https://doi.org/10.5194/egusphere-2026-1408
Preprint. Discussion started: 2 June 2026


# A new method for updating snow fields in the NWP models using satellite snow extent based 'Snow Barrel' pseudo-observations as applied to HARMONIE-AROME cycle 43

Mikael Hasu[1], Niilo Siljamo[1], Ekaterina Kurzeneva[1], and Laura Rontu[1]

[1]Finnish Meteorological Institute

**Correspondence:** Mikael Hasu (mikael.hasu@fmi.fi)

**Abstract.** This paper introduces the "snow barrel" method, a new approach to integrate satellite-derived snow observations into Numerical Weather Prediction (NWP) models. Snow is a key component of the environment, helping to regulate surface temperature, atmospheric and soil conditions, and playing a key role in the water cycle. However, assimilating satellite snow data into NWP models remains challenging due to resolution mismatches and the complexity of handling snow extent observations. The snow barrel method addresses these challenges by aggregating satellite pixel observations from the EUMETSAT H-SAF H32 intermediate product into $10 \times 10$ pixel areas and creating pseudo-observations that align with NWP model scales. Implemented within the HARMONIE-AROME model in the MetCoOp operational domain covering northern Europe, this approach selectively applies snow barrel observations where they conflict with the model's background field, particularly in regions with thin or patchy snow cover. The results demonstrate improved representation of snow cover during the transitional seasons without disrupting areas of solid cover or imposing a significant computational burden. The method effectively combines the spatial coverage advantages of satellite data with the precision of in situ measurements, particularly benefiting areas with sparse ground observations. Although constrained by cloud cover and lighting conditions inherent to optical satellite products, the snow barrel methodology offers a flexible framework that could be expanded to other satellite platforms and potentially adapted for additional surface parameters beyond snow cover.

## 1 Introduction

Snow plays a critical role in the environmental system as a key regulator of many natural processes. Snow on the ground influences the atmosphere and soil over different timescales by altering the surface heat balance. Snow acts as an insulator, protecting the soil from atmospheric influence, increasing surface albedo, and absorbing heat during the melting process (Zhang, 2005). The accumulation and melting of snow are vital components of the hydrological cycle, which impact the water supply for natural ecosystems, agriculture, and hydropower resources. In addition, snow can pose natural hazards, such as floods and avalanches, and create transportation challenges (Wang et al., 2022).

Snow cover typically evolves seasonally, with accumulation of snow during the colder months and melting of it as temperatures rise. The duration and extent of snow cover depend on local climate conditions, with polar and high-altitude regions experiencing persistent snow cover, while temperate zones may see intermittent or seasonal snow. Snow cover is rarely uni-

https://doi.org/10.5194/egusphere-2026-1408
Preprint. Discussion started: 2 June 2026


form, as it is influenced by factors such as terrain, vegetation, wind patterns, and solar radiation. Uneven snow distribution can affect local weather. Patches of snow retain cold conditions longer, while exposed areas warm more quickly (Marsh et al., 1997). Therefore, obtaining accurate spatial and temporal information on snow cover is essential to understand and predict its environmental and societal impacts.

Snow can be characterised through several key parameters. The most straightforward is the depth of the snow, which quantifies the thickness of the snow layer in metres. However, snow density can vary widely, meaning that the snowpack in two points with the same depth may contain very different amounts of water. A more comprehensive metric used in snow studies is Snow Water Equivalent (SWE), which quantifies the water content within a snowpack, typically measured in kilogrammes per square metre ($kg/m^2$). SWE is particularly useful for NWP models, as it provides a more detailed representation of the characteristics of snow, influencing the predictions of the energy required for snow melting and the available water resources. Snow can also be characterised by area coverage, usually by using remote sensing instruments. Coverage is typically expressed as a percentage of a region covered by snow or as a total area in square kilometres.

Accurate monitoring and forecasting of snow cover, including its depth, albedo, and SWE, are crucial for weather prediction and climate studies (de Rosnay et al., 2015). In situ observations of snow cover, conducted at ground stations, are a vital component of snow monitoring. These ground-based measurements provide high-quality data, although spatial resolution of these observations is very limited, particularly in sparsely populated regions. Therefore, the other observation types are highly needed for more comprehensive coverage.

Satellite-based snow products are invaluable for providing snow data where ground observations are sparse or absent. Two widely used products are SWE and the extent of the snow cover. SWE, derived from microwave instruments, provides information about the snow water content, but with a coarse resolution and with certain limitations. Snow extent products, based on optical sensors, indicate the presence or absence of snow with fine spatial resolution, but they are affected by cloud cover and poor illumination in the polar regions (Takala et al., 2011). European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) operates geostationary (Meteosat Second Generation (MSG), Meteosat Third Generation (MTG)) and polar orbiting (Meteorological Operational satellite (MetOp)) weather satellites, offering operational snow extent products such as H31, H32, and H34 (Siljamo and Hyvärinen, 2011; Siljamo et al., 2020). Projects like EUMETSAT Satellite Application Facility on Support to Operational Hydrology and Water Management (H SAF) and CryoClim (Solberg et al., 2014; Rudjord et al., 2015) contribute to global snow data by automatically generating snow extent and SWE products adapted for various applications.

Hybrid systems such as the Interactive Multisensor Snow and Ice Mapping System (IMS) combine optical, microwave, and ground-based data to improve snow monitoring (Ramsay, 1998; Helfrich et al., 2007). The IMS is not generated automatically and thus may not be updated regularly in all areas.

Assimilating of snow observations is essential for reducing systematic errors in NWP models. An accurate initial representation of snow conditions is critical to correctly simulate snow accumulation and melting processes. Studies have shown that incorporating snow data can significantly reduce both over- and underestimations of snow depth while, for instance, improving temperature forecast accuracy (Drusch et al., 2004; Li et al., 2022; Gichamo et al., 2025). However, current snow data assim-

https://doi.org/10.5194/egusphere-2026-1408
Preprint. Discussion started: 2 June 2026


ilation techniques in NWP remain limited, restricted to using in situ measurements. Data assimilation algorithms target snow depth or SWE. The native resolution of satellite-based snow data is not suitable for direct assimilation into NWP models, which poses challenges for their effective use. H SAF data can support the performance of NWP models by providing extensive and reliable snow information with fine spatial resolution. However, the integration of satellite data into NWP models remains challenging. Consequently, there is a need for alternative approaches that take advantage of satellite-derived observations, offering broader spatial coverage.

