



Evaluation of the performance of a dataset for snow water equivalent in southern Quebec, obtained using a spatialized particle filter

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Abstract. A dataset of daily snow water equivalent (SWE) grids was created for southern Quebec, in eastern Canada, using the HYDROTEL snow model and a spatialized particle filter to assimilate snow data observations. Our aim was to compare this dataset, called “UdeS Grids”, to independent observation data used as reference, as well as to five other gridded datasets (ERA5-Land, Crocus-ERA5, MERRA-2, SNODAS, and C3S Satellite SWE). First, we evaluated the ability of these datasets to estimate SWE using correlation coefficients, relative bias, and the normalized root mean square error (nRMSE). Next, we evaluated their ability to represent snow cover duration using three indicators: start date of snow cover, start date of snowmelt, and end date of snow cover. Our findings show that the best performing dataset is UdeS Grids, followed by ERA5-Land and Crocus-ERA5, while datasets derived from satellite data, such as MERRA-2 and C3S Satellite SWE, perform the worst. The UdeS Grids dataset produces the best representation of snow cover duration compared to the reference data. UdeS Grids is well-correlated to reference data, and has a relatively low nRMSE. However, it underestimates SWE values, particularly SWE_{max} . Data from Crocus-ERA5 are of similar magnitude to reference data, but show more rapid snowmelt, resulting in a much shorter duration of melting. ERA5-Land and SNODAS overestimate SWE values, and melting begins two to three weeks later than for other datasets. Furthermore, these two datasets have much longer melting periods than the other datasets. MERRA-2 and C3S Satellite SWE underestimate reference data by more than 50%.

1 Introduction

Snow is a complex medium that undergoes considerable changes in space and time, especially in mountainous terrain where both the accumulation process of solid precipitation and the snowpack melting process are highly variable (Taheri and Mohammadian, 2022; Clark et al., 2011). While it is possible to take sporadic measurements of snow water equivalent (SWE), continuous estimates over larger geographic areas are necessary for many applications, such as evaluating climate models (Mudryk et al., 2018), seasonal climate prediction (Sospedra-Alfonso et al., 2016), determining freshwater availability (Siirila-Woodburn et al., 2021; Musselman et al., 2021), and others. These applications require temporally and spatially coherent SWE grids. Numerous products of this type have been created on a global scale, based on a variety of methods, including



coupled reanalysis systems, snow model simulations driven by meteorological forcing, estimates from satellite passive microwave remote-sensing (Taheri and Mohammadian, 2022; Mudryk et al., 2025), and others. Despite their widespread use, and the steadily growing number of available SWE gridded products, these datasets are subject to uncertainties of varying severity (Meromy et al., 2013), which arise from the model parametrization and forcing data (Günther et al., 2019; Menard et al., 2021). Multiple studies, including those of Mudryk et al. (2015), Mortimer et al. (2020), and Mudryk et al. (2025), have evaluated the performance of more than twenty global SWE products in the northern hemisphere, and found that no single product consistently out-performs the others across all regions. Performance depends on factors including the study region, type of vegetation cover, and elevation. For example, datasets exhibit greater consistency in low-altitude regions and regions of boreal forest than in mountainous regions. However, reanalysis products and snow model based products such as ERA5 (Hersbach et al., 2020), ERA5-Land (Muñoz-Sabater et al., 2021), and the Crocus model (Vionnet et al., 2012), seem to perform best.

As well as global SWE products, available at a worldwide scale, ongoing efforts by the scientific community have produced regional datasets by assimilating available data from observation networks. Regional datasets can respond to specific needs at regional or national scales, while seeking to reduce uncertainties associated with the data. For example, the SNODAS dataset (Barrett, 2003) provides data on snow in the U.S., while Margulis et al. (2016) and Fang et al. (2022) have produced snow datasets for the Sierra Nevada and the western U.S. Other datasets are also available for Austria (Olefs et al., 2020), high mountain zones of Asia (Liu et al., 2021), the Iberian Peninsula (Alonso-González et al., 2018), Italy (Avanzi et al., 2023), Switzerland (Oberrauch et al., 2026), and for the French Alps, the Pyrenees, and Corsica (Vernay et al., 2022). Along the same lines, Cantet et al. (2019) developed a snow dataset covering southern Quebec, in eastern Canada. This dataset was created based on the HYDROTEL Snowpack Model (HSM) of snow accumulation and melting (Turcotte et al., 2007), with observation data from sporadic manual snow surveys assimilated using a spatialized particle filter. Subsequently, Odry et al. (2022) produced an improved version of the dataset grids with better spatial consistency, which now is used operationally for hydrological forecasting by the Government of Quebec. A major challenge in assimilating snow data is a lack of independent data to validate the method, since researchers usually try to assimilate all available data. This dataset was validated using the “leave-one-out” cross-validation method with the same observation data used in the dataset. It is therefore prudent to compare different snow datasets in order to evaluate our dataset’s strengths and weaknesses, with a view toward future production of an improved version of the dataset.

The goal of the present study is to evaluate the performance of the dataset created by Cantet et al. (2019) and Odry et al. (2022), hereafter referred to as “UdeS Grids” (named for the Université of Sherbrooke). We compare UdeS Grids both to independent in situ observation data, and to five other gridded datasets. Three of these datasets are global reanalyses: ERA5-Land (Muñoz-Sabater et al., 2021) and Crocus-ERA5 (Ramos Buarque et al., 2025), which use the meteorological forcing from the ERA-5 reanalysis (Hersbach et al., 2020), and MERRA-2 (Gelaro et al., 2017), which essentially assimilates satellite observations. The other two datasets are SNODAS (Barrett, 2003), originally produced for the U.S. but now available for southern Canada, and C3S Satellite SWE (C3S, 2026), which is derived from passive microwave radiometer measurements onboard polar-orbiting satellites. Based on the availability of in situ observations, this comparison was carried out for the period 2013–2023. We based our comparison of snow data only on SWE, which represents the quantity of water contained in



the snowpack, expressed per unit area (Seibert et al., 2021). SWE was chosen because it is often considered the most important snow variable. Dataset performance was evaluated using statistical metrics such as correlation coefficients, bias, and root mean square error. Moreover, the ability of the SWE datasets to represent snow cover duration was evaluated using three indicators: start date of snow cover, start date of snowmelt, and end date of snow cover.

The rest of the article is organized as follows. Section 2 provides a list of gridded SWE datasets, as well as the reference data used, and its preprocessing before comparisons. Section 3 describes the study zone. Section 4 describes our overall evaluation strategy, as well as the specific indicators evaluated. Sections 5 and 6 illustrate the specific performance of each dataset using different statistical metrics, and provide a discussion of our main results. We present our conclusions in Section 7.

2 Datasets and data preprocessing

2.1 Datasets

2.1.1 ERA5-Land

ERA5-Land (Muñoz-Sabater et al., 2021) constitutes an enhancement of the ERA5 reanalysis (Hersbach et al., 2020) for the land component. It is produced within the C3S (Copernicus Climate Change Service) by the ECMWF (European Centre for Medium-Range Weather Forecasts). This dataset provides hourly and monthly data since 1950 for fifty surface variables, including snow water equivalent, on a grid covering the entire planet with a spatial resolution of 0.1° . However, ERA5-Land does not provide data for lakes and other large-area water bodies. The ERA5-Land reanalysis is produced using the ECMWF land surface model, the Carbon Hydrology-Tiled ECMWF Scheme for Surface Exchanges over Land (CHTESSEL). Instead of directly assimilating in situ observations, ERA5-Land assimilates the atmospheric forcing from ERA5 through a four-dimensional variational assimilation system (4D-Var) and simplified extended Kalman filter (SEKF) systems as described in Hersbach et al. (2020). Although it doesn't directly assimilate in situ observations, this dataset benefits from assimilating tens to hundreds of millions of daily observations from ERA5 (Hersbach et al., 2020). The ERA5 reanalysis incorporates an advanced system for assimilating terrestrial data, optimized to improve the representation of hydrological variables such as soil moisture and snow depth. This observation data comes from multiple satellites, as well as measurements at ground level and above the ocean surface, high-altitude sensors, and atmospheric measurements from aircraft instruments.

2.1.2 Crocus-ERA5

SWE data from Crocus-ERA5 (Ramos Buarque et al., 2025) are available for the period 1950–2023 with a daily time-step and a spatial resolution of 0.25° . This dataset follows the same methodological approach as ERA5-Land, in that it uses a physically-based model and assimilates the atmospheric data from the ERA5 reanalysis. The main difference between Crocus-ERA5 and ERA5-Land is the physical model used. ERA5-Land uses CHTESSEL, while Crocus-ERA5 uses the Crocus snowpack model (Vionnet et al., 2012), which simulates albedo, thermal diffusion, and phase change, as well as the mass, density, and metamorphism of snow grains, based on empirical laws (Brun et al., 1989, 1992; Vionnet et al., 2012). Specifically, the



model represents the vertical structure of the snowpack dynamically by dividing it into 3 to 50 layers depending on depth and stratification (Vionnet et al., 2012). This layer approach makes it possible to consider temperature gradients as well as the conservation of mass and heat during melting and accumulation, while representing key processes such as solar absorption, water retention, thermal diffusion, and compaction. Moreover, the Crocus snowpack model is coupled to the ISBA (Interactions between Soil, Biosphere, and Atmosphere) land surface scheme (Vionnet et al., 2012; Brun et al., 2013), which allows Crocus to interact with other surface components such as soil, low vegetation, and atmosphere, within a consistent framework.

95 2.1.3 SNODAS

SNODAS (Snow Data Assimilation System) is produced by the National Operational Hydrologic Remote Sensing Center (NOHRSC) of the National Oceanic and Atmospheric Administration (NOAA) Weather Service. This dataset provides SWE and other snow-related data, and is available since 2003 for all of the U.S., with a daily time-step and a spatial resolution of 0.01° (Barrett, 2003). SNODAS mainly covers the continental U.S.; however, since 2013, its spatial coverage has also been extended to southern Canada (to 58°N). However, SNODAS does not provide data east of longitude 62°W.

SNODAS is produced using the NOHRSC snow model, which has many spatially distributed, but uncoupled, layers, and incorporates energy and mass balances. The model consists of three snow layers and two soil layers. Meteorological forcing is from RUC2 NWP (Rapid Update Cycle Numerical Weather Prediction) (Benjamin et al., 2002). Several types of snow data (from satellites, airborne platforms, and ground stations) are assimilated in the snow model using nudging or Newtonian relaxation. The latter is a simple form of data assimilation that consists of adding a forcing term (relaxation) to the predictive equations of the model (Hoke and Anthes, 1976; Kalnay, 2003). The forcing term is proportional to the difference between the model state and the observation.

2.1.4 MERRA-2

The atmospheric reanalysis MERRA-2 (Modern-Era Retrospective Analysis for Research and Applications, Version 2) is produced by the GMAO (Global Modeling and Assimilation Office) of NASA (National Aeronautics and Space Administration). Data begins in 1980, and is available with a daily time-step with a resolution of 0.5° (Gelaro et al., 2017). MERRA-2, which replaces the MERRA reanalysis (Rienecker et al., 2011), uses the general atmospheric circulation model GEOS-5 (Goddard Earth Observing System Model, Version 5), as well as an improved version of the data assimilation system 3DVAR based on the GSI (Global Statistical Interpolation) analysis scheme of Wu et al. (2002). MERRA-2 assimilates tens of millions of satellite observations per 6-hour cycle. The main reason MERRA-2 replaced MERRA is because the latter's data assimilation system was frozen in 2008, and cannot integrate several important new data types. As older satellite instruments fall out of operation, the number of observations available for assimilation in MERRA is rapidly decreasing. MERRA-2 uses GEOS-5, v. 5.12.4, which can use new instrumentation such as microwave sensors and hyperspectral infrared radiation sounders.



2.1.5 C3S Satellite SWE

120 The C3S Satellite SWE data (C3S, 2026), produced on behalf of the Copernicus Climate Change Service by the Finnish Meteorological Institute, cover the Northern Hemisphere and are available from 1979 for winter seasons only (October to May), with a daily time-step and a spatial resolution of 0.1° . This product is based on passive scanning multi-channel microwave radiometer (SMMR) measurements onboard the NIMBUS-7 satellite, as well as the sensors SSM/I and SSMIS (Special Sensor Microwave Imager/Sounder) of the DMSP (Defense Meteorological Satellite Program) Series F satellites. The algorithm for
 125 calculating SWE, which is based on the work of Pulliainen and Hallikainen (2001), Takala et al. (2011), and Luoju et al. (2021), is a radiative transfer based semi-empirical Snow Emission Model developed at the Helsinki University of Technology (HUT) (Pulliainen et al., 1999). It estimates SWE data from the brightness temperature of snow layers in the frequency range 11 to 94 GHz, based on data provided by passive microwave radiometer measurements. Moreover, the algorithm assimilates synoptic in situ observations of snow thickness using a Bayesian non-linear iterative method.

