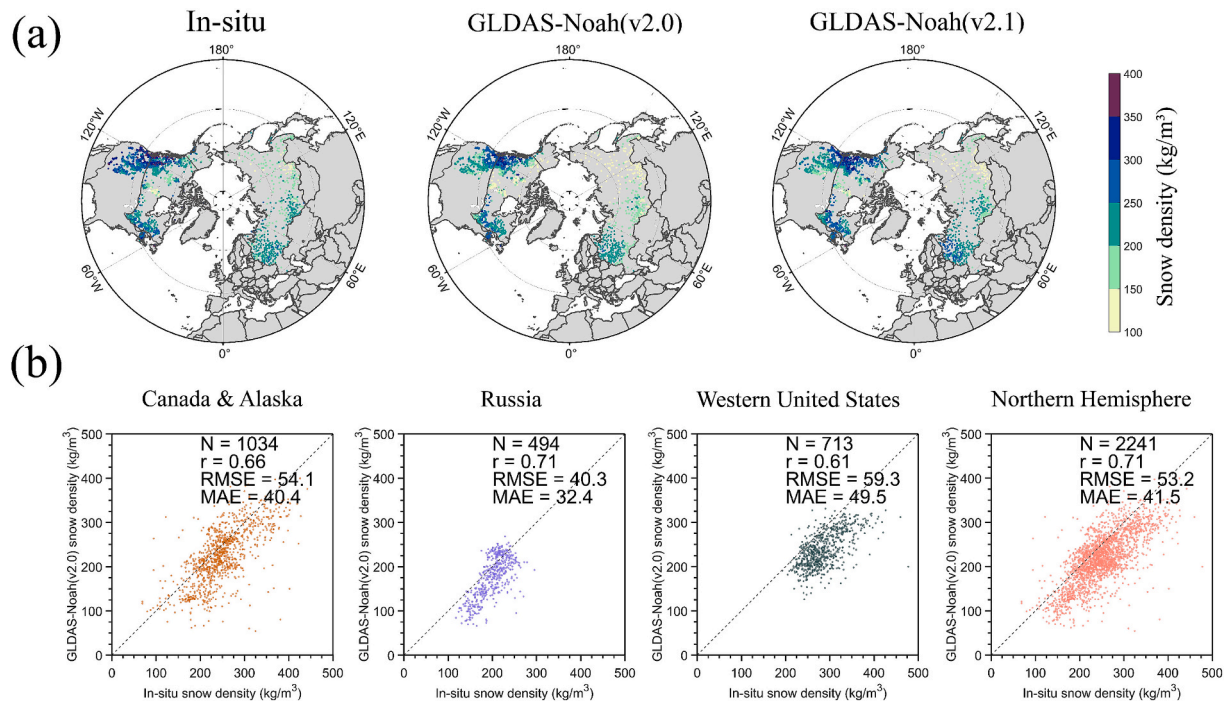


Fig. 8. Spatial accuracy of snow density from GLDAS-Noah (v2.0) during WY 2001–2014. (a) Spatial distribution of snow density from in-situ observations, GLDAS-Noah (v2.0), and GLDAS-Noah (v2.1) during WY 2001–2014. (b) Comparison of the multi-year mean snow density from GLDAS-Noah (v2.0) with in-situ observations across different regions.