To address this, this article introduces a method of using pseudo-observations of snow extent called "snow barrels". These pseudo-observations are derived from the H SAF H32 intermediate product, based on MetOp data. The concept involves aggregation of the classification labels in satellite pixels over a predefined area and converting them into a single observation. Then, the NWP snow analysis algorithms, based on statistical interpolation, combine these aggregated data with the Surface Synoptic Observation (SYNOP) station data and the model background field. Snow barrel observations are better aligned with the spatial and temporal scales of NWP models, showing the potential to improve the representation of SWE fields, particularly during the transitional seasons of autumn and spring.

This paper is organised as follows. Section 2 details the satellite data sources available and highlights the advantages and challenges of various products. Section 3 explains the implementation of the snow barrel approach and describes the setup of the model experiments. Section 4 presents the results of the assimilation experiments, comparing the performance of the model with and without the snow barrel data. Section 5 discusses the findings and explores potential future developments, while Section 6 concludes the study, summarising the key results.

## 2 Data

Although satellite-derived SWE products hold significant potential for NWP applications, their use remains challenging for several reasons. The primary issue is the coarse spatial resolution of these products. For instance, the European Space Agency (ESA) Global Snow Monitoring for Climate Research (GlobSnow) SWE product has a resolution of 25 km (Luojus et al., 2020), which is substantially larger than the grid spacing of regional NWP models. Another problem is the integration of satellite observations with ground-based measurements. Typically, SWE products are generated using a Bayesian assimilation technique, combining satellite brightness temperatures with in situ snow depth observations and employing a snow emission model to connect them with snowpack properties (Pulliainen, 2006). This reliance on ground-based data poses a challenge for NWP, as the same observations may be assimilated twice—once through the SWE product and again directly from in situ measurements. Higher-resolution products, such as the Copernicus 5 km dataset (Copernicus Land Monitoring Service, 2024), are also affected by this dependency. Consequently, snow extent products remain the more practical choice for NWP applications.

The H SAF offers an extensive selection of satellite-derived products tailored to diverse applications. These include the H31 and H34 snow extent products from geostationary MSG/Spinning Enhanced Visible Infra-Red Imager (SEVIRI) satellites and the H32 snow extent product from polar-orbiting MetOp/Advanced Very High Resolution Radiometer (AVHRR) satellites.

https://doi.org/10.5194/egusphere-2026-1408
Preprint. Discussion started: 2 June 2026


However, the geostationary H31, H34 and H43 products have a resolution that is insufficient for northern Europe, while the H32 product is reprojected to a 0.01-degree lat-lon grid, leading to an artificially small grid step in meters, which poses additional challenges for the direct NWP use. Similar products will be available for newer EUMETSAT missions, such as MTG and Meteorological Operational Satellite - Second Generation (MetOp-SG).

An alternative method involves using the intermediate H32 snow product, which is delivered on the original satellite grid. This product provides high-resolution data that cover most of the Earth's surface on a daily basis. The MetOp/AVHRR H32 intermediate snow extent product is provided as HDF5 files. Each file contains approximately three minutes of observational data, forming what is known as a Product Dissemination Unit (PDU). PDUs offer a spatial resolution of around 1 km at the nadir. Each pixel within the PDU is classified into one of several categories: "snow", "no snow", "partial snow", "water", "unclassified", and "not processed". The "partial snow" category rarely occurs in the product. "Unclassified" is a common category as it is most often due to clouds covering the pixel or lack of light. These classification labels come as a result of empirically defined threshold-based rules. Comprehensive algorithmic details and product specifications are available in the H32 product documentation (accessible through the H SAF website) and in the reference publication by Siljamo et al. (2020). MetOp satellites pass over northern Europe in the morning (Figure 1), and as an optical product, H32 may suffer from low-light conditions. This is especially problematic in mid-winter when illumination is not sufficient for accurate snow detection. Furthermore, as an optical product, H32 may be significantly affected by cloud cover.

To address key limitations of optical satellite products, we developed the 'snow barrel' method. This approach computes a distribution of classification labels (e.g. "snow", "no snow", "partial snow", "water", etc.) using data from multiple pixels within a defined area, resulting in a compact and efficient representation of snow cover suitable for assimilation into NWP models. Each snow barrel consists of an $n \times n$ pixel block from the satellite grid ($n = 10$ in this study), sampled sequentially without gaps along the central line of the swath, as illustrated in Figure 2.

Each barrel includes metadata such as observation time, average geographic location, and distribution of classification labels. The average geographic coordinates are calculated using the spherical mean position, which accounts for the Earth's curvature. This is done by converting the latitude and longitude of all 100 pixels into 3D Cartesian coordinates on a unit sphere, averaging these, and then converting the result back into geographic coordinates. Snow barrel data are stored in text format for subsequent analysis.

The H32 snow extent product, like any other snow product using optical detection methods, is subject to inherent limitations. The relatively coarse spatial resolution of satellite imagery can result in misclassification when smaller surface features, such as vegetation, water bodies, roads, or buildings, are present within a single pixel. For instance, small water bodies that are partly ice-covered can significantly influence pixel classification. In addition, snow cover within dense evergreen forests is difficult to detect due to canopy obstruction. These issues are further worsened by the satellite's viewing angle, where oblique perspective increase the likelihood of surface elements (trees, buildings, or terrain) obstructing the view. Validation of the H32 product has been conducted using ground-based weather station data, specifically snow depth and surface state observations, as detailed in Siljamo et al. (2020).

https://doi.org/10.5194/egusphere-2026-1408
Preprint. Discussion started: 2 June 2026