130 2.1.6 UdeS Grids

The UdeS Grids SWE data cover southern Quebec and are available from 1961, with a daily time-step on regular grids with a spatial resolution of 0.1° . The complete methodology used to produce these data is described in detail in the works of Cantet et al. (2019), Odry et al. (2020), and Odry et al. (2022). Briefly, the SWE grids were produced by assimilating SWE data from sporadic manual snow surveys using a spatialized particle filter and the HYDROTEL Snowpack Model (HSM) of snow
 135 accumulation and melting (Turcotte et al., 2007). The HSM is based on a temperature index which provides a simplified representation of the water and energy balance of the snowpack. This relatively simple model only requires daily precipitation and minimum and maximum air temperatures as input data. The UdeS Grids SWE data were produced by kriging over a regular grid with a resolution of 0.1° (Bergeron, 2016), using in situ measurements from meteorological stations obtained through the RMCQ (Réseau météorologique coopératif du Québec). Subsequently, Odry et al. (2022) improved this method by applying
 140 the “Schake shuffle” technique (Clark et al., 2004), which maintains a better spatial coherency between “particles.” Odry et al. (2022) also tested the possibility of assimilating other types of data, such as SWE estimates from automatic measurements of snow depth (SR50), and an artificial neural network (Odry et al., 2020). The new method proposed by Odry et al. (2022) reduced the root mean square error (RMSE) between SWE estimates and validation sites, and substantially improved the Pearson correlation coefficient. This means that the uncertainty of the SWE estimate at an ungauged site would, in theory, be
 145 significantly reduced.

Table 1 summarizes the gridded datasets used in this study, with the snow model, assimilation method, and forcing used.

2.1.7 In situ SWE observation datasets

The main SWE dataset used in our analysis was the Canadian Historical SWE Dataset (CanSWE), produced by Vionnet et al. (2021). This dataset combines historical manual and automatic SWE observations collected by national, provincial, and
 150 territorial entities, as well as by hydroelectric utility companies. Metadata errors were corrected, duplicate data were merged



Table 1. Characteristics of the Snow Water Equivalent datasets used.

Name	Resolution	Model Used	Assimilation Method	Atmospheric Forcing
UdeS Grids	0.1° / 24h	HSM	particle filter	Kriging of in situ observations
ERA5-Land	0.1° / 1h	CHTESSEL	4D-Var / SEKF	ERA5
Crocus-ERA5	0.25° / 24h	Crocus snow-pack	ISBA	ERA5
MERRA-2	0.5° / 24h	GEOS-5	3D-Var / GSI	Satellite data
SNODAS	0.01° / 24h	NOHRSC	Nudging / Newtonian relaxation	RUC2 NWP
C3S Satellite SWE	0.1° / 24h	HUT	Bayesian non-linear iterative method	Passive microwave radiometer measurements

and deleted, and dataset quality was verified by homogenizing the data quality indicators used by different organizations and deleting outlier values. This study used 174 CanSWE stations, including 92 automatic stations, that had available data in our study zone between 2013 and 2023. The majority of the stations came from Hydro-Québec, a hydroelectric utility company in the province of Quebec, and from the mining company Rio Tinto Alcan.

155 The automatic stations in CanSWE are GMON stations, which measure natural gamma radiation from the ground and its attenuation by the snow cover (Choquette et al., 2008; Ducharme et al., 2015). We used these data to obtain SWE estimates over a region of about 100 m². GMON stations were developed and patented by Hydro-Québec. According to Choquette et al. (2008), GMON stations can measure SWE to the desired accuracy for values up to 400 mm. As well as the CanSWE data, Hydro-Québec also provided us with data from 138 GMON stations with variable data collection periods. The oldest stations
 160 collected data going back to 2016, while others only began to collect data in 2023. Most stations had less than three years of daily data collection, and only 29 had more than five years.

2.2 Data preprocessing

2.2.1 Preprocessing of independent in situ datasets

The CanSWE dataset consists of 2,943 stations in Canada, of which 231 are in Quebec. Of these, 199 are in our study zone, and
 165 174 collected data for the period 2013–2023. In addition to the CanSWE stations, Hydro-Québec also provided us with data from 138 stations located in Quebec, of which 108 collected data between 2013 and 2023 in our study zone. We established a procedure to merge or delete duplicate data between GMON and CanSWE. This analysis found that 64 of the 108 Hydro-Québec GMON stations were duplicates. Thus, 218 stations were retained as independent in situ stations for our study: the 174 CanSWE stations, and the remaining 44 Hydro-Québec GMON stations.



170 2.2.2 Independence of in situ observation data and the gridded datasets

Except for UdeS Grids, none of the gridded datasets assimilated in situ SWE observations from our study zone, and their data were therefore completely independent from our reference data. However, the UdeS Grids dataset assimilates in situ observations and, since the CanSWE dataset which we used as reference data includes all historic data for Canada, it is possible that certain stations assimilated in UdeS Grids are also found in CanSWE. On the other hand, the geographic distribution of stations suggests that the stations assimilated in the UdeS Grids dataset are largely different from those in CanSWE. Most of the stations assimilated in UdeS Grids (see Cantet et al. (2019) and Odry et al. (2022)) are located south of 49°N, while over half of the stations used in our study are located north of this latitude. Furthermore, many of the stations assimilated in UdeS Grids are located southwest of our study zone, whereas very few of the stations that we used as reference data are located in this region. The different geographic distribution of the stations assimilated in UdeS Grids and those we used as reference data suggests that we can consider our reference data to be independent.

2.2.3 Grid definition and resolution

For this study, we used the same reference grid as UdeS Grids, covering the area between 81°W and 57°W and between 43°N and 53°N, with a spatial resolution of 0.1°. We therefore resampled all of the gridded products described in Sections 2.1.1 to 2.1.5 using the spatial mean of their gridpoints to obtain new grids with the same resolution as UdeS Grids. These were then trimmed to the same geographic area as UdeS Grids. This resulted in over-sampling of SNODAS, which went from 0.01° to 0.1°, and under-sampling of the MERRA-2 and Crocus-ERA5 data. The ERA5-Land and C3S Satellite SWE had identical spatial resolution as UdeS Grids, and did not change scale. However, the centroids of their grids were shifted to correspond to those of UdeS Grids.

3 Study zone

Our study zone, shown in Fig. 1, corresponds to southern Quebec (south of 53°N) in eastern Canada, and covers approximately 875,000 km². It is divided into 17 administrative regions. The northerly maritime location of southern Quebec results in a cool, moist climate with a large temperature range between hot and cold seasons: the daily mean temperature is around 15°C from June to August, compared to around -13.8°C from December to February. Average precipitation is 960 mm per year (about 2.6 mm per day), of which about 75% is as rain. Average monthly precipitation is more than 50 mm, and more than 90 mm in summer. Snow may begin to fall in October, but does not tend to accumulate on the ground until November. Snowfall then increases to 60 cm per month from December to March. Maximum snow accumulation is observed in March, with a SWE that is usually above 200 mm (Bathelemy et al., 2026).

Following the classification of Sturm and Liston (2021), our study zone is characterized by four snow classes, as shown in Fig. 1. This classification is based on air temperature, precipitation, and wind speed data. The two snow classes found in the northern part of our zone, Boreal Forest and Tundra, are both characterized by relatively low temperatures and precipitation.

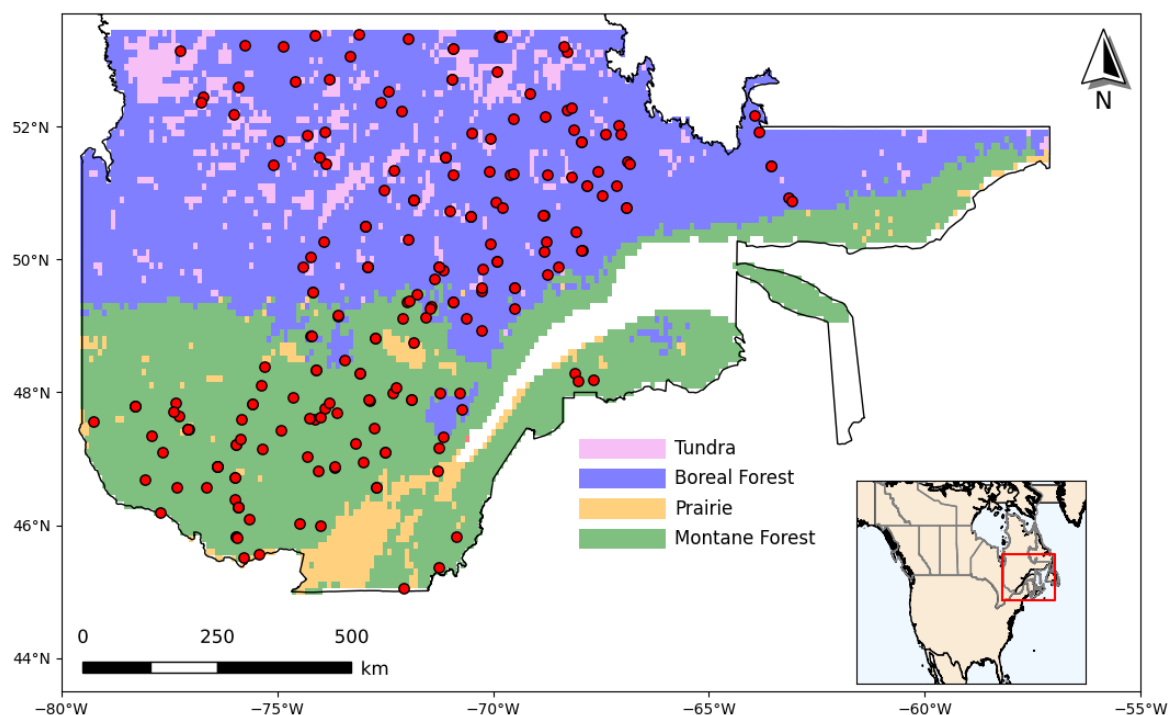


Figure 1. Map of the study zone, showing locations of in situ observation stations, and snow classes following the classification of Sturm and Liston (2021).

However, the Boreal Forest class is characterized by relatively low wind speed, and the Tundra class by relatively high wind speed. The two classes in the southern part of our study zone, Montane Forest and Prairie, are characterized by higher temperatures than the other two classes, and by relatively low precipitation. Furthermore, Montane Forest is characterized by relatively low wind speed, and Prairie by relatively high wind speed.

205 4 Evaluation of the overall performance of SWE datasets

4.1 Comparison strategy

Two complementary strategies were used to compare the SWE datasets. The first, called “point-to-pixel,” consists of comparing the time-series from each independent in situ station (points) to the corresponding values of the nearest cell of the grid (pixels). This approach can show which gridded datasets provide the best representation of the reference data. Although useful, this comparison has certain limitations: (i) The in situ reference data are available over a relatively short time period; (ii) the spatial density of stations in the study zone is relatively sparse; and (iii) SWE has a high spatial variability that depends on the station’s location within the cell, meaning that data from a single station may not be representative of the entire 10 km × 10 km cell area. To overcome these limitations, we adopted a second strategy, called “pixel-to-pixel.” In this approach, all the pixels of



the gridded datasets are compared against those of UdeS Grids, allowing comparison over a longer time period, and with better
215 spatial representation of the results. This approach does not show which dataset is the most realistic, only the amount of the
deviation between UdeS Grids and the other datasets.

4.2 Performance indicators

The performance of the SWE datasets was evaluated based on two criteria: the ability to represent snow cover duration, and
the ability to correctly estimate SWE values.

220 The ability of the SWE datasets to represent snow cover duration was evaluated using three indicators, as described by
Ramos Buarque et al. (2025): start date of snow cover, which corresponds to the first day of continuous snow; start date of
snowmelt, which corresponds to the date of maximum SWE; and end date of snow cover, which corresponds to the last day of
continuous snow.

The ability of the datasets to correctly estimate SWE data was evaluated using the following four metrics: maximum annual
225 SWE, correlation coefficients, relative bias, and nRMSE (normalized root mean square error). Maximum annual SWE is a
widely used indicator in snow hydrology, because it seems to influence spring peak flows during snowmelt (Dibike et al.,
2021). Correlation coefficients evaluate the linear relationship between the gridded data and the reference data. Coefficients
vary between -1 and +1, with -1 indicating a perfect negative correlation and +1 a perfect positive correlation. However,
correlation coefficients cannot evaluate whether the data from different datasets are of similar magnitude. We therefore used
230 two other statistics to quantify the differences between gridded data and reference data: relative bias and nRMSE. The latter,
also called unbiased RMSE, is obtained by calculating the RMSE from centered data (obtained by subtracting the mean from
each value). Relative bias measures the overall tendency of gridded product values to overestimate (bias > 0%) or underestimate
(bias < 0%) the reference SWE data. nRMSE is used as a measure of mean absolute error, with an optimal value of 0 mm. It
is related to other statistical metrics by the following equation:

$$235 \quad nRMSE^2 = \sigma_r^2 + \sigma_g^2 - 2\sigma_r\sigma_g R \quad (1)$$

Where σ_r^2 is the standard deviation of the reference data; σ_g^2 is the standard deviation of the gridded data; and R is the correlation
coefficient. This equation is used to construct a Taylor diagram, which is often used in hydrometeorology to evaluate models
or datasets (Taylor, 2001). The equations and metrics used are shown in Table 2.

5 Results

240 5.1 Point-to-pixel comparison

This section presents the results of the comparison between sporadic in situ data, treated as reference data, and the five gridded
SWE datasets. Figure 2 shows the main results for the three statistical metrics: correlation coefficients, relative bias, and
nRMSE. The top row of Fig. 2 shows that the gridded datasets are well-correlated to reference data, except for MERRA-2,



Table 2. List of statistical metrics used to evaluate snow water equivalent (SWE) dataset performance: X_i : reference data; $\bar{X}$: mean of reference data; Y_i : gridded SWE datasets; $\bar{Y}$: mean of gridded datasets; n : length of time-series.