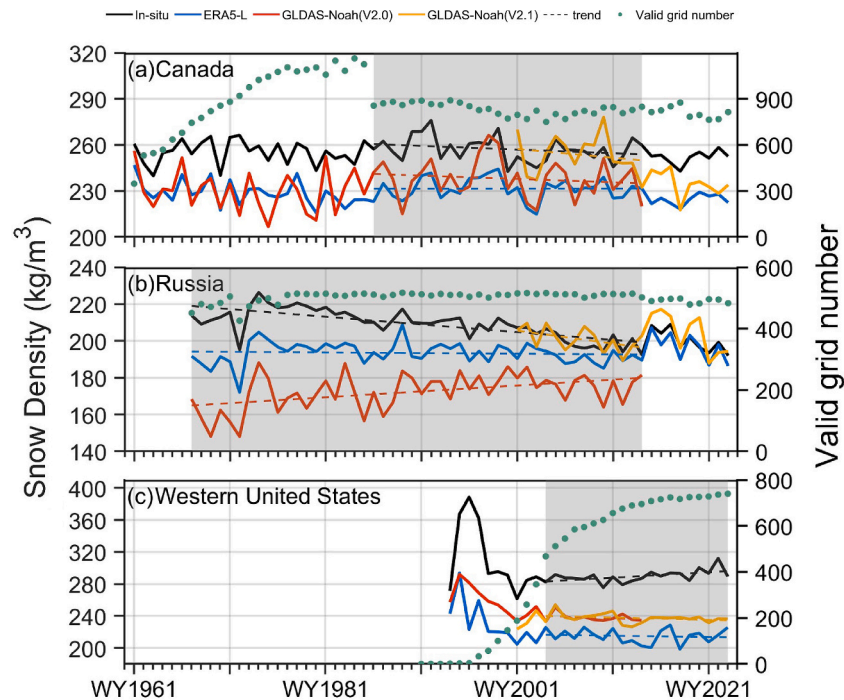


Fig. 9. Long-term comparison of annual snow density between reanalysis datasets and in-situ observations. (a) Interannual snow density trends from different data sources in Canada. (b) and (c) are the same as (a), but for Russia and the WUS, respectively. The shaded areas indicate the time periods over which the trends are calculated, and the green dots represent the number of valid grid points in each corresponding year. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

snow density, with no significant trend in Canada (WY 1986–2014), a significant decrease in Russia (WY 1967–2014) primarily in early-winter months, and a recent increase in the WUS (WY 2004–2023, noting the limited duration). Even for the best-performing products, ERA5-L and GLDAS-Noah do not faithfully reproduce these observed trends,

exposing obvious limitations in their ability to capture snow density variability across time and regions.