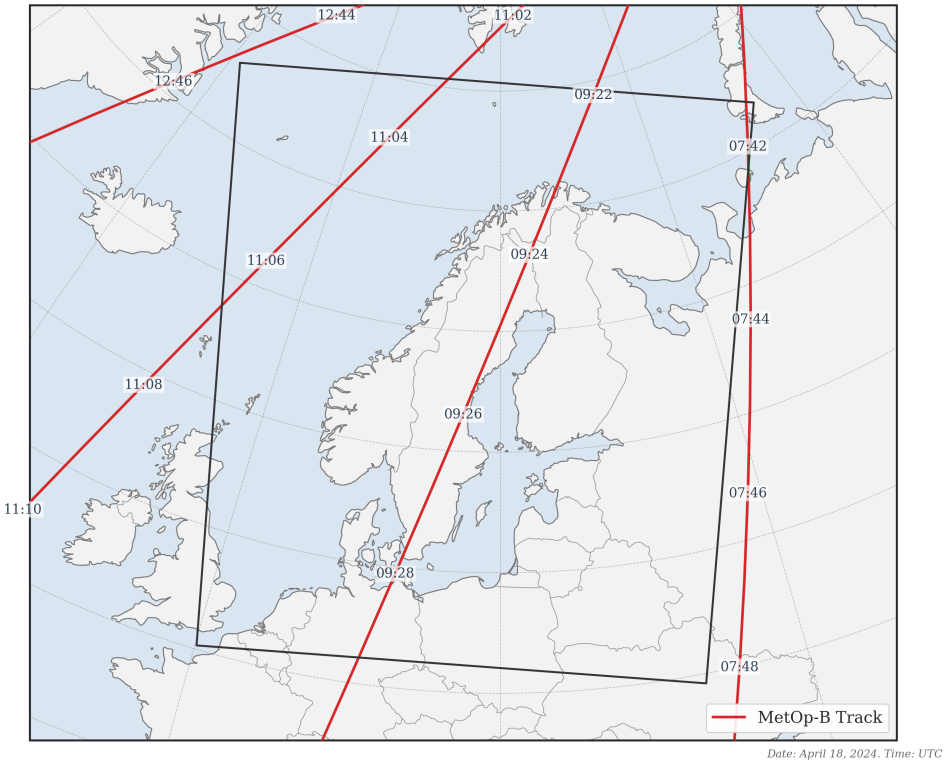


**Figure 1.** Metop-B satellite crossings over the domain of the operational NWP model running for Meteorological Cooperation on Operational Numerical Weather Prediction (MetCoOp) on April 18, 2024. The day's barrels are collected over three to four passes, depending on the specific day. Metop-B satellite data courtesy of EUMETSAT (https://www.eumetsat.int).

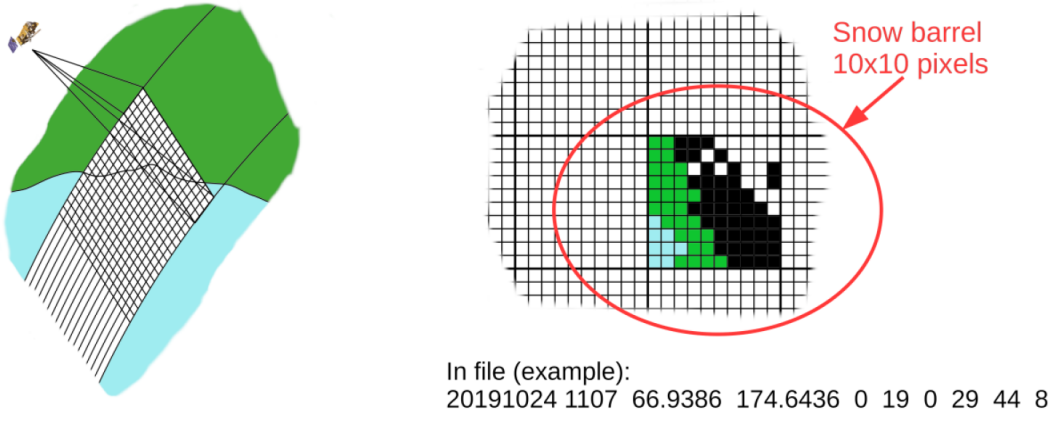


**Figure 2.** Generation of $10 \times 10$ pixel barrels from the original satellite grid. Each barrel contains meta-data (Date, Time, average Latitude and Longitude of pixels) and the number of pixels in each classification category ("snow", "no snow", "partial snow", "water", "unclassified", and "not processed").

https://doi.org/10.5194/egusphere-2026-1408
Preprint. Discussion started: 2 June 2026


## 3 Model and Methods

The Hirlam Aladin Research towards Mesoscale Operational NWP in Europe (HARMONIE-AROME) model is a convection-permitting NWP model developed in frames of A Consortium for Convection-scale Modelling Research and Development (ACCORD), which includes 26 countries in Europe and Northern Africa. It features a high-resolution horizontal grid spacing, allowing for explicit simulation of deep convection, and incorporates advanced physical parametrizations for radiation, cloud dynamics and microphysics, turbulence, shallow convection (Gleeson et al., 2024) and land-surface processes with Surface externalis´ee (SURFEX) land surface modelling system (Le Moigne, 2018).

The MetCoOp is a collaboration for convective-scale operational weather modelling, jointly developed and operated by Norwegian Meteorological Institute (Met Norway), the Swedish Meteorological and Hydrological Institute (SMHI), the Finnish Meteorological Institute (FMI), the Estonian Environment Agency (ESTEA) and the Latvian Environment, Geology and Meteorology Centre (LEGMC). The MetCoOp Ensemble Prediction System (MEPS) is a NWP system that is running the HARMONIE-AROME model cycle 43 operationally. MEPS is an ensemble system. The unperturbed control run is updated by data assimilation every three hours. Perturbed members are updated by data assimilation hourly, and at each update five new ensemble members start, each running for up to 66 hours (Müller et al., 2017). By combining forecasts from the past six hours, a 30-member ensemble is created, producing predictions up to 61 hours ahead. The MEPS domain covers a large part of Northern Europe, including Scandinavia, Finland, the Baltic countries, the Baltic Sea, and nearby land and ocean regions (Figure 1).