Statistical metrics	Units	Equations
R	-	$\frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}}$
$RMSE$	mm	$\sqrt{\frac{\sum_{i=1}^n (X_i - Y_i)^2}{n}}$
$nRMSE$	mm	$\sqrt{\frac{\sum_{i=1}^n [(X_i - \bar{X}) - (Y_i - \bar{Y})]^2}{n}}$
σ_r	mm	$\sqrt{\frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n}}$
$bias$	%	$\frac{\bar{Y} - \bar{X}}{\bar{X}}$

for which more than 70% of stations have correlation coefficients below 0.8. ERA5-Land and UdeS Grids have the strongest
 245 correlations to reference data, with correlation coefficients above 0.90 for over 55% of stations, and only about 20% of stations
 with correlation coefficients below 0.8. The other datasets, in decreasing order of performance, are Crocus-ERA5, SNODAS,
 C3S Satellite SWE, and lastly, MERRA-2. Furthermore, most of the datasets show stronger correlations in the southern part of
 our study zone. The middle row of Fig. 2 shows that, except for ERA5-Land, the gridded SWE datasets tend to underestimate
 SWE relative to reference data. The underestimation is greatest for MERRA-2 and C3S Satellite SWE, with SWE values
 250 underestimated by more than 50% in over half the stations. The UdeS Grids and Crocus-ERA5 datasets underestimate SWE
 by about 10 to 35%, relative to the reference data, while ERA5-Land overestimates SWE by 10 to 25%. SNODAS seems to
 overestimate SWE in the northern part of the study zone, and underestimate it in the southern part. UdeS Grids and ERA5-Land
 have similar nRMSE scores, with about 15% of stations having nRMSE scores below 25 mm, and 60% having nRMSE scores
 between 25 and 50 mm. Stations with higher nRMSE scores are generally located in the north and northeast. Crocus-ERA5 has
 255 slightly higher nRMSE scores, with more than 30% stations having scores above 50 mm, compared to 25% for UdeS Grids and
 ERA5-Land. SNODAS, C3S Satellite SWE, and MERRA-2 have the highest nRMSE scores, with more than 53% of stations
 having nRMSE scores above 50 mm for SNODAS and C3S Satellite SWE, and more than 65% of stations having nRMSE
 scores above 50 mm for MERRA-2.

Indicators related to snow cover were calculated for the 109 automatic stations for which continuous data were available,
 260 with the results shown in Fig. 3. According to the reference data, snow cover begins between the middle and end of November
 south of latitude 48°N, in mid-November in the east, and between late October and early November in the north and west.
 UdeS Grids, Crocus-ERA5, and C3S Satellite SWE appear to give a good representation of the start of snow cover, particularly
 in the north, albeit with a start date of snow cover one to two weeks earlier than the reference data in the south. The snow cover

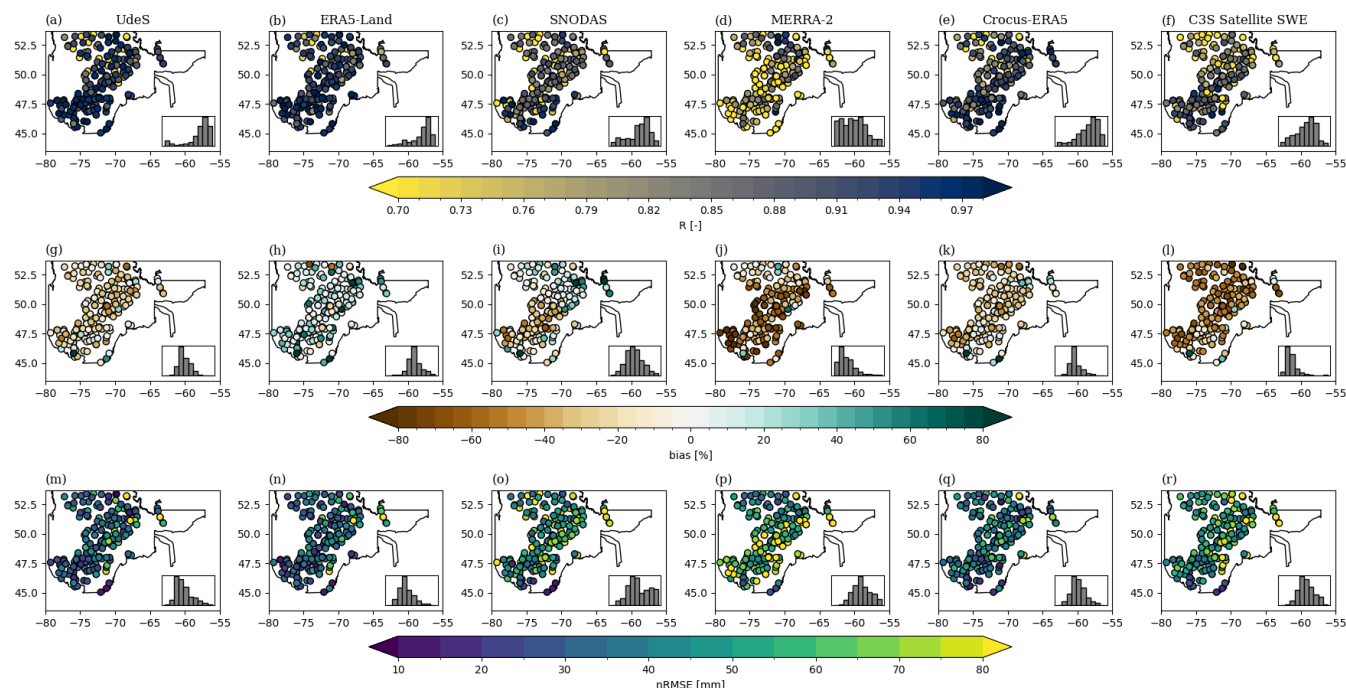


Figure 2. Maps showing correlation coefficients (top row), bias (middle row), and nRMSE (bottom row) between the reference data and the six gridded datasets (each column is a dataset).

of ERA5-Land, SNODAS, and MERRA-2 starts two to three weeks earlier than the reference data, with the biggest difference
265 in the north.

According to the reference data, the snow begins to melt between the beginning and the middle of April, toward the end
of April for stations in the north, and at the end of March for a few southern stations. The snow begins to melt one to two
weeks earlier than the reference data for UdeS Grids and Crocus-ERA5, and from more than three to four weeks earlier for
MERRA-2 and C3S Satellite SWE. Conversely, the snow begins to melt later for ERA5-Land and SNODAS, particularly in
270 the north, where melting begins toward the end of April for ERA5-Land and the beginning of May for SNODAS.

According to the reference data, the end of snow cover occurs between the beginning and the middle of May in the south,
and generally between the end of May and the beginning of June in the east and north. However, for a few stations located
across the entire study zone, snow cover ends in late June. When we excluded these stations for which the snow cover ends in
late June, UdeS Grids provides a representation of the snow cover similar to the reference data, although the snow cover ends
275 a few days earlier for some stations. Snow cover ends much later for ERA5-Land and SNODAS, especially in the north where
it ends one to two weeks later than the reference data. Conversely, snow cover ends very early for MERRA-2, C3S Satellite
SWE, and Crocus-ERA5, in early April in the south and early May in the north.

SWE_{max} , an indicator widely used to describe the hydrology of northern watersheds, is shown in the bottom row of Fig.
3. Reference data SWE_{max} generally lay between 240 and 340 mm, though no spatial pattern emerged. None of the datasets

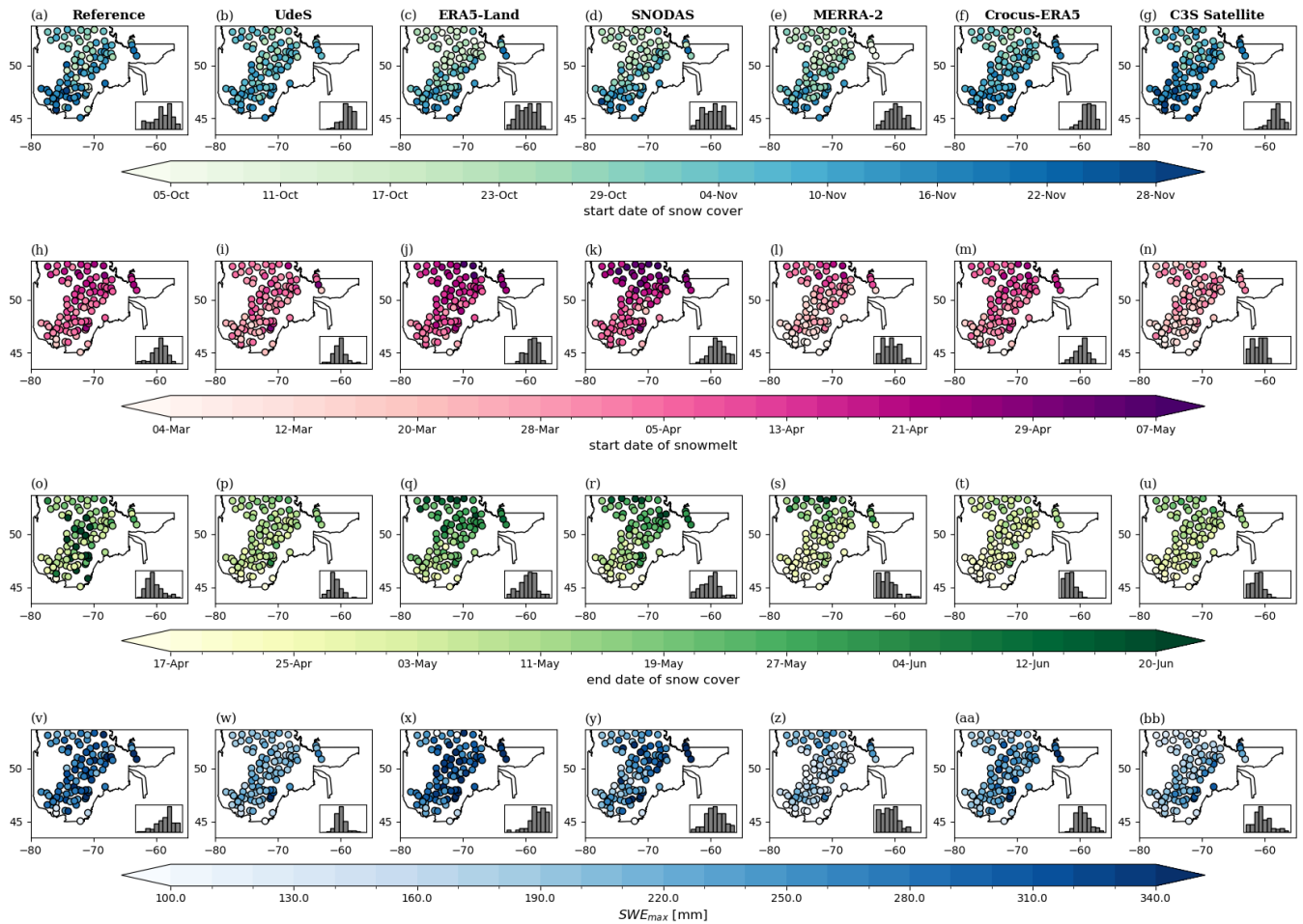


Figure 3. Maps showing the start date of snow cover (top row), start date of snowmelt (second row), end date of snow cover (third row), and SWE_{max} (bottom row) for the reference data and the six gridded datasets (each column is a dataset).

provides a satisfactory estimate of the reference data SWE_{max} . Indeed, the datasets UdeS Grids, SNODAS, MERRA-2, C3S Satellite SWE, and Crocus-ERA5 underestimate the reference data SWE_{max} by a large margin, with SWE_{max} values below 180 mm for MERRA-2, between 180 and 240 mm for UdeS Grids and C3S Satellite SWE, up to 260 mm for Crocus-ERA5 and SNODAS, and sometimes exceeding 300 mm for some stations in SNODAS. ERA5-Land overestimates SWE_{max} relative to reference data, with values between 220 and 340 mm in the south and north of 52°N, and between 320 and 400 mm in the central area between latitudes 48°N and 52°N.



5.2 Pixel-to-pixel comparison

We compared the UdeS Grids dataset to the other gridded SWE datasets, thereby providing a common basis of comparison in order to discern the differences among them. The resulting statistical metrics are shown in Fig. 4. The top row of this figure shows that, except for MERRA-2, all the other SWE datasets are well-correlated to UdeS Grids. Crocus-ERA5 has the strongest correlation to UdeS Grids, with coefficients between 0.90 and 0.94, except in the east where the coefficients dip to 0.8, and even as low as 0.7 in the northeast. ERA5-Land is also well-correlated to the UdeS Grids dataset south of 48°N, with coefficients between 0.9 and 0.96. However, the correlation coefficients fall to less than 0.7 in the southernmost region, below 46°N. The correlation coefficients between UdeS Grids and ERA5-Land decrease north of 49°N, especially in the area between 70°W and 64°W, where the coefficients are between 0.7 and 0.8. C3S Satellite SWE is well-correlated to UdeS Grids data in the south and the west, with coefficients between 0.84 and 0.92, but falling to about 0.7 in the east. The correlation coefficients between UdeS Grids and SNODAS are generally between 0.7 and 0.8, and rise to 0.92 south of 46°N.