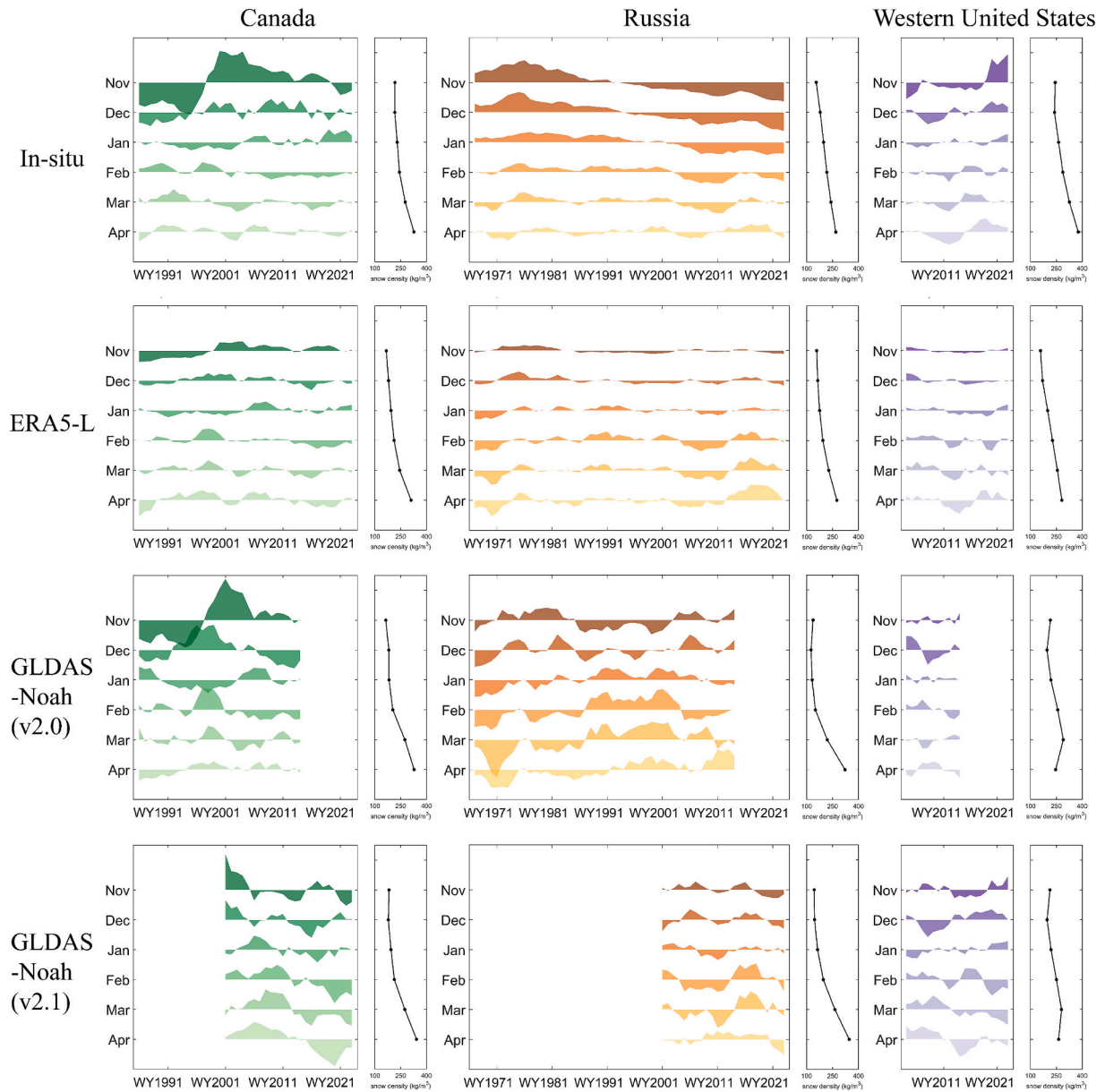


Fig. 10. Comparison of monthly snow density variations between reanalysis datasets and in-situ observations. The ridge plots display the monthly snow density anomalies for each sub-region and data source, with anomalies calculated as five-year moving averages. The scatter plots with connecting lines show the multi-year mean of monthly snow density for each corresponding period. The subplots are organized from left to right by region and from top to bottom by data source.

4.5. Impact of snow density on SD in reanalysis datasets

Since the SD in reanalysis datasets is influenced by both SWE and snow density, we compare the monthly SD, SWE and snow density from the reanalysis datasets with observations during November to April in WY 2001–2014, as shown in Fig. 11a–c. The average SD, SWE, and snow density from both reanalysis and in-situ data in three sub-regions during this period are calculated and shown in Fig. 11d–f. According to Equation (4), the slope of the line connecting each scatter point to the origin in Fig. 11a–c represents the ratio of the SD from the reanalysis datasets to that from observations. Therefore, points located above the diagonal solid line indicate that the monthly SD in the reanalysis datasets for that grid point is overestimated, while those below the line suggest an underestimation. The results indicate that the contribution of snow density to SD biases varies across different reanalysis datasets and regions.

For ERA5-L, Fig. 11a shows more monthly data points in Canada and Alaska with an underestimation of SWE. However, since snow density is

also underestimated, this results in more accurate monthly SD estimates at corresponding points. In other words, the underestimation of snow density partially offsets the SWE bias, leading to a correction effect on SD. Similarly, in the WUS, the situation is analogous to Canada, where the underestimation of snow density compensates for the SWE bias to a certain extent, leading to more accurate SD results (Fig. 11c). Conversely, in Russia, SWE is overestimated, while snow density is underestimated, causing a greater overestimation of SD (Fig. 11b). In this case, the snow density bias exacerbates the SD bias. For GLDAS-Noah (v2.0), more monthly data points show that both SWE and snow density are underestimated in all three sub-regions, resulting in the snow density bias acting as a correction for the underestimated SD. Notably, this correction effect could be substantial, as indicated by the red “+” markers in Fig. 11b. It may lead to a “false accuracy” in SD, where reanalysis SD data appear close to observations, despite SWE and snow density being significantly lower than observations. This correction is also evident in multi-year averages (red bars in Fig. 11e). For GLDAS-