For the MetCoOp runs, the HARMONIE-AROME model is currently configured with 2.5 km grid horizontal resolution and 65 hybrid terrain-following vertical levels, extending from around 12 meters above the ground to the 10 hPa pressure level in the stratosphere. The numerical forecast calculation uses semi-implicit 75-second time stepping. The system receives boundary conditions four times per day from European Centre for Medium-Range Weather Forecasts (ECMWF)'s global forecast model. Additional post-processing steps also enhances the MEPS forecasts from original 2.5 km grid by statistically refining surface-level meteorological parameters on a finer 1 km grid.

The temporal evolution of the snowpack is simulated in HARMONIE-AROME by the SURFEX modeling system with the D95 snow scheme, originally developed by Douville et al. (1995). This scheme models snow as a single layer with the time-varying snow water equivalent, albedo and density (Le Moigne, 2018). It explicitly accounts for snow accumulation, sublimation, compaction and melting. The snow layer notably influences surface radiative fluxes, primarily through its impact on albedo, which varies with recent snowfall and melting events. Additionally, snow cover enhances the surface emissivity.

The first techniques of the objective analysis of the snow depth were based on the successive corrections' method (Cressman, 1959). For example, Eerola (1995) describes its implementation into the operational weather forecast with the High Resolution Limited Area Model (HIRLAM) model (Undén et al., 2002) at FMI. Subsequent advances of the snow analysis technique within the HIRLAM model included the use of the Optimal Interpolation (OI) method (Gandin, 1965; Cansado and Navascues, 2003; Rodriguez et al., 2003; Järvenoja, 2000). The HARMONIE-AROME NWP system also uses the OI method for the snow analysis. Technically it is done with the Code for the Analysis Necessary for Arpege for its Rejects and its Initialization (CANARI)

https://doi.org/10.5194/egusphere-2026-1408
Preprint. Discussion started: 2 June 2026


| Date | Time | Latitude | Longitude | Not Processed | Snow | Partial Snow | No Snow | Unclassified | Water |
|---|---|---|---|---|---|---|---|---|---|
| 20230331 | 0934 | 61.0542 | 16.4928 | 0 | 95 | 0 | 0 | 0 | 5 |
| 20230331 | 0934 | 60.8931 | 17.3180 | 0 | 9 | 0 | 0 | 2 | 89 |
| 20230331 | 0934 | 62.1314 | 8.9604 | 0 | 0 | 0 | 89 | 11 | 0 |
| 20230331 | 0934 | 62.2543 | 25.1193 | 0 | 37 | 0 | 0 | 63 | 0 |

**Table 1.** An example of snow barrel data. Besides the date and location information, the columns indicate how pixels are classified within one barrel observation ($10 \times 10$ pixels). Class "water" refers to all water bodies on the Earth's surface

framework (Taillefer, 2002; Gaytandjieva et al., 2000), similarly to the Aire Limitée Adaptation dynamique Développement International (ALADIN) NWP system (Termonia et al., 2018). As HIRLAM, the operational HARMONIE-AROME system initially assimilated exclusively snow depth observations from the SYNOP stations. Assimilation of the satellite-based snow extent data in HARMONIE-AROME was first applied by Homleid and Killie (2013) in the Copernicus Arctic Regional Reanalysis (CARRA) project (Schyberg et al., 2020) for the CryoClim products (Solberg et al., 2014). It follows the method developed at the ECMWF (de Rosnay et al., 2015). The H32 snow extent product is assimilated with the same method but adjusted to the use of snow barrel pseudo-observations, as explained below.

Snow analysis in the operational MEPS system is conducted during the morning hours, because the SYNOP snow observations are usually performed in the morning. Snow barrel observations are assimilated into the system on a daily basis as well. As only five forecast members run each hour, the assimilation process occurs over a three-hour window (07/08/09 UTC). Because the snow barrel data are collected during the previous day, the same set of observations is used for all members, even though the later members are updated up to two hours after the first ones.

When using global snow barrel data in a NWP model, strict pre-processing is required and their use must be carefully limited. Since limited-area models like HARMONIE-AROME only need data for a specific domain, relevant data must be extracted from the global dataset. Only useful barrels must be selected. Unnecessary data may slow down the assimilation process without providing additional benefit.

In our current approach, one snow barrel observation includes the number of pixels of each category, with total number of pixels equal to $10 \times 10$, as in the example shown in Table 1. From this type of data, it is relatively easy to filter out observations that are not useful. At present, a barrel is accepted to data assimilation if more than 20% of pixels are classified as either "snow" or "no snow" (partial snow is counted as snow). In the example given by Table 1, the second row would be excluded based on this criterion because of large percentage of water surface.

Although snow barrel observations are collected across the entire domain, not all of them are used in the snow analysis. They are only applied when they conflict with the model's background field, namely when the model indicates snow, but the barrel does not, or vice versa. This is because the model prognostic variable corrected by the snow data assimilation is the SWE, while the satellite observes only the presence of snow. The actual SWE is not known from these observations, it only can be assumed. Therefore, the influence of these observations is mostly restricted to areas with thin snow cover — for example,

https://doi.org/10.5194/egusphere-2026-1408
Preprint. Discussion started: 2 June 2026


| Month | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Density (kg/m$^3$) | 222 | 233 | 240 | 278 | 312 | 312 | 312 | 143 | 143 | 161 | 182 | 213 |

**Table 2.** Climatological snow density values applied uniformly across the domain for converting snow barrel observations to SWE (Eerola, 1995).