The SWE values of Crocus-ERA5 are the closest to UdeS Grids, with the lowest biases. Crocus-ERA5 overestimates UdeS Grids data by 5 to 20% in the central and eastern part of the study zone, and underestimates them by 10 to 15% in the west. C3S Satellite SWE underestimates UdeS Grids data by more than 10 to 40%, while MERRA-2 underestimates them by more than 30 to 80%. ERA5-Land overestimates the UdeS Grids data, except in the area south of 46°N, where it underestimates them by about 10%. ERA5-Land overestimates the UdeS Grids data by 10 to 20% in the south between 46°N and 48°N, and 30 to 60% in the west and north. SNODAS underestimates UdeS Grids data by about 15% in the central and southern part, and overestimates them in the rest of the study zone, by 20 to 30% in the west, and by 40 to 70% in the north and east.

Crocus-ERA5 and C3S Satellite SWE have the best nRMSE scores of all the SWE datasets, with values between 25 and 40 mm in the west and south, and between 40 and 65 mm in the north and east. ERA5-Land also performs well in the south, with scores around 30 mm. However, the nRMSE scores of ERA5-Land are as high as 40–60 mm in the west and north, and more than 70 mm in the east. The nRMSE scores of SNODAS are between 20 and 30 mm south of 46°N, between 60 and 75 mm in the rest of the study area, and higher than 90 mm in the east. The nRMSE scores of MERRA-2 are generally between 35 mm and 65 mm.

The above results were synthesized as Taylor diagrams for the four snow classes occurring in our study zone (Fig. 5). These diagrams show that the correlations between the gridded datasets and UdeS Grids data are strongest for the snow classes Prairie and Montane Forest. Moreover, nRMSE scores for Prairie are generally lower. Standard deviations are also lower for this snow class, indicating a smaller temporal variability compared to the other three classes. For all four snow classes, Crocus-ERA5 is the closest to the UdeS Grids data, with similar standard deviations, high correlation coefficients, and the lowest nRMSE. ERA5-Land and SNODAS behave similarly for the classes Boreal Forest and Montane Forest: both datasets show a higher temporal variability than UdeS Grids for these two snow classes, and have similar nRMSE scores and correlation coefficients. However, SNODAS exhibits greater temporal variability than UdeS Grids for the other two snow classes (Tundra and Prairie), whereas the temporal variability of ERA5-Land sharply decreases to a similar magnitude as UdeS Grids for the snow class Tundra, and is lower for the snow class Prairie. MERRA-2 and C3S Satellite SWE have markedly lower temporal variability

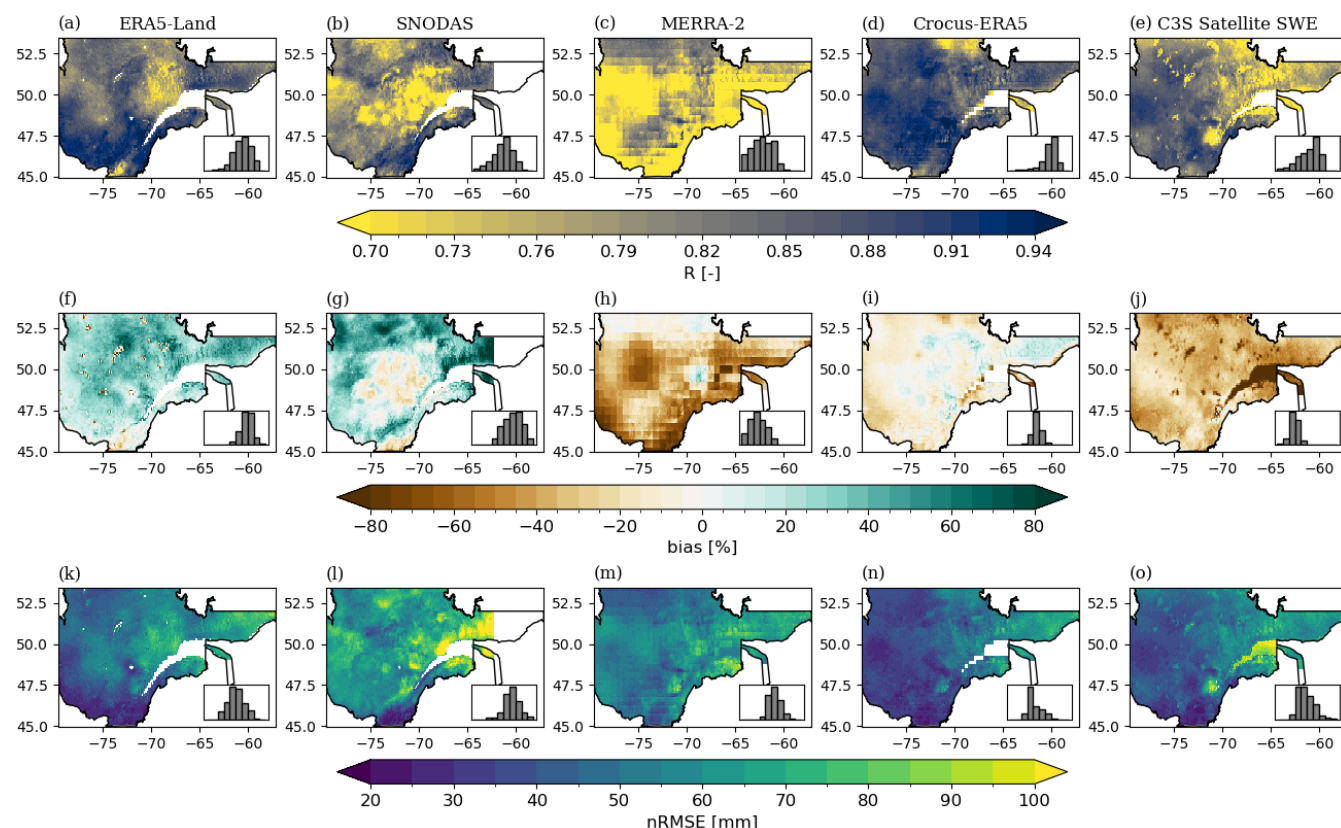


Figure 4. Maps showing correlation coefficients (top row), bias (second row), and nRMSE (bottom row) between UdeS Grids and the five other gridded datasets (each column is a dataset).

than UdeS Grids for all snow classes. The standard deviation of C3S Satellite SWE is of similar magnitude to MERRA-2 for the snow class Boreal Forest, higher for the classes Prairies and Montane Forest, and lower for the snow class Tundra.

The top row of Fig. 6 shows that snow cover generally starts later for UdeS Grids, C3S Satellite SWE, and Crocus-ERA5 than for the other three datasets. For the Tundra and Boreal Forest snow classes, snow cover begins in mid-October for ERA5-Land, SNODAS, and MERRA-2, and the end of October for UdeS Grids, C3S Satellite SWE, and Crocus-ERA5. For the Prairie and Montane Forest snow classes, it begins at the end of October for ERA5-Land, SNODAS, and MERRA-2, and between early to mid-November for UdeS Grids, C3S Satellite SWE, and Crocus-ERA5. Most of the datasets show a similar temporal variability. For example, all datasets identified an early snow cover in 2016, 2019, and 2021 for the Tundra and Boreal Forest snow classes, and a late snow cover in 2014, 2020, 2022, and 2023 for the Prairie and Montane Forest snow classes. However, in some years the dates varied greatly between datasets. For example, for the Tundra and Boreal Forest snow classes, UdeS Grids, C3S Satellite SWE, and Crocus-ERA5 identified a late snow cover in 2015 and 2023, while the other three datasets identified an early snow cover. Likewise, for the Prairie and Montane Forest snow classes, UdeS Grids, SNODAS, C3S Satellite SWE, and Crocus-ERA5 identified a late snow cover in 2013, 2014, and 2018.

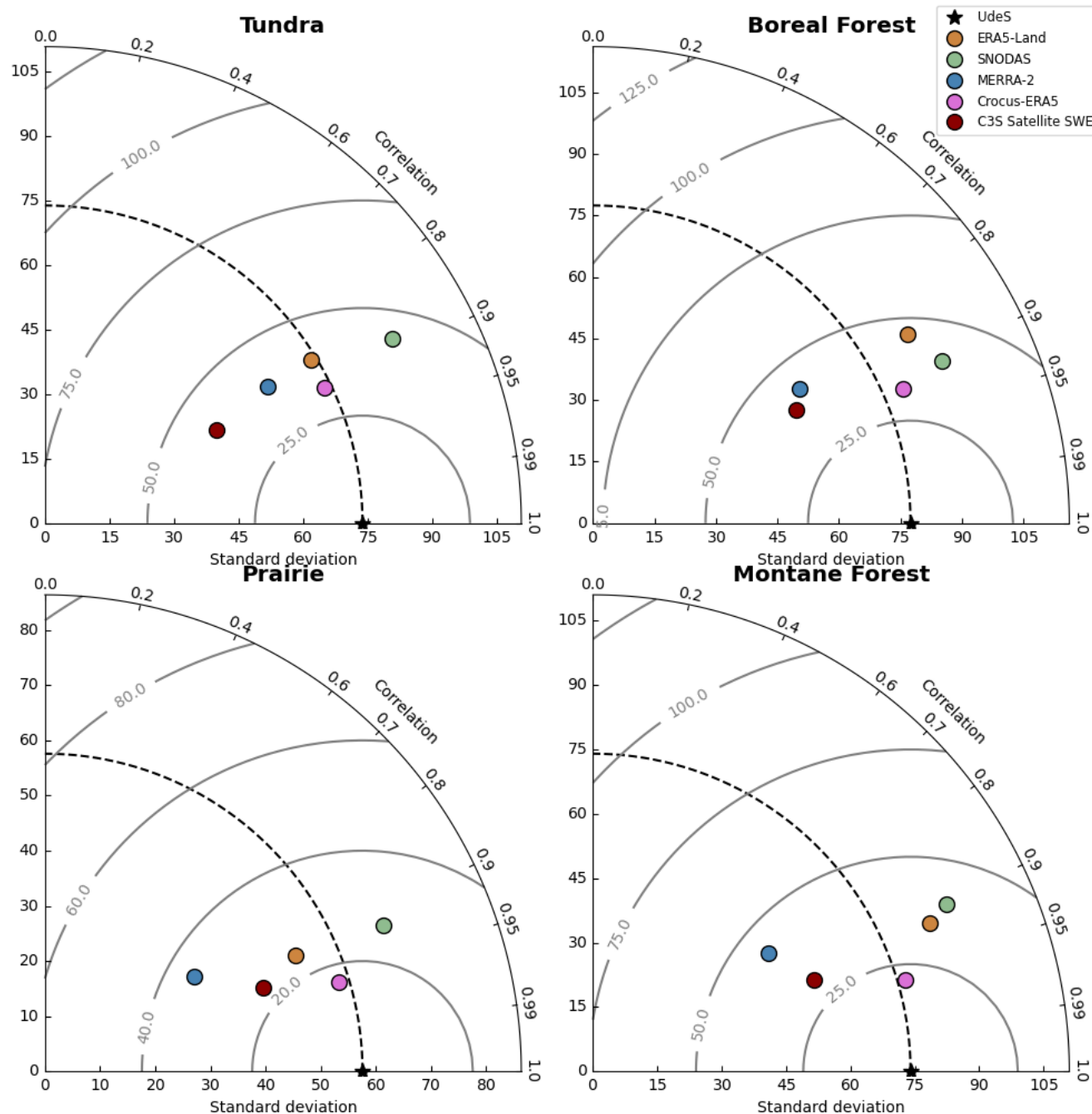


Figure 5. Statistical metrics synthesized as Taylor diagrams.

The second row of Fig. 6 shows that snowmelt begins very early for the snow class Prairie, where it is observed around mid-March for all datasets except MERRA-2, for which it is observed at the end of February. For the snow classes Tundra,



335 Boreal Forest, and Montane Forest, the start dates of snowmelt for ERA5-Land and SNODAS occur about two weeks later than for other datasets. For the snow classes Tundra and Boreal Forest, snowmelt begins between the middle and end of April for ERA5-Land and SNODAS, the beginning of April for UdeS Grids and Crocus-ERA5, and the end of March for MERRA-2 and C3S Satellite SWE. For the snow class Montane Forest, snowmelt begins at the beginning of April for ERA5-Land and SNODAS, the end of March for UdeS Grids and Crocus-ERA5, and between the beginning and middle of March for MERRA-2 and C3S Satellite SWE. All of the datasets identified an early start date of snowmelt in 2021 for all snow classes, and in 2016 and 2020 for the snow class Prairie.

The third row of Fig. 6 shows that the end dates of snow cover vary greatly by dataset, particularly for the snow classes Tundra and Boreal Forest. The end dates of MERRA-2, C3S Satellite SWE, and Crocus-ERA5 are observed between the beginning and middle of May, those of UdeS Grids at the end of May, those of SNODAS between the beginning and middle of June, and those of ERA5-Land between the end of June and beginning of July. Moreover, for some years such as 2013, 2014, 2018, 2019, and 2022, snow cover ended extremely late for ERA5-Land and SNODAS, near the beginning of September. For the snow classes Prairie and Montane Forest, snow cover ends around the beginning of May for MERRA-2, C3S Satellite SWE, and Crocus-ERA5, in mid-May for SNODAS and UdeS Grids, and at the end of May for ERA5-Land, although all datasets showed an earlier end of snow cover in 2021 and 2023.