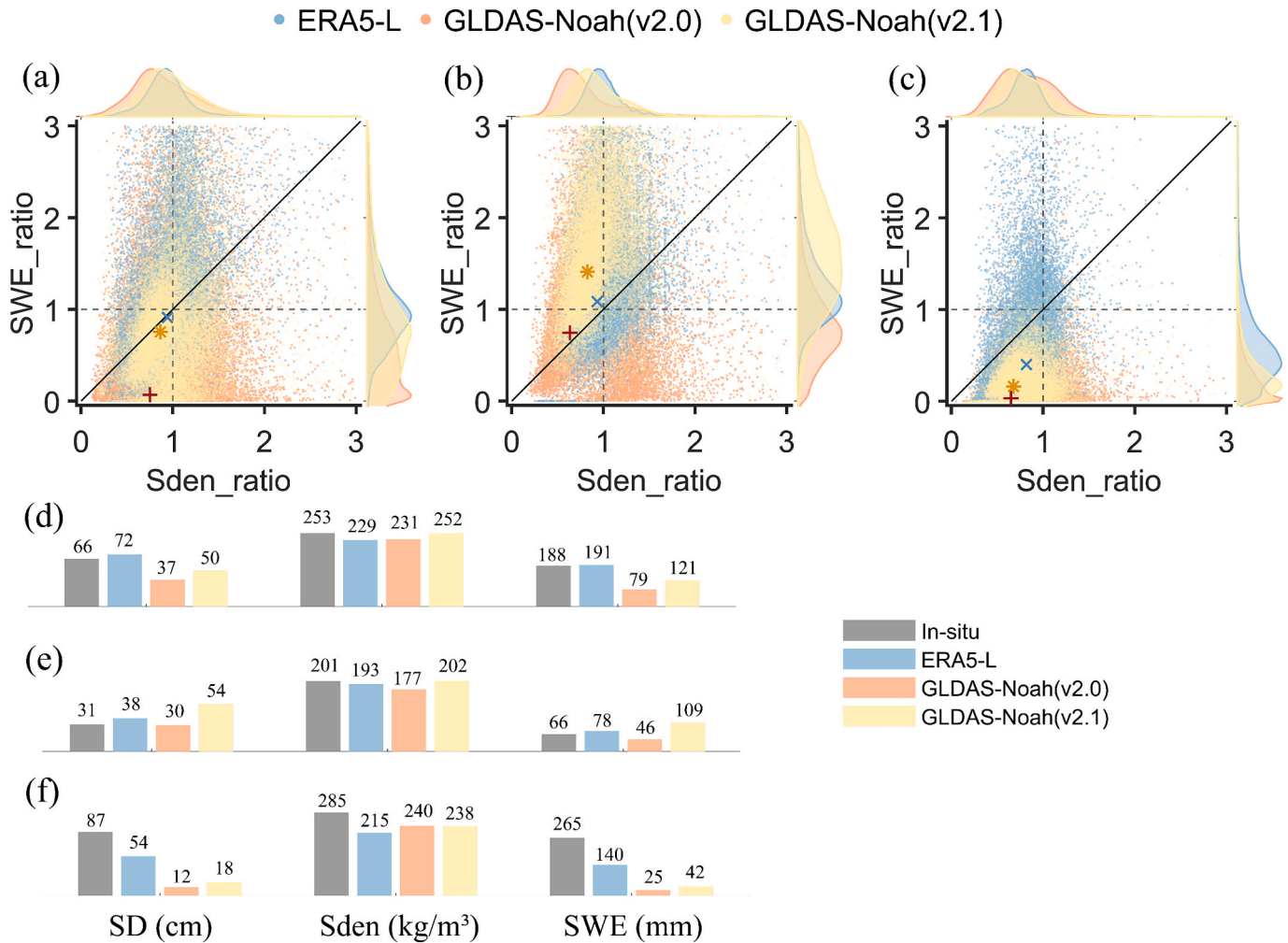


Fig. 11. Relationship between snow density biases and SD biases across different regions and reanalysis datasets. (a) Contributions of SWE and snow density biases to SD biases in Canada and Alaska. (b) and (c) are the same as (a), but for Russia and the WUS, respectively. (d) The average SD, snow density and SWE in Canada and Alaska from November to April during WY 2001–2014 for observations and reanalysis datasets. (e) and (f) are the same as (d), but for Russia and the WUS, respectively. The dots in (a)–(c) indicate the ratios of monthly snow data from ERA5-L (blue), GLDAS-Noah (v2.0) (red), and GLDAS-Noah (v2.1) (yellow) to observations from November to April during WY 2001–2014. The shaded plots along the borders indicate the density distribution of the scatter points, while the “x”, “+”, and “*” symbols mark the most concentrated areas of the scatter point distribution for ERA5-L, GLDAS-Noah (v2.0), and GLDAS-Noah (v2.1), respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Noah (v2.1), the snow density bias corrects the underestimated SD in Canada and Alaska and the WUS (Fig. 11a, c), while in Russia, it further amplifies the SD overestimation (Fig. 11b).

In summary, SD biases in reanalysis datasets result from combined SWE and snow density errors, with their interaction varying by region and dataset. In some cases, underestimated snow density offsets SWE biases, improving SD accuracy. However, this compensation can lead to “false accuracy.” In other regions, snow density bias worsens SD errors, highlighting complex, region-dependent interactions among snow variables.

5. Discussion