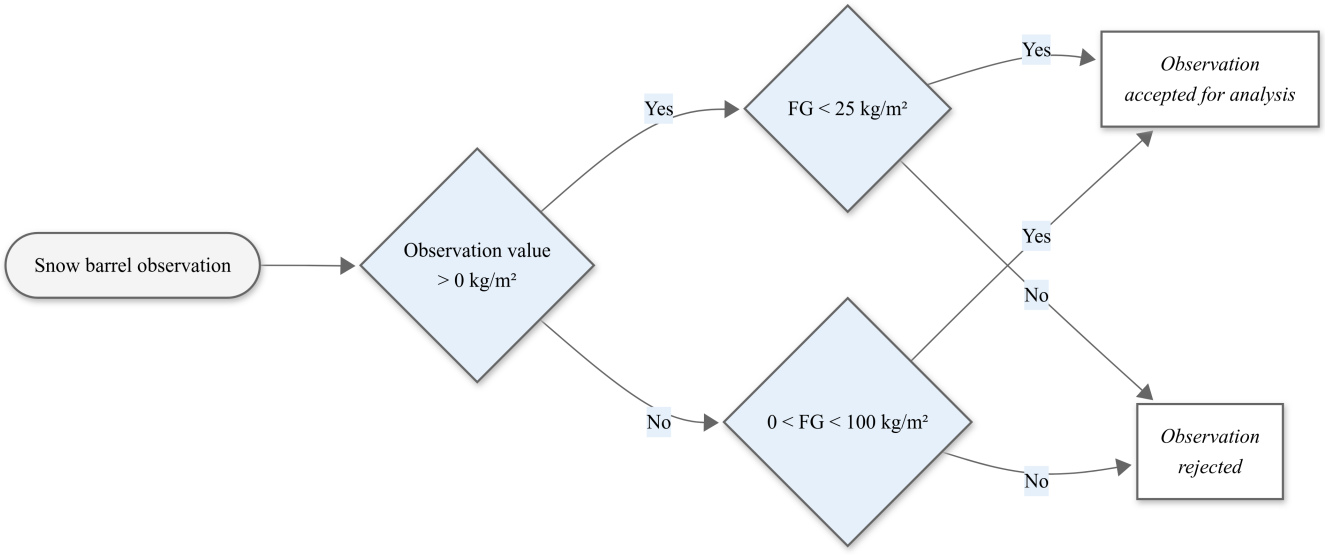


**Figure 3.** A flowchart illustrating the criteria for accepting barrels in the assimilation process. The core concept involves comparing barrel observations with the first guess (FG) values at the observation locations. In essence, barrels are utilized when they are inconsistent with background field within predefined limits

during melting periods, along snowlines, or at the beginning of snowfall. These are also the situations where the barrel data offer the most value.

After filtering, the selected barrel observations are converted into pseudo-observations of the SWE, expressed in kg/m$^2$. Since the satellite does not observe snow depth or mass, we assume a pseudo-observation in a range of 0–10 cm (equivalent to appr. 0–31 kg/m$^2$, depending on snow density). In other words, each barrel can introduce a maximum change of 10 cm to the model snow field. This limit was chosen as a reasonably large depth of thin snow, taking into account that it can be assimilated only if there is no snow in the model background field. To obtain the pseudo-observation of the snow depth, we multiply the fraction of "snow" pixels in the barrel by the maximum value of 10 cm. Snow depth is then converted to snow mass using monthly climatological snow density values from Eerola (1995), which range from 143 to 312 kg/m$^3$ (see Table 2). For instance, if a barrel is entirely classified as "snow", it would result in a pseudo-observation of about 28 kg/m$^2$ in April, assuming a snow density of 278 kg/m$^3$. If only 50% of the pixels are snow, the observation would be 14 kg/m$^2$. These pseudo-observations are then formatted in the specific ASCII structure required by the CANARI assimilation system.

https://doi.org/10.5194/egusphere-2026-1408
Preprint. Discussion started: 2 June 2026


Figure 3 illustrates the selection process for barrels used in the data assimilation procedure. The term FG refers to the SWE value of the model background (first guess) field, which in our case is the previous forecast field, at the location of the snow barrel observation. The criterion for selecting of the non-zero snow barrel observations (upper row in the figure) is that the FG value at this location is below 25 kg/m$^2$. This criterion effectively excludes barrel observations that indicate snow in areas already characterized by substantial snow cover. Given that barrels can introduce a maximum SWE of approximately 30 kg/m$^2$, this measure ensures that the barrels do not erroneously reduce the amount of snow in these regions. In the case of zero snow barrel observations (lower row in the figure), we reject them in regions where the model indicates the SWE exceeding a threshold of 100 kg/m$^2$. This filter is crucial to prevent unrealistic snow removal. In most cases, if the snow amount in a given area is substantial and the barrels still report zero observations, it is more likely that the barrel observation is an outlier rather than a reflection of rapid snow melt. Also, as mentioned above, barrels that indicate zero observations in areas where the FG field is already zero, are excluded as well because they do not provide additional information.

Snow barrel observations are converted to SWE observations while passing through this filtering process, to be assimilated within the system. However, considering that the snow barrel SWE values are pseudo-observations, they are indirect and are primarily dependent on adjustments, a slightly larger observation error value is assigned to them compared to the SYNOP snow observations. Specifically, the error standard deviations for both the SYNOP snow observations and the first-guess snow field are set to 5 kg/m$^2$, whereas a slightly higher value of 8 kg/m$^2$ is assigned to the satellite-based snow barrel observations. This approach assigns slightly larger weights to the SYNOP observations and the background field relative to the snow barrel observations during data assimilation.

## 4 Results

In this study, the implementation of snow barrel observations in NWP models was developed and evaluated for the operational MEPS configuration. We present results from our own experimental setup, which is comparable to the operational MetCoOp system.