350 The fourth row of Fig. 6 shows that UdeS Grids and Crocus-ERA5 have similar SWE_{max} for the four snow classes, with values around 240 mm for the class Boreal Forest, 215 mm for the classes Tundra and Montane Forest, and 160 mm for the class Prairie. ERA5-Land and SNODAS show higher SWE_{max} values, close to 250 and 300 mm respectively, except for the snow class Prairie, for which ERA5-Land exhibits fairly low SWE_{max} , with values around 145 mm. The datasets MERRA-2 and C3S Satellite SWE show the lowest SWE_{max} , mostly below 180 mm. All datasets showed higher than normal SWE_{max} between 2013 and 2015, as well as in 2018, 2019, and 2022. However, for the snow classes Tundra and Boreal Forest, SNODAS and ERA5-Land have much higher SWE_{max} values than the other datasets, above 400 mm.

The bottom row of Fig. 6 synthesizes the results in the top four rows in order to show the SWE regime. For the snow class Tundra, the SWE regimes of ERA5-Land and SNODAS appear similar, with a much longer period of snow accumulation compared to other datasets. Snow begins to accumulate sooner than for the other datasets, and the accumulation rate for these two datasets is of similar magnitude at the beginning of the accumulation period. Beginning in mid-January, snow accumulation for SNODAS occurs at a much higher rate than for ERA5-Land. This accumulation continues until the beginning of May, whereas by this date, the other datasets show most of the snowpack already melted. The accumulation periods produced by UdeS Grids, Crocus-ERA5, and MERRA-2 appear similar to each other, although, starting in January, MERRA-2 has a lower rate of snow accumulation than the other two datasets. Snowmelt begins around the same date for these three datasets, but the snowpack melts much more rapidly for Crocus-ERA5 and MERRA-2 than for UdeS Grids. C3S Satellite SWE shows 1.5 to 2 times less snow than the other datasets.

We identify three distinct regimes for the snow classes Boreal Forest and Montane Forest. The first regime, found in the SNODAS and ERA5-Land datasets, is characterized by a larger quantity of snow, a longer period of accumulation, later melting, and a faster rate of melting. The second regime type is found in the UdeS Grids and Crocus-ERA5 datasets, with



370 a shorter snow accumulation period, a 25% lower quantity of snow, and earlier melting. The third regime type, found in the
MERRA-2 and C3S Satellite SWE, shows a quantity of snow 0.5 to 2.5 times lower than the other datasets. For the snow
class Prairie, snow accumulation periods are similar for the datasets UdeS Grids, ERA5-Land, Crocus-ERA5, and SNODAS,
although SNODAS has a higher quantity of snow while ERA5-Land, conversely, has a lower quantity. These datasets are
observed to diverge during the melting period, which is longer for ERA5-Land. The snowpack also melts more rapidly for
375 Crocus-ERA5.

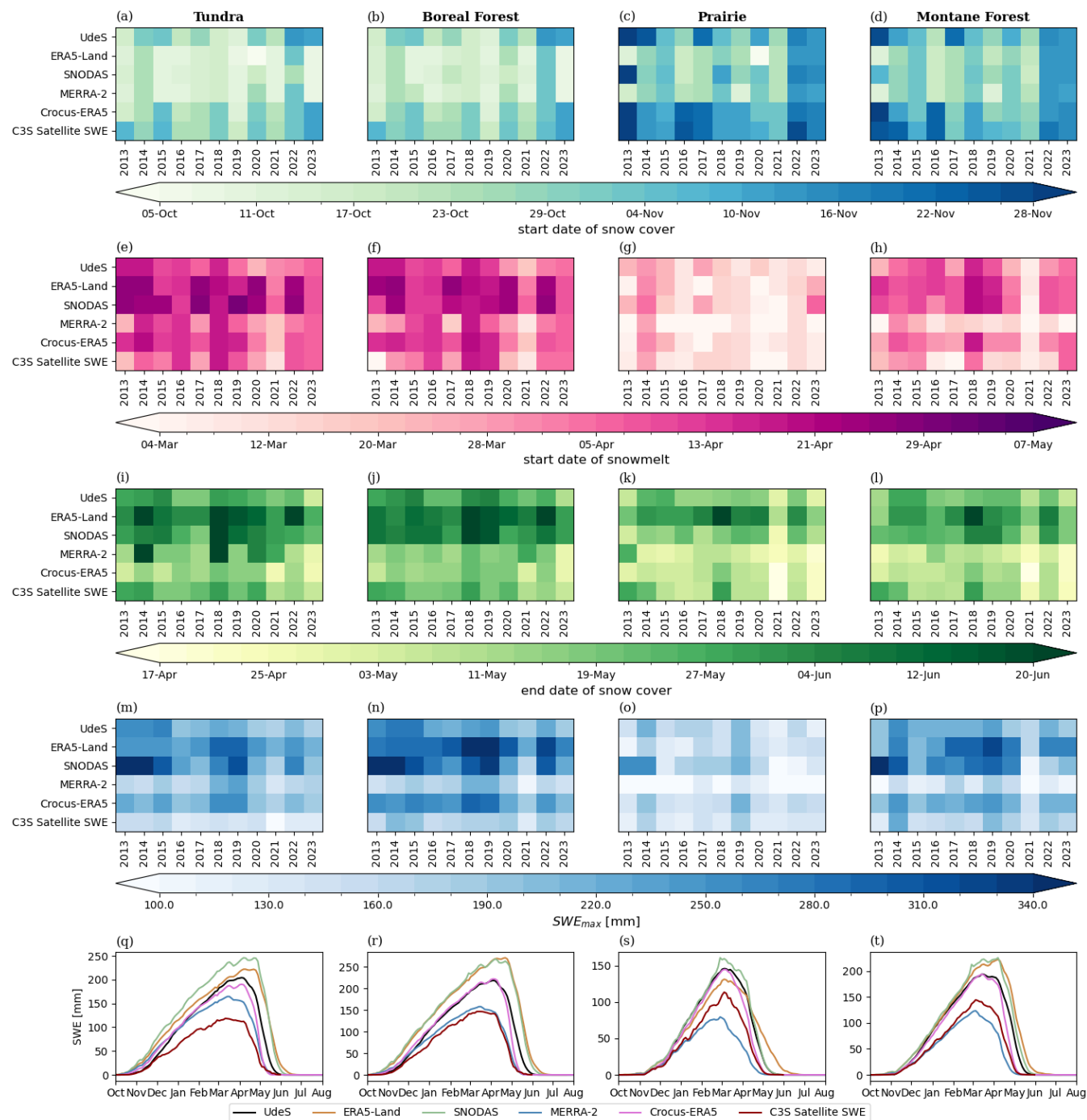


Figure 6. Interannual comparison of the start dates of snow cover (top row) and snowmelt (second row), the end dates of snow cover (third row), and SWE_{max} (fourth row). For the top four rows, the x-axis shows years and the y-axis shows datasets. The bottom row shows the snow water equivalent (SWE) regime for different datasets. Each column shows results for a different snow class.



6 Discussion

6.1 Uncertainties associated with point-to-pixel comparisons

The results of the point-to-pixel comparison are given in Section 5.1. A number of sources of uncertainty are associated with these results, of which the most important are the following: (i) the length of the available time series; (ii) the measurement of reference data; (iii) the comparison of sporadic data to data averaged over a surface.

Almost 40% of reference data came from manual sampling stations where measurements were conducted weekly or monthly. Furthermore, out of 218 stations, fewer than 50 had data from more than five years. The reference data used were therefore too sparse to draw robust conclusions that are representative of long-term trends based only on this preliminary comparison. Additionally, the measurements of these reference data are themselves beset with uncertainty. Manual in situ measurements are subject to errors whose exact nature depends on the method used, for example the type of density meter, the tube diameter, the quality of the sampling (which depends on the operator), and the presence of ice lenses in the snowpack (Royer et al., 2021). Although snowpack measurement error has been extensively discussed, there is still no established international standard protocol (Kinar and Pomeroy, 2015; López-Moreno et al., 2020). During the World Meteorological Organization (WMO) Solid Precipitation Intercomparison Experiment, Smith et al. (2017) showed that GMON stations overestimate SWE compared to manual measurements by 30 to 35%. Furthermore, Royer et al. (2021) have also shown that GMON stations are sensitive to surface soil moisture, which can lead to an overestimation of SWE in the case of rain-on-snow events.

SWE data are characterized by high spatial variability. Compounding this variability is the fact that data from two neighbouring stations can be more or less similar depending on the installation site, for example if the site is open or overgrown, well-drained or not. Major melting or rainfall events can lead to water puddling beneath the snow, affecting the soil moisture and causing measurement errors. Thus, a sporadic measurement may not be representative of average SWE over a 10 km × 10 km grid cell, and therefore cannot necessarily be compared to gridded datasets. This issue is illustrated in Fig. 7, which shows the Mean Absolute Error (MAE) and the RMSE as a function of distance between stations. The figure shows that MAE and RMSE are relatively low between stations which are less than 10 m apart. However, from 10 m to 10 km distance, the MAE and RMSE are relatively high, although no clear trend emerges between error and distance between stations.

Because of the uncertainties associated with point-to-pixel comparisons, we added a pixel-to-pixel comparison to the analysis, to corroborate the results of the point-to-pixel comparison and to verify whether the results from the two methods were congruent. Both approaches showed that the data from UdeS Grids and Crocus-ERA5 are of similar magnitude, while ERA5-Land and SNODAS overestimate the data. Moreover, both approaches showed that SNODAS and ERA5-Land do not provide a good representation of snow cover duration. Conversely, SWE values estimated from satellite data, such as in the MERRA-2 and C3S Satellites SWE datasets, are markedly lower than in the other datasets. Our two approaches also showed that ERA5-Land and SNODAS produce a much longer snow cover duration than other datasets, mainly because of a longer accumulation period and later melting. Thus, these two complementary comparisons were generally consistent with each other, and made it possible to show the similarities and differences between different SWE datasets.

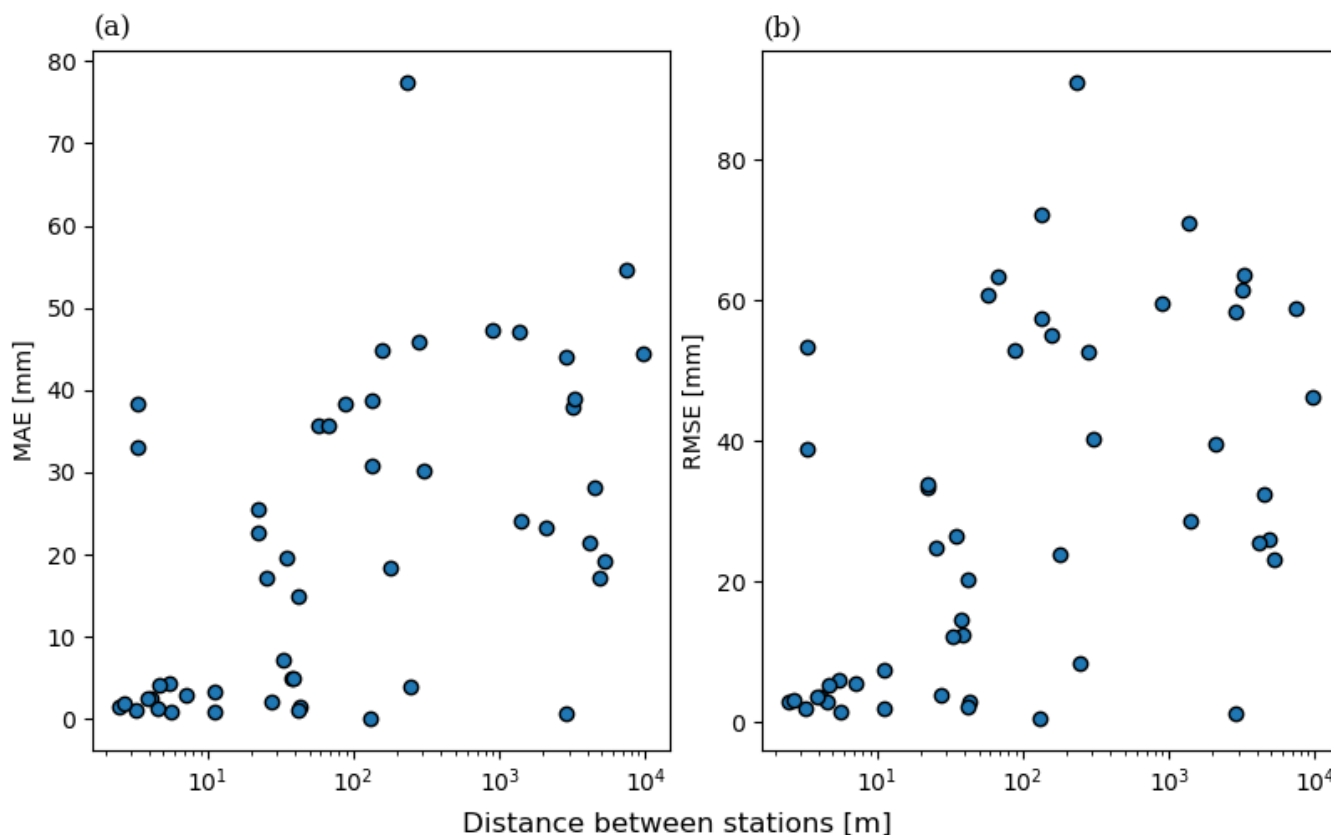


Figure 7. Mean Absolute Error (MAE) (a) and Root Mean Square Error (RMSE) (b) as a function of distance between stations.