In this study, we aim to evaluate the applicability of snow density data from five reanalysis datasets. However, there are several limitations in this study due to data processing. We average the observations from multiple stations located within each 0.1° grid cell to represent the in-situ value for that grid, which is then used to evaluate the reanalysis data. Although previous studies have suggested that the spatial heterogeneity of snow density is much smaller than that of variables like SD and SWE (López-Moreno et al., 2013; Mizukami and Perica, 2008), this

averaging approach may still introduce some inaccuracies. This issue is particularly pronounced in regions with complex terrain, such as the WUS. Additionally, the observations used in this region were sourced exclusively from SNOTEL stations, which are primarily located in high-elevation areas. As a result, the dataset lacks representation of snow conditions at lower elevations, further increasing the uncertainty of evaluation results in the WUS. Another limitation lies in Section 4.5, where SD and SWE from SNOTEL are directly compared with reanalysis data, which represent grid-averaged values. Given the high spatial heterogeneity of SD and SWE, this comparison may be subject to substantial uncertainties. Nevertheless, even without perfect matching between reanalysis and in-situ observations, our work still allows for a qualitative comparison of the relative magnitudes of SD and SWE simulated by different reanalysis datasets in the WUS.

We also identify several issues deserving further investigation, such as the sources of snow density bias in reanalysis datasets. It is reasonable to assume that meteorological variables can introduce biases. The discrepancies between GLDAS-Noah (v2.0) and GLDAS-Noah (v2.1) support this notion—both employ the same LSM and thus the same snow schemes, yet their meteorological forcing data differ. These differences, including variations in precipitation, air temperature, and wind speed,

lead to divergent snow density diagnostics.