Figure 4 displays an example of snow barrel observations for two different days. For comparison, the left-hand panel shows satellite imagery from the VIIRS instrument, where the bright red colour denotes snow-covered areas, and the lighter red or white colours indicate cloud at different heights. The colour of each dot on the middle or right-hand side panel indicates the snow observation value inferred by the snow barrel at that geographical location. As described above, the snow barrel data are utilized only in regions where they are inconsistent with the model's background field. This figure illustrates the filtering process by comparing the total number of the collected snow barrel observations (middle panel) with the subset of observations actually used in the analysis (right-hand panel). It can be also noticed that the accepted snow barrel observations are primarily located along the snowline. This is the melting zone, typical for spring, where snow barrels provide the most added value, as they are better in detecting small snow-free patches and changes in patchy snow cover comparing with the conventional in-situ observations.

https://doi.org/10.5194/egusphere-2026-1408
Preprint. Discussion started: 2 June 2026


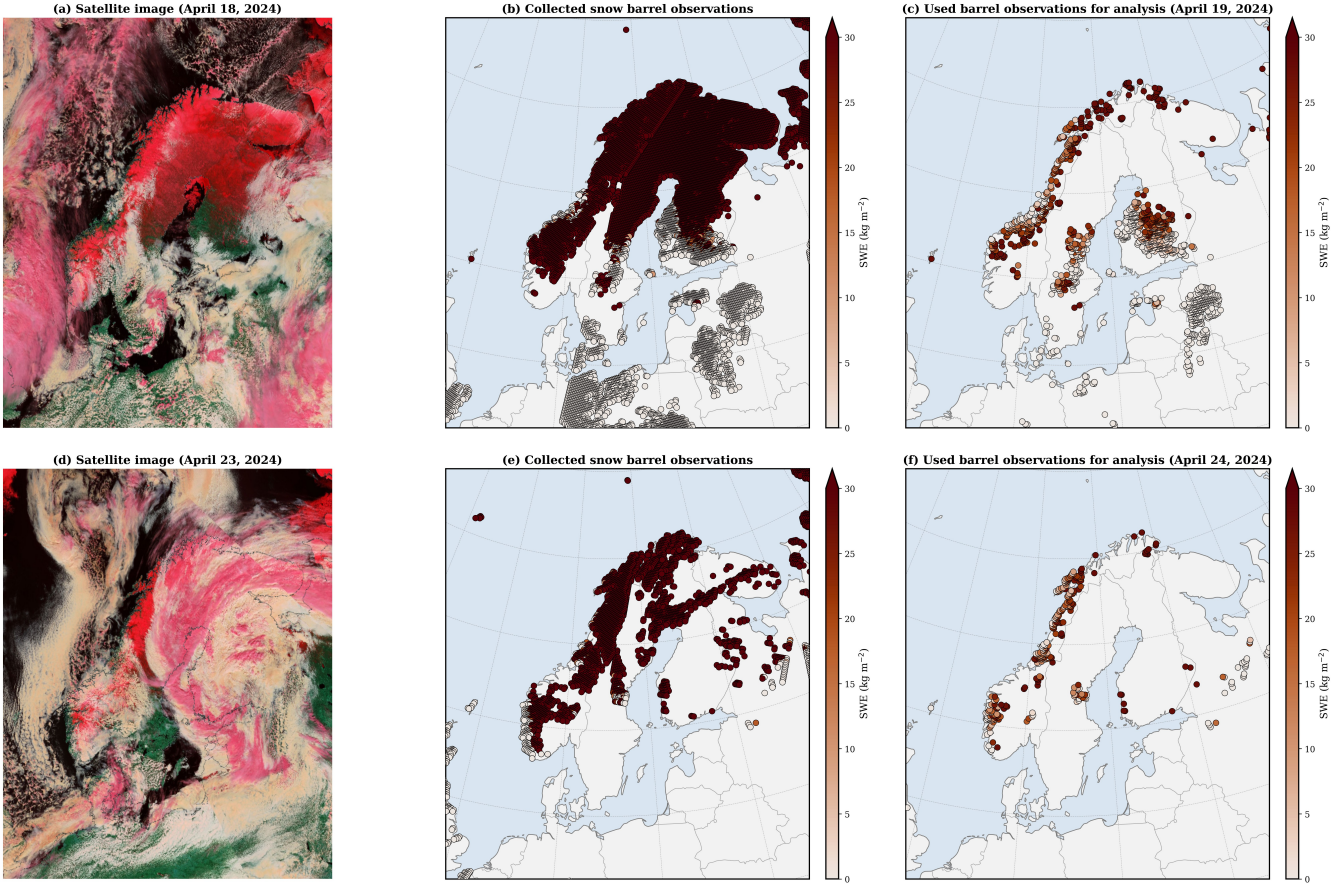


**Figure 4.** All snow barrel observations (middle panel) and the observations used in the analysis (right panel) on 18 of April 2024 (upper row) and 23 of April 2024 (lower row). Left panel shows independent Visible Infrared Imaging Radiometer Suite (VIIRS) satellite images, taken the day before (when the barrels were actually collected), where snow appears in bright red, and white and light red colours indicate clouds on different heights. VIIRS satellite imagery courtesy of NASA Earthdata (https://earthdata.nasa.gov).

https://doi.org/10.5194/egusphere-2026-1408
Preprint. Discussion started: 2 June 2026


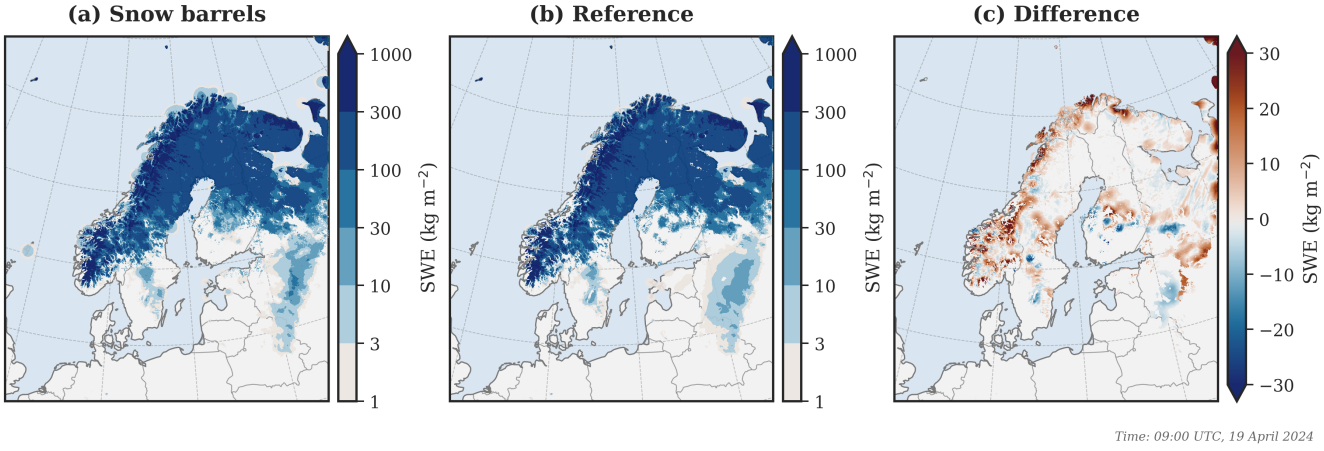


**Figure 5.** Impact of snow barrels on the NWP model's SWE field, the example is given for April 19, 2024. The left panel shows the snow analysis with the barrels included, and the middle panel shows the analysis without them. The right panel displays the difference between the two.