6.2 Are there other factors that influence the performance of gridded datasets?

410 In this section, we look at the impact of two other factors, topography and resampling of gridded SWE data, on the performance of these datasets. Figure 8 shows the performance of gridded products for six altitude classes, showing that as altitude increases, gridded products are less and less similar to the UdeS Grids data. Above 500 m, correlation coefficients are observed to decrease, and the nRMSE increases for all datasets. This effect is particularly noticeable for the Crocus-ERA5 dataset, for which the nRMSE increases by more than 150%, with a significant change in standard deviations above 500 m. Furthermore, 415 bias significantly increases above 500 m for ERA5-Land and SNODAS (not shown), going from an average of 25% to more than 35%. This highlights that it is difficult for the algorithms to correctly estimate SWE at higher altitudes, because topography, along with land cover, can promote the redistribution of snow by the wind, away from peaks and toward valleys (Anderton et al., 2004; Snauffer et al., 2016).

The gridded datasets used in this study were resampled onto the same grids used by the UdeS Grids dataset, which may have 420 had an impact on their performance. This is particularly relevant for SNODAS, for which the resolution was reduced from 0.01° to 0.1° . For this analysis, we first calculated the statistical metrics between the 218 reference stations and the gridpoints of the

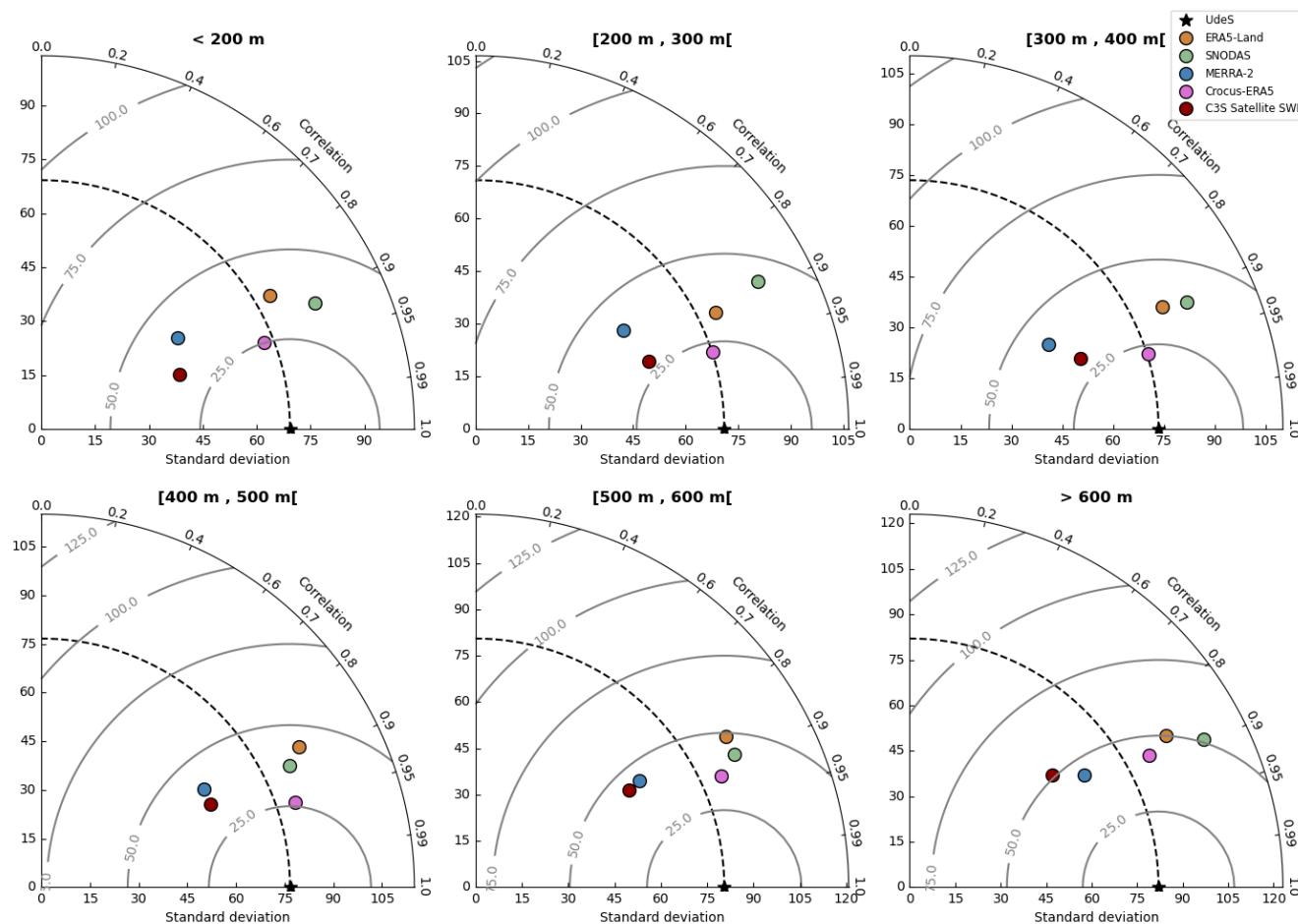


Figure 8. Statistical metrics synthesized as Taylor diagrams for six altitude classes.

resampled datasets, and then between the reference data and the original gridpoints. The results shown in Fig. 9 demonstrate that, for all five resampled datasets, including SNODAS, the scores of the four statistical metrics do not vary greatly between the original and resampled data. Resampling therefore appears to have minimal impact on the performance of the gridded SWE datasets.

6.3 Strengths and weaknesses of the SWE datasets

The UdeS Grids dataset, along with ERA5-Land and Crocus-ERA5, give the best representations of the reference data. One of the strengths of UdeS Grids is that it is good at representing periods of snow cover and melting dates, which are essential for using these data in hydrology applications. However, the UdeS Grids dataset also has certain drawbacks. It tends to underestimate SWE data, and particularly SWE_{max} , especially in the northern and eastern parts of the study zone. This might be because the data assimilated into the UdeS Grids dataset are more sparse in the north and east. Additionally, most of the

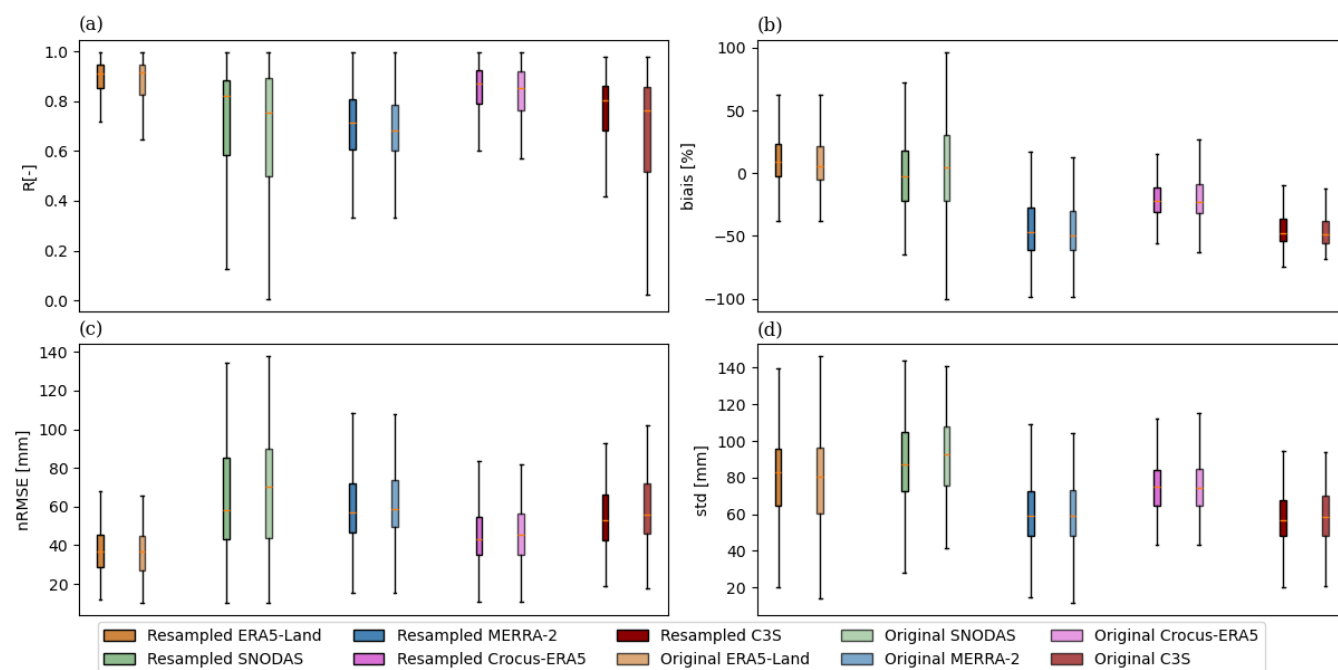


Figure 9. Comparison of statistical metrics obtained from the resampled and original grids of datasets.

assimilated data comes from manual stations, and most measurements are not taken at the moment of maximum SWE. One avenue to improve future versions of the UdeS Grids dataset would be to also assimilate the GMON stations, in order to benefit from the good coverage of spatial and temporal variability of these data.

435 The data from Crocus-ERA5 and ERA5-Land are of similar magnitude to the reference data. These two datasets, both from the ECMWF, both integrate the atmospheric data of the ERA5 reanalysis. The Crocus-ERA5 dataset is very similar to UdeS Grids, except that Crocus-ERA5 is unable to correctly estimate the end date of snow cover and the duration of melting. ERA5-Land tends to overestimate SWE data relative to the reference data, particularly in the northern and eastern parts of the study zone. Furthermore, the snow cover durations found by ERA5-Land are much too long, and melting begins late, which would be
 440 a problem in using these data for hydrological applications. One reason for this overestimation could be atmospheric forcing, as illustrated in Fig. 10. Indeed, this figure shows that the precipitation values used for forcing in ERA5-Land and Crocus-ERA5 are generally 20 to 40% higher than those used in UdeS Grids. Another aspect that must be taken into account is the snow model used. Although Crocus-ERA5 uses the precipitation data from ERA5 for forcing, it uses a more complete snow model that takes into account many more physical parameters and allows it to produce much more realistic SWE data.

445 The overall results show that the SNODAS data are of similar magnitude to the other datasets in the southern part of our study zone, that is, south of 48°N. However, marked differences are observed in the east and north, where SNODAS overestimates SWE relative to the other datasets. Furthermore, SNODAS tends to produce a longer period of snow cover, with an earlier start of snow cover and later snowmelt. These results agree with the findings of Lv et al. (2019), who evaluated the ability of

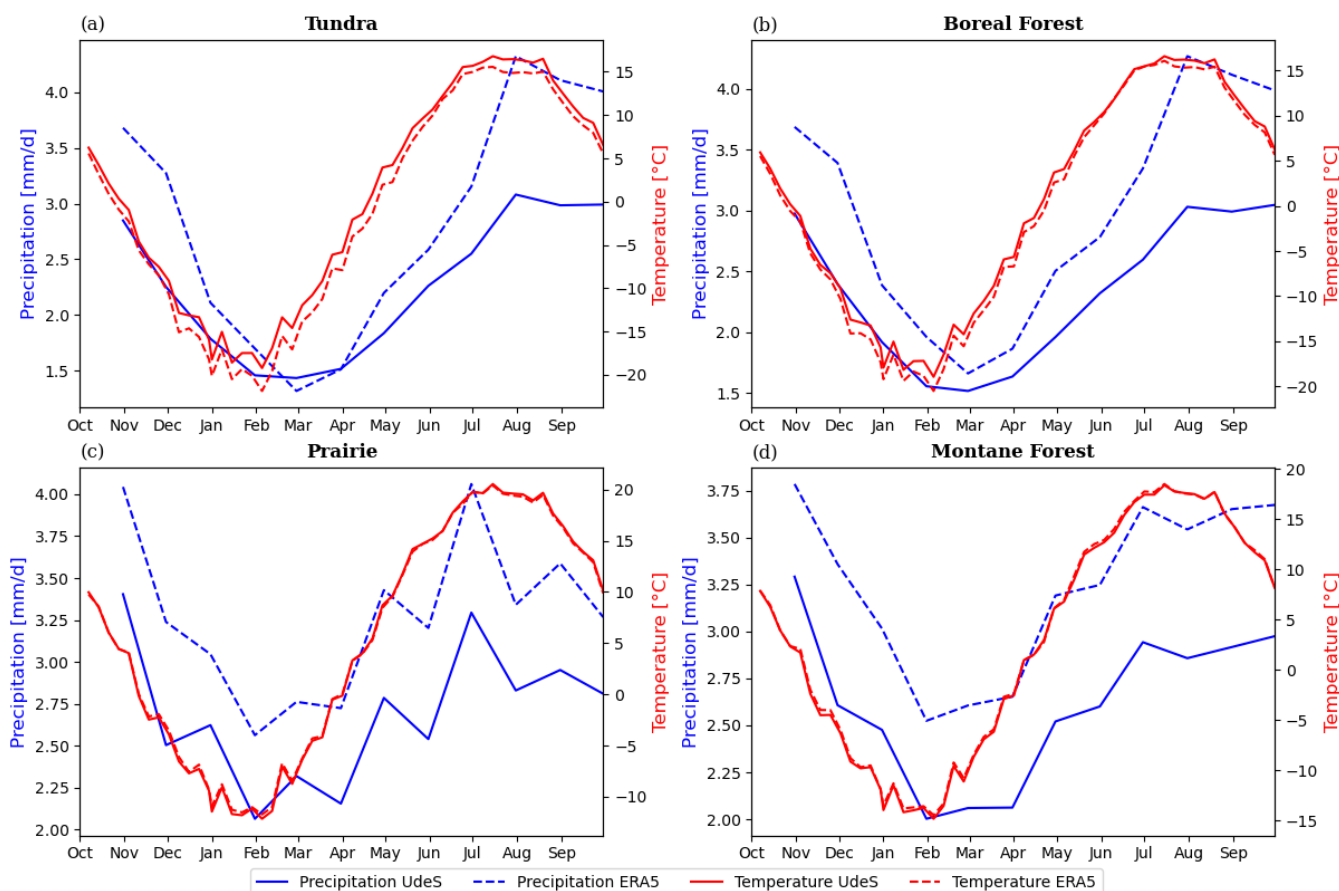


Figure 10. Comparison of atmospheric forcing used in UdeS Grids and the two ERA5-based datasets (ERA5-Land and Crocus-ERA5).