Additionally, the three GLDAS-2.0 datasets used in this study differ only in their LSMs, yet they produce varying results. This suggests that differences in snow density parameterization schemes across various LSMs also constitute a significant factor contributing to bias. In HTESSEL, fresh-snow density depends on near-surface air temperature and wind speed, and the density formulation accounts for the effects of overburden, metamorphism, and refreezing-driven compaction. The snow density is typically constrained within a threshold range of 50–450 kg/m³ (Dutra et al., 2010). In Noah, fresh-snow density depends mainly on near-surface air temperature (Koren et al., 1999), and snow density evolves through an Anderson-type compaction and metamorphism formulation with strong exponential temperature dependence and a high-density suppression term. When the snowpack reaches 0°C, an additional melting–refreezing adjustment accelerates densification (Anderson, 1976; Anderson, 2006). Besides, the Noah LSM sets an upper limit of 400 kg/m³ on snow density, which may suppress late winter densification and produce excessively low density values—particularly evident in the WUS during April. CLSM (Catchment LSM) represents snow with three layers, each newly formed layer is initialized at 150 kg/m³ and then compacts and ages (Toure et al., 2018). This fixed initial value compresses the left tail of the density distribution, weakening spatial correlations and producing regional bias patterns consistent with our findings—overestimation in very cold regions (e.g., Russia) where observed early-season snow density can be lower than 150 kg/m³, but underestimation in melt-affected mountains (e.g., the WUS) where densities can far exceed 150 kg/m³. CLSM parameterizes snow densification through two main pathways: mechanical compaction under overburden and wet-snow densification associated with liquid–water storage and refreezing (Stieglitz et al., 2001). It does not include a separate temperature-driven dry-snow metamorphism term. In GLDAS-VIC, the two-layer energy-balance snow model diagnoses fresh-snow density from air temperature using the experiential formula proposed by Hedstrom and Pomeroy (1998), and then updates density with a formulation in which overburden and metamorphism contributions are computed. However, the formulation does not explicitly simulate refreezing effects, instead, it rather roughly doubles a parameter within the metamorphism term when liquid water is present. In addition, VIC commonly sets a maximum density near 700 kg/m³. Consistent with these mechanics, Dawson et al. (2017) reported that VIC tends to overestimate density and showed among the largest errors in prairie and alpine snow classes relative to SNOTEL, which is similar to our results.

In sum, while LSMs generally classify snow density evolution into overburden compaction, temperature-dependent metamorphism, and wet-snow densification (via liquid water and refreezing), they differ in how these processes are represented, in the parameterization of fresh-snow density, and in the upper and lower bounds imposed on density. These design choices produce systematic differences in the magnitude and spatial patterns of snow density across reanalysis datasets. The specific impacts of above factors (meteorological variables and snow schemes in LSMs) on snow density simulation remain to be thoroughly explored in future studies, which would enhance our understanding of model behavior and support the improvement of snow parameterization schemes.

Furthermore, a key finding of this study is that snow density from ERA5-L and GLDAS-Noah attenuates interannual trends in early winter (November–January) but erroneously reproduces or exaggerates interannual trends in late winter (February–April). Based on the above discussion of factors contributing to reanalysis snow density bias, we propose several reasonable explanations. Existing study indicated that wind speeds from ERA5-L exhibit negative biases in Siberia, particularly underestimating high wind speeds significantly, while temperatures are overestimated during December–January (Clelland et al., 2024). In early winter, estimates of fresh-snow density significantly influence overall density accuracy in reanalysis datasets. Therefore, if reanalysis datasets

fail to capture early-winter meteorological field anomalies or long-term trends (e.g., the observed November–January decrease in wind speed over Russia; Reshetko et al., 2016), or even omit effect of some meteorological variables entirely in the parameterization, fresh-snow density is likely misestimated. Under frequent snowfall, this bias propagates into the snow density time series and dampens the reproduced interannual signal. Second, density evolution, which is mainly governed by compaction and metamorphism, is highly sensitive to thermal conditions in these snow schemes. Densification processes are weak when temperatures are far below freezing, while responses intensify near 0°C (Dawson et al., 2017; Cao et al., 2020). Consequently, even minor temperature differences between February and April can translate into amplified density trends—or occasionally trend reversals. In addition, we note that the snow density formulas in these models have been in use for a long time and are revised infrequently. Combined with the simplified single layer structure, this aging of model structures is likely to result in persistent trend biases. We present the above as reasonable hypotheses based on the literature. It should be pointed that obtaining complete mechanistic proof requires conducting targeted sensitivity experiments.