Cloud cover significantly impacts the availability of snow barrel observations, causing the number of observations to fluctuate greatly between different days. For instance, when comparing the satellite images from April 18 and April 23, 2024, as shown in Figure 4, it is evident that thick cloud cover on April 23 greatly reduced the number of collected observations compared to the relatively cloud-free conditions on April 18. The spatial distribution of snow barrel data aligns closely with areas free of cloud cover.

Figure 5 illustrates the impact of snow barrels on the model's SWE field, the example is given for April 19, 2024. In Central Finland, barrels primarily add snow to snow-free areas, whereas in some small regions of Russia they completely remove snow cover. Additionally, snow barrels modify snow field in regions where cover is thin or patchy in the reference field. The magnitude of the difference between the analysed fields with and without snow barrels is approximately 30 kg/m$^2$, depending on the monthly snow density. In areas with solid snow cover (where barrels are not used), there is no significant difference between the two analysed fields, as expected. When comparing this figure with the satellite image from April 18, 2024 (Figure 4), it is visible that the SWE field incorporating snow barrel data aligns more closely with the snow coverage observed in the Southern Finland area. Furthermore, when comparing the used barrels on April 19 (Figure 4) with the SWE difference field for the same day (Figure 5), it becomes evident that the SWE field has been adjusted in areas where the barrel observations show changes.

Figure 6 shows how the number of barrel observations vary throughout the year within the MetCoOp domain. The left panel presents all available observations, while the right panel displays those selected for analysis. As seen in the figure, a significant portion of the available data is excluded based on the filtering criteria described earlier. The left-hand panel, showing the total number of available barrels, reveals a seasonal pattern that closely follows the variation in daylight hours in the Nordic region, peaking during summer and reaching a minimum in mid-winter. During summer, the number of barrel observations is

https://doi.org/10.5194/egusphere-2026-1408
Preprint. Discussion started: 2 June 2026


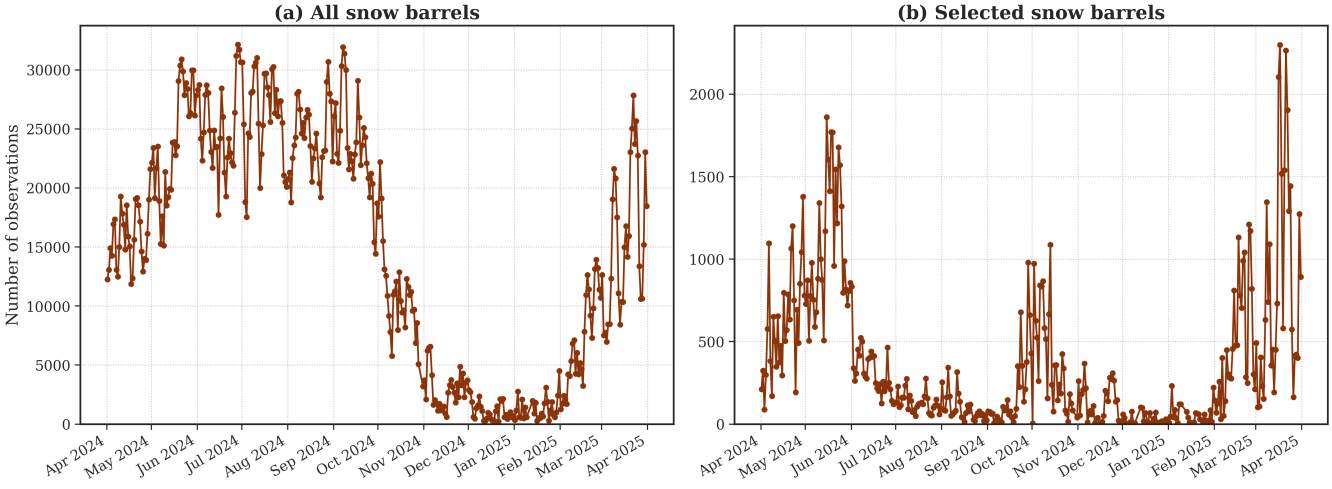


**Figure 6.** Number of available barrel observations during the year. The left panel shows snow barrels available inside the NWP model domain and the right panel selected barrels for the snow analysis. Note the different scales of the vertical axis.

huge, exceeding 30,000. However, most of these are zero observations, meaning they do not indicate snow presence. These are typically not useful, as the background model field already reflects snow-free conditions in summertime.

In contrast, the selected observations (right-hand panel) show a different seasonal trend, with the highest peak occurring in spring and a secondary, smaller peak in autumn. This pattern highlights the periods when barrel observations provide the most added value. In spring, as snow begins to melt, barrels are particularly useful for identifying snow-free areas that differ from the background model. A similar benefit is seen in autumn during the first snowfall events. However, fewer observations are available in autumn due to more frequent cloud cover, which limits satellite-based snow detection. As time progresses toward winter, decreasing daylight further reduces the number of useful barrel observations.

Figure 7 presents the root mean square error (RMSE) and bias statistics for the SWE analysis conducted with and without assimilation of snow barrels. The results show that incorporating barrels together with SYNOP observations reduces the RMSE and slightly improves the bias during the spring period. This behavior is expected, as snow barrels provide the most benefit under conditions where snow cover evolves rapidly. In autumn and winter, the analysis including barrels also exhibits slightly improved performance compared to the analysis without barrels. The pronounced wintertime peaks are related to snowfall events, when the daily snow analysis has not yet adapted to the fast changes in the snow cover. Still, even in these rapidly changing conditions, the snow barrels show a small positive effect. It is notable that there is very limited amount of barrels available in mid-winter due to lack of day light.