SNODAS to correctly estimate SWE in three environments in western Canada: boreal forest, prairie, and the Canadian Rockies.

450 The main results of Lv et al. (2019) showed that SNODAS tends to overestimate SWE data in all three of the environments studied. The authors found that the accuracy of data in SNODAS is strongly affected by fact that the mass balance calculation does not account for blowing snow transport, or the energetics of melting, snow interception and sublimation processes under forest canopies, as well as by erroneous precipitation data in the surface snow model of SNODAS.

7 Conclusions

455 The aim of this article was to compare the UdeS Grids SWE dataset to reference data from the CanSWE dataset and the Hydro-Québec GMON stations, as well as to five other gridded datasets that are widely used around the world, namely ERA5-Land, Crocus-ERA5, SNODAS, MERRA-2, and C3S Satellite SWE. The ability of the datasets to correctly estimate SWE values was evaluated using correlation coefficients, relative bias, and normalized RMSE. The ability of the datasets to represent the



duration of snow cover was evaluated using three indicators, start date of snow cover, start date of snowmelt, and end date of
460 snow cover. Two comparison strategies were used: the first, called point-to-pixel, allowed us to compare reference stations to
the closest gridpoints in the gridded datasets, while the second, called pixel-to-pixel, allowed us to compare the grids between
datasets.

Our main findings show that, except for MERRA-2, all of the datasets are well-correlated to the reference data, with corre-
lation coefficients generally above 0.85. ERA5-Land and SNODAS overestimate SWE relative to the reference data, whereas
465 the other datasets, including UdeS Grids, underestimate it. Moreover, the datasets are observed to perform best in the southern
part of the study zone, and worse at higher altitudes in the eastern part of the study zone. The UdeS Grids dataset provides
the best representation of the duration of snow cover relative to the reference data. ERA5-Land and SNODAS produce periods
of snow cover that are much longer than the reference data, with a longer period of snow accumulation and a later melting
period. MERRA-2, Crocus-ERA5, and C3S Satellite SWE are able to provide good representations of the duration of snow
470 accumulation, but melting in these datasets is more rapid, resulting in much shorter melting periods. To summarize, UdeS
Grids performs best of all the datasets, followed by ERA5-Land and Crocus-ERA5, while datasets derived from satellite data,
such as MERRA-2 and C3S Satellite SWE, perform the worst.

Future work could improve the UdeS Grids SWE dataset by taking into account the following two important points. First, the
current method does not distinguish between covered and open areas, meaning that forested and open areas are parametrized
475 in the same way. In reality, the forest canopy has an important effect on the dynamics of snow accumulation and melting,
which should be reflected by the model. Second, the assimilation of GMON data would allow us to benefit from the spatial and
temporal coverage of these stations, which would reduce underestimation relative to the reference data. Finally, to ensure the
reproducibility of the method used to produce the UdeS Grids data and make it more accessible to the research community, we
plan to add the source code of the next version to the open source Hydrological Analysis Library xHydro (Fortier Filion et al.,
480 2026).

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References

- Alonso-González, E., López-Moreno, J. I., Gascoin, S., García-Valdecasas Ojeda, M., Sanmiguel-Valladolid, A., Navarro-Serrano, F., Revuelto, J., Ceballos, A., Esteban-Parra, M. J., and Essery, R.: Daily Gridded Datasets of Snow Depth and Snow Water Equivalent for the Iberian Peninsula from 1980 to 2014, *Earth System Science Data*, 10, 303–315, <https://doi.org/10.5194/essd-10-303-2018>, 2018.
- 495 Anderton, S. P., White, S. M., and Alvera, B.: Evaluation of Spatial Variability in Snow Water Equivalent for a High Mountain Catchment, *Hydrological Processes*, 18, 435–453, <https://doi.org/10.1002/hyp.1319>, 2004.
- Avanzi, F., Gabellani, S., Delogu, F., Silvestro, F., Pignone, F., Bruno, G., Pulvirenti, L., Squicciarino, G., Fiori, E., Rossi, L., Puca, S., Toniazio, A., Giordano, P., Falzacappa, M., Ratto, S., Stevenin, H., Cardillo, A., Fioletti, M., Cazzuli, O., Cremonese, E., Morra di Cella, U., and Ferraris, L.: IT-SNOW: A Snow Reanalysis for Italy Blending Modeling, in Situ Data, and Satellite Observations (2010–2021), *Earth System Science Data*, 15, 639–660, <https://doi.org/10.5194/essd-15-639-2023>, 2023.
- 500 Barrett, A. P.: National Operational Hydrologic Remote Sensing Center Snow Data Assimilation System (SNODAS) Products at NSIDC, Special Report 11, National Snow and Ice Data Center, Cooperative Institute for Research in Environmental Sciences, University of Colorado, USA, 2003.
- Bathelemy, R., Boucher, M.-A., Redondo Tilano, S. A., and Hamelin, J.: Spring flooding in Southern Quebec: a hydrometeorological assessment of the 2017 and 2019 events, *Canadian Water Resources Journal/Revue canadienne des ressources hydriques*, 51, 231–254, <https://doi.org/10.1080/07011784.2026.2652238>, 2026.
- 505 Benjamin, S. G., Brown, J. M., Brundage, K. J., Devenyi, D., Grell, G. A., Kim, D., Smirnova, T. G., Smith, T. L., Schwartz, B. E., and Weygandt, S. S.: The 20-Km Rapid Update Cycle–Overview and Implications for Aviation Applications, in: *Proc. 10th Conf. on Aviation, Range and Aerosp. Meteor.*, AMS, Boston, 2002.
- 510 Bergeron, O.: *Grilles Climatiques Quotidiennes Du Programme de Surveillance Du Climat Du Québec: Guide d'utilisation* (2016), Développement durable, environnement et lutte contre les changements climatiques, ISBN 2-550-73568-4, 2016.
- Brun, E., Martin, E., Simon, V., Gendre, C., and Coleou, C.: An Energy and Mass Model of Snow Cover Suitable for Operational Avalanche Forecasting, *Journal of Glaciology*, 35, 333–342, <https://doi.org/10.3189/S0022143000009254>, 1989.
- Brun, E., David, P., Sudul, M., and Brunot, G.: A Numerical Model to Simulate Snow-Cover Stratigraphy for Operational Avalanche Forecasting, *Journal of Glaciology*, 38, 13–22, <https://doi.org/10.3189/S0022143000009552>, 1992.
- 515 Brun, E., Vionnet, V., Boone, A., Decharme, B., Peings, Y., Valette, R., Karbou, F., and Morin, S.: Simulation of Northern Eurasian Local Snow Depth, Mass, and Density Using a Detailed Snowpack Model and Meteorological Reanalyses, *Journal of Hydrometeorology*, <https://doi.org/10.1175/JHM-D-12-012.1>, 2013.
- C3S: Snow Water Equivalent for the Northern Hemisphere from 1979 to Present Derived from Satellite Observations, <https://doi.org/10.24381/B1C98D44>, 2026.
- 520 Cantet, P., Boucher, M. A., Lachance-Coutier, S., Turcotte, R., and Fortin, V.: Using a Particle Filter to Estimate the Spatial Distribution of the Snowpack Water Equivalent, *Journal of Hydrometeorology*, <https://doi.org/10.1175/JHM-D-18-0140.1>, 2019.
- Choquette, Y., Lavigne, P., Nadeau, M., Ducharme, P., Martin, J. P., Houdayer, A., and Rogoza, J.: GMON, a new sensor for snow water equivalent via Gamma monitoring, in: *International Snow Science Workshop*, 2008.
- 525 Clark, M., Gangopadhyay, S., Hay, L., Rajagopalan, B., and Wilby, R.: The Schaake Shuffle: A Method for Reconstructing Space–Time Variability in Forecasted Precipitation and Temperature Fields, *Journal of Hydrometeorology*, 2004.



- Clark, M. P., Hendrikx, J., Slater, A. G., Kavetski, D., Anderson, B., Cullen, N. J., Kerr, T., Örn Hreinsson, E., and Woods, R. A.: Representing Spatial Variability of Snow Water Equivalent in Hydrologic and Land-Surface Models: A Review, *Water Resources Research*, 47, <https://doi.org/10.1029/2011WR010745>, 2011.
- 530 Dibike, Y. B., Shrestha, R. R., Johnson, C., Bonsal, B., and Coulibaly, P.: Assessing Climatic Drivers of Spring Mean and Annual Maximum Flows in Western Canadian River Basins, *Water*, 13, 1617, <https://doi.org/10.3390/w13121617>, 2021.
- Ducharme, P., Houdayer, A., Choquette, Y., Kapfer, B., and Martin, J. P.: Numerical Simulation of Terrestrial Radiation over a Snow Cover, *Journal of Atmospheric and Oceanic Technology*, <https://doi.org/10.1175/JTECH-D-14-00100.1>, 2015.
- Fang, Y., Liu, Y., and Margulis, S. A.: A Western United States Snow Reanalysis Dataset over the Landsat Era from Water Years 1985 to
535 2021, *Scientific Data*, 9, 677, <https://doi.org/10.1038/s41597-022-01768-7>, 2022.
- Fortier Fillion, T.-C., Smith, T. J., Langlois, S., Ospina, J., and Maarite, K.: Xhydro: Hydrological Analysis Library Built with Xarray., 2026.
- Gelaro, R., McCarty, W., Suárez, M. J., Todling, R., Molod, A., Takacs, L., Randles, C. A., Darmenov, A., Bosilovich, M. G., Reichle, R., Wargan, K., Coy, L., Cullather, R., Draper, C., Akella, S., Buchard, V., Conaty, A., da Silva, A. M., Gu, W., Kim, G.-K., Koster, R., Lucchesi, R., Merkova, D., Nielsen, J. E., Partyka, G., Pawson, S., Putman, W., Rienecker, M., Schubert, S. D., Sienkiewicz, M.,
540 and Zhao, B.: The Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2), *Journal of Climate*, <https://doi.org/10.1175/JCLI-D-16-0758.1>, 2017.
- Günther, D., Marke, T., Essery, R., and Strasser, U.: Uncertainties in Snowpack Simulations—Assessing the Impact of Model Structure, Parameter Choice, and Forcing Data Error on Point-Scale Energy Balance Snow Model Performance, *Water Resources Research*, 55, 2779–2800, <https://doi.org/10.1029/2018WR023403>, 2019.
- 545 Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., Chiara, G. D., Dahlgren, P., Dee, D., Diamantakis, M., Dragani, R., Flemming, J., Forbes, R., Fuentes, M., Geer, A., Haimberger, L., Healy, S., Hogan, R. J., Hólm, E., Janisková, M., Keeley, S., Laloyaux, P., Lopez, P., Lupu, C., Radnoti, G., de Rosnay, P., Rozum, I., Vamborg, F., Villaume, S., and Thépaut, J.-N.: The ERA5 Global Reanalysis, *Quarterly Journal of the Royal Meteorological Society*, 146, 1999–2049, <https://doi.org/10.1002/qj.3803>, 2020.
- 550 Hoke, J. E. and Anthes, R. A.: The Initialization of Numerical Models by a Dynamic-Initialization Technique, *Monthly Weather Review*, 104, 1551–1556, 1976.
- Kalnay, E.: *Atmospheric Modeling, Data Assimilation and Predictability*, Cambridge university press, ISBN 0-521-79179-0, 2003.
- Kinar, N. J. and Pomeroy, J. W.: Measurement of the Physical Properties of the Snowpack, *Reviews of Geophysics*, 53, 481–544, <https://doi.org/10.1002/2015RG000481>, 2015.
- 555 Liu, Y., Fang, Y., and Margulis, S. A.: Spatiotemporal Distribution of Seasonal Snow Water Equivalent in High Mountain Asia from an 18-Year Landsat–MODIS Era Snow Reanalysis Dataset, *The Cryosphere*, 15, 5261–5280, <https://doi.org/10.5194/tc-15-5261-2021>, 2021.
- Luoju, K., Pulliainen, J., Takala, M., Lemmetyinen, J., Mortimer, C., Derksen, C., Mudryk, L., Moisander, M., Hiltunen, M., Smolander, T., Ikonen, J., Cohen, J., Salminen, M., Norberg, J., Veijola, K., and Venäläinen, P.: GlobSnow v3.0 Northern Hemisphere Snow Water
560 Equivalent Dataset, *Scientific Data*, 8, 163, <https://doi.org/10.1038/s41597-021-00939-2>, 2021.
- Ly, Z., Pomeroy, J. W., and Fang, X.: Evaluation of SNODAS Snow Water Equivalent in Western Canada and Assimilation Into a Cold Region Hydrological Model, *Water Resources Research*, 55, 11 166–11 187, <https://doi.org/10.1029/2019WR025333>, 2019.
- López-Moreno, J. I., Leppänen, L., Luks, B., Holko, L., Picard, G., Sanmiguel-Vallelado, A., Alonso-González, E., Finger, D. C., Arslan, A. N., Gillemot, K., Sensoy, A., Sorman, A., Ertaş, M. C., Fassnacht, S. R., Fierz, C., and Marty, C.: Intercomparison of Measurements