6. Conclusions

In this study, we systematically evaluate the applicability of snow density data from five reanalysis datasets (ERA5-L, GLDAS-Noah, GLDAS-CLSM, GLDAS-VIC, and JRA-3Q) across major snow-covered regions in the Northern Hemisphere during WY 2001–2023. The major conclusions are summarized below.

The evaluation results indicate that ERA5-L and GLDAS-Noah consistently outperform the other datasets in both spatial and temporal dimensions. Spatially, ERA5-L and GLDAS-Noah exhibit lower RMSE (57.9 kg/m³ and 49.6 kg/m³, respectively), higher spatial correlation coefficients (0.58 and 0.65, respectively), and higher TSS (0.35 and 0.46, respectively). Additionally, ERA5-L and GLDAS-Noah exhibit varying performance across sub-regions, performing best in Russia and worst in the WUS. Temporally, the annual means and multi-year monthly averaged snow density of these two datasets are highly consistent with in-situ observations with higher CI values (0.92 and 0.88, respectively), suggesting a better performance in reproducing the interannual variability of snow density. Moreover, when detecting whether snow density bias correlate with SD condition, ERA5-L and GLDAS-Noah also exhibit more pronounced SD-dependence, with the bias range gradually shrinking as SD increases.

The analysis of long-term snow density variations indicates different interannual trends across regions. From WY 1967 to WY 2014, observation indicates a significant decreasing trend in Russia, with most of these changes in both regions occurring in November, December, and January. In the WUS, an increasing trend in snow density is also observed during WY 2004–2023. However, neither ERA5-L nor GLDAS-Noah (v2.0/2.1) accurately capture these patterns, highlighting limitations in their ability to reproduce snow density variability.

Finally, we find that the influence of snow density bias on SD bias varied across regions and among different reanalysis datasets. Although snow density is generally underestimated, the effect of this bias on SD depended on the corresponding SWE bias in each dataset and region. In some cases, where SWE is underestimated and SD is consequently too low, the low snow density act to partially correct the underestimation. In other cases, where SWE is overestimated and SD is already higher than observations, the underestimated snow density further amplifies the SD bias.

In summary, this study provides a systematic evaluation of snow density accuracy across major reanalysis datasets. We further reveal pronounced spatial heterogeneity and monthly variations in observed snow density trends. However, the reanalysis datasets fail to accurately capture long-term trends and early-winter interannual variability in snow density. Our results also demonstrate that the contribution of snow

density to SD biases varies across regions and datasets. These findings highlight the limitations of reanalysis products in reproducing snow density across the Northern Hemisphere, and offer a novel perspective for understanding biases of different snow variables in reanalysis products.

CRediT authorship contribution statement

Yizhuo Li: Data curation, Formal analysis, Methodology, Writing – original draft. **Xin Miao:** Methodology, Supervision, Writing – review & editing. **Xinyun Hu:** Writing – review & editing. **Le Wang:** Writing – review & editing. **Xueliang Zhang:** Writing – review & editing. **Pengfeng Xiao:** Writing – review & editing. **Weidong Guo:** Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Canadian historical Snow Water Equivalent dataset (CanSWE, 1928–2023) is available at <https://zenodo.org/records/10835278>. The in-situ data in Russia can be found at <http://meteo.ru/>. The SNOTEL data is available at <https://www.nrcs.usda.gov/>. ERA5-L data can be downloaded at <https://cds.climate.copernicus.eu/>. All GLDAS datasets can be found at <https://disc.gsfc.nasa.gov/datasets?keywords=GLDAS>. JRA-3Q dataset is available at <https://rda.ucar.edu/datasets/d640000/>.

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