- 565 of Bulk Snow Density and Water Equivalent of Snow Cover with Snow Core Samplers: Instrumental Bias and Variability Induced by
Observers, *Hydrological Processes*, 34, 3120–3133, <https://doi.org/10.1002/hyp.13785>, 2020.
- Margulis, S. A., Cortés, G., Giroto, M., and Durand, M.: A Landsat-Era Sierra Nevada Snow Reanalysis (1985–2015), *Journal of Hydrometeorology*, <https://doi.org/10.1175/JHM-D-15-0177.1>, 2016.
- Menard, C. B., Essery, R., Krinner, G., Arduini, G., Bartlett, P., Boone, A., Brutel-Vuilmet, C., Burke, E., Cuntz, M., Dai, Y., Decharme, B.,
570 Dutra, E., Fang, X., Fierz, C., Gusev, Y., Hagemann, S., Haverd, V., Kim, H., Lafaysse, M., Marke, T., Nasonova, O., Nitta, T., Niwano,
M., Pomeroy, J., Schädler, G., Semenov, V. A., Smirnova, T., Strasser, U., Swenson, S., Turkov, D., Wever, N., and Yuan, H.: Scientific
and Human Errors in a Snow Model Intercomparison, *Bulletin of the American Meteorological Society*, [https://doi.org/10.1175/BAMS-](https://doi.org/10.1175/BAMS-D-19-0329.1)
D-19-0329.1, 2021.
- Meromy, L., Molotch, N. P., Link, T. E., Fassnacht, S. R., and Rice, R.: Subgrid Variability of Snow Water Equivalent at Operational Snow
575 Stations in the Western USA, *Hydrological Processes*, 27, 2383–2400, <https://doi.org/10.1002/hyp.9355>, 2013.
- Mortimer, C., Mudryk, L., Derksen, C., Luojus, K., Brown, R., Kelly, R., and Tedesco, M.: Evaluation of Long-Term Northern Hemisphere
Snow Water Equivalent Products, *The Cryosphere*, 14, 1579–1594, <https://doi.org/10.5194/tc-14-1579-2020>, 2020.
- Mudryk, L., Mortimer, C., Derksen, C., Elias Chereque, A., and Kushner, P.: Benchmarking of Snow Water Equivalent (SWE) Products
Based on Outcomes of the SnowPEX+ Intercomparison Project, *The Cryosphere*, 19, 201–218, <https://doi.org/10.5194/tc-19-201-2025>,
580 2025.
- Mudryk, L. R., Derksen, C., Kushner, P. J., and Brown, R.: Characterization of Northern Hemisphere Snow Water Equivalent Datasets,
1981–2010, *Journal of Climate*, <https://doi.org/10.1175/JCLI-D-15-0229.1>, 2015.
- Mudryk, L. R., Derksen, C., Howell, S., Laliberté, F., Thackeray, C., Sospedra-Alfonso, R., Vionnet, V., Kushner, P. J., and Brown, R.:
Canadian Snow and Sea Ice: Historical Trends and Projections, *The Cryosphere*, 12, 1157–1176, <https://doi.org/10.5194/tc-12-1157-2018>,
585 2018.
- Musselman, K. N., Addor, N., Vano, J. A., and Molotch, N. P.: Winter Melt Trends Portend Widespread Declines in Snow Water Resources,
Nature Climate Change, 11, 418–424, <https://doi.org/10.1038/s41558-021-01014-9>, 2021.
- Muñoz-Sabater, J., Dutra, E., Agustí-Panareda, A., Albergel, C., Arduini, G., Balsamo, G., Boussetta, S., Choulga, M., Harrigan, S.,
Hersbach, H., Martens, B., Miralles, D. G., Piles, M., Rodríguez-Fernández, N. J., Zsoter, E., Buontempo, C., and Thépaut, J.-
590 N.: ERA5-Land: A State-of-the-Art Global Reanalysis Dataset for Land Applications, *Earth System Science Data*, 13, 4349–4383,
<https://doi.org/10.5194/essd-13-4349-2021>, 2021.
- Oberrauch, M., Cluzet, B., Magnusson, J., Mazzotti, G., Mott, R., Quéno, L., Webster, C., Zolles, T., and Jonas, T.: A High-Resolution Snow
Dataset for Switzerland (2016–2025) Combining Physics-Based Simulations and in Situ Observations, *The Cryosphere*, 20, 3387–3403,
<https://doi.org/10.5194/tc-20-3387-2026>, 2026.
- 595 Odry, J., Boucher, M. A., Cantet, P., Lachance-Cloutier, S., Turcotte, R., and St-Louis, P. Y.: Using Artificial Neural Networks to Estimate
Snow Water Equivalent from Snow Depth, *Canadian Water Resources Journal / Revue canadienne des ressources hydriques*, 45, 252–268,
<https://doi.org/10.1080/07011784.2020.1796817>, 2020.
- Odry, J., Boucher, M.-A., Lachance-Cloutier, S., Turcotte, R., and St-Louis, P.-Y.: Large-Scale Snow Data Assimilation Using a Spatialized
Particle Filter: Recovering the Spatial Structure of the Particles, *The Cryosphere*, 16, 3489–3506, <https://doi.org/10.5194/tc-16-3489-2022>,
600 2022.
- Olefs, M., Koch, R., Schöner, W., and Marke, T.: Changes in Snow Depth, Snow Cover Duration, and Potential Snowmaking Conditions in
Austria, 1961–2020—A Model Based Approach, *Atmosphere*, 11, 1330, <https://doi.org/10.3390/atmos11121330>, 2020.



- Pulliainen, J. and Hallikainen, M.: Retrieval of Regional Snow Water Equivalent from Space-Borne Passive Microwave Observations, *Remote Sensing of Environment*, 75, 76–85, [https://doi.org/10.1016/S0034-4257\(00\)00157-7](https://doi.org/10.1016/S0034-4257(00)00157-7), 2001.
- 605 Pulliainen, J., Grandell, J., and Hallikainen, M.: HUT Snow Emission Model and Its Applicability to Snow Water Equivalent Retrieval, *IEEE Transactions on Geoscience and Remote Sensing*, 37, 1378–1390, <https://doi.org/10.1109/36.763302>, 1999.
- Ramos Buarque, S., Decharme, B., Barbu, A. L., and Franchisteguy, L.: Insights into the North Hemisphere Daily Snowpack at High Resolution from the New Crocus–ERA5 Product, *Earth System Science Data*, 17, 7227–7249, <https://doi.org/10.5194/essd-17-7227-2025>, 2025.
- 610 Rienecker, M. M., Suarez, M. J., Gelaro, R., Todling, R., Bacmeister, J., Liu, E., Bosilovich, M. G., Schubert, S. D., Takacs, L., Kim, G.-K., Bloom, S., Chen, J., Collins, D., Conaty, A., da Silva, A., Gu, W., Joiner, J., Koster, R. D., Lucchesi, R., Molod, A., Owens, T., Pawson, S., Pegion, P., Redder, C. R., Reichle, R., Robertson, F. R., Ruddick, A. G., Sienkiewicz, M., and Woollen, J.: MERRA: NASA's Modern-Era Retrospective Analysis for Research and Applications, <https://doi.org/10.1175/JCLI-D-11-00015.1>, 2011.
- Royer, A., Roy, A., Jutras, S., and Langlois, A.: Review Article: Performance Assessment of Radiation-Based Field Sensors for Monitoring the Water Equivalent of Snow Cover (SWE), *The Cryosphere*, 15, 5079–5098, <https://doi.org/10.5194/tc-15-5079-2021>, 2021.
- 615 Seibert, J., Jenicek, M., Huss, M., Ewen, T., and Viviroli, D.: Snow and Ice in the Hydrosphere, in: *Snow and Ice-Related Hazards, Risks, and Disasters*, Hazards and Disasters Series, pp. 93–135, Elsevier, second edition edn., ISBN 978-0-12-817129-5, <https://doi.org/10.1016/B978-0-12-817129-5.00010-X>, 2021.
- Siirila-Woodburn, E. R., Rhoades, A. M., Hatchett, B. J., Huning, L. S., Szinai, J., Tague, C., Nico, P. S., Feldman, D. R., Jones, A. D., Collins, W. D., and Kaatz, L.: A Low-to-No Snow Future and Its Impacts on Water Resources in the Western United States, *Nature Reviews Earth & Environment*, 2, 800–819, <https://doi.org/10.1038/s43017-021-00219-y>, 2021.
- 620 Smith, C. D., Kontu, A., Laffin, R., and Pomeroy, J. W.: An Assessment of Two Automated Snow Water Equivalent Instruments during the WMO Solid Precipitation Intercomparison Experiment, *The Cryosphere*, 11, 101–116, <https://doi.org/10.5194/tc-11-101-2017>, 2017.
- Snauffer, A. M., Hsieh, W. W., and Cannon, A. J.: Comparison of Gridded Snow Water Equivalent Products with in Situ Measurements in British Columbia, Canada, *Journal of Hydrology*, 541, 714–726, <https://doi.org/10.1016/j.jhydrol.2016.07.027>, 2016.
- 625 Sospedra-Alfonso, R., Mudryk, L., Merryfield, W., and Derksen, C.: Representation of Snow in the Canadian Seasonal to Interannual Prediction System. Part I: Initialization, *Journal of Hydrometeorology*, <https://doi.org/10.1175/JHM-D-14-0223.1>, 2016.
- Sturm, M. and Liston, G. E.: Revisiting the Global Seasonal Snow Classification: An Updated Dataset for Earth System Applications, *Journal of Hydrometeorology*, <https://doi.org/10.1175/JHM-D-21-0070.1>, 2021.
- 630 Taheri, M. and Mohammadian, A.: An Overview of Snow Water Equivalent: Methods, Challenges, and Future Outlook, *Sustainability*, 14, 11 395, <https://doi.org/10.3390/su141811395>, 2022.
- Takala, M., Luojus, K., Pulliainen, J., Derksen, C., Lemmetyinen, J., Kärnä, J.-P., Koskinen, J., and Bojkov, B.: Estimating Northern Hemisphere Snow Water Equivalent for Climate Research through Assimilation of Space-Borne Radiometer Data and Ground-Based Measurements, *Remote Sensing of Environment*, 115, 3517–3529, <https://doi.org/10.1016/j.rse.2011.08.014>, 2011.
- 635 Taylor, K. E.: Summarizing Multiple Aspects of Model Performance in a Single Diagram, *Journal of Geophysical Research: Atmospheres*, 106, 7183–7192, <https://doi.org/10.1029/2000JD900719>, 2001.
- Turcotte, R., Fortin, L.-G., Fortin, V., Fortin, J.-P., and Villeneuve, J.-P.: Operational Analysis of the Spatial Distribution and the Temporal Evolution of the Snowpack Water Equivalent in Southern Québec, Canada, *Hydrology Research*, 38, 211–234, <https://doi.org/10.2166/nh.2007.009>, 2007.



- 640 Vernay, M., Lafaysse, M., Monteiro, D., Hagenmuller, P., Nheili, R., Samacoïts, R., Verfaillie, D., and Morin, S.: The S2M Meteorological
and Snow Cover Reanalysis over the French Mountainous Areas: Description and Evaluation (1958–2021), *Earth System Science Data*,
14, 1707–1733, <https://doi.org/10.5194/essd-14-1707-2022>, 2022.
- Vionnet, V., Brun, E., Morin, S., Boone, A., Faroux, S., Le Moigne, P., Martin, E., and Willemet, J.-M.: The Detailed Snowpack Scheme
Crocus and Its Implementation in SURFEX v7.2, *Geoscientific Model Development*, 5, 773–791, <https://doi.org/10.5194/gmd-5-773->
645 2012, 2012.
- Vionnet, V., Mortimer, C., Brady, M., Arnal, L., and Brown, R.: Canadian Historical Snow Water Equivalent Dataset (CanSWE, 1928–2020),
Earth System Science Data, 13, 4603–4619, <https://doi.org/10.5194/essd-13-4603-2021>, 2021.
- Wu, W.-S., Purser, R. J., and Parrish, D. F.: Three-Dimensional Variational Analysis with Spatially Inhomogeneous Covariances, *Monthly
Weather Review*, 2002.