During the summer period, from mid-June to mid-August, the analysis including barrels performs slightly worse than the reference analysis. This behaviour is caused by misclassification in the satellite product with convective clouds and is discussed further in the following section. For operational use, we therefore decided to disable the use of snow barrels during the convective period, which is relatively short at the latitudes of our study domain.

https://doi.org/10.5194/egusphere-2026-1408
Preprint. Discussion started: 2 June 2026


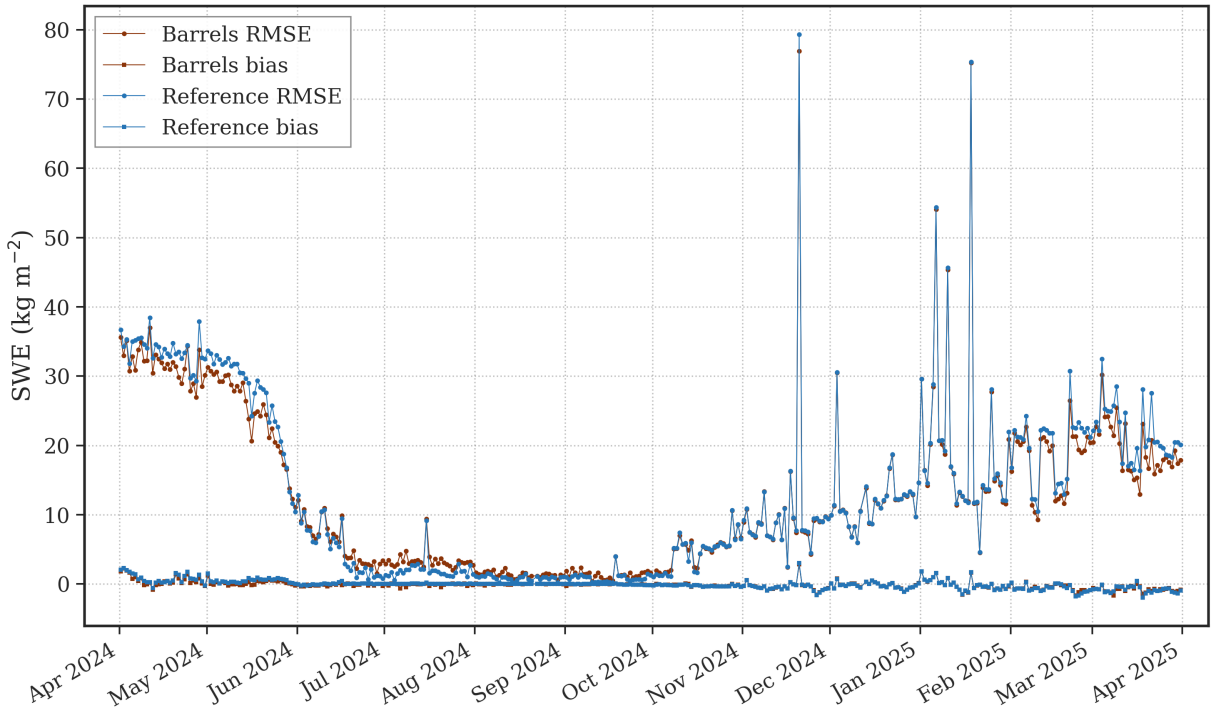


**Figure 7.** The MEPS 09 UTC SWE analysis statistics for the period from April 1st 2024 to March 31st 2025, show that incorporating snow barrels (represented by the red curves) has a positive impact in spring time, reducing both root mean square error and bias compared to the analysis without snow barrels (blue curves).

## 5 Discussion

The snow barrel observations and the method to assimilate them showed promising results within the MetCoOp prediction system. Visual comparison shows that the model's snow cover field has improved by incorporating barrel observations, particularly in regions with thin or patchy snow coverage. A key strength of the snow barrels is their ability to capture local snow cover variations, compared to relying solely on the SYNOP observations. This capability is especially valuable in regions with sparse conventional observations or rapidly changing snow cover, where the method effectively gives additional benefit for NWP modelling results.

The method to assimilate snow barrels also appeared to be computationally efficient, suitable for an operational system. Given the time-sensitive nature of operational NWP modeling, it is essential to maintain the efficient performance during production runs. Testing revealed that assimilating the snow barrel observations has little impact on computational time, making it a viable addition to the model.

Snow barrels offer several advantages over the pure H32 satellite snow product when used in NWP models. One significant benefit is their ability to reduce classification errors by aggregating multiple satellite pixels into a single observation. This

https://doi.org/10.5194/egusphere-2026-1408
Preprint. Discussion started: 2 June 2026


spatial aggregation ensures that each barrel is more representative of the actual snow conditions than an individual pixel classification, making them a more reliable data source. Furthermore, snow barrels align better with the spatial scale of NWP models, which typically operate at a coarser resolution than the native H32 pixel size. This is important, because the data assimilation algorithms, such as OI, were primarily designed for the situation, when the observational network is coarser, than the atmospheric model grid (Gandin, 1965).

Snow barrels can also help to mitigate the impact of the cloud cover. By combining data from several pixels, they can offer useful snow information even if some pixels are cloud-obscured, unlike the raw H32 snow product, which excludes such pixels. Although barrels cannot either provide data under total cloud cover, their ability to function in partially cloudy conditions significantly enhances the reliability of the snow data.

However in summertime, it was noticed that the H32 snow extent product seems to miss-classify convective high clouds as snow. As a result, snow barrel observations represent wrongly the snow patches, as shown in Figure 8. From the left-hand side plot showing the SWE field, it can be seen that only Norwegian mountain tops really have snow and other spots are created based on wrong classifications by the product. Since this happens only during the convective season, which is relatively short at the latitudes of our computional domain, we decided to deactivate assimilation of barrels for summer period (from 15th of June to 15th of August) when snow is mostly absent anyway. For future development, better quality control with checking against other model parameters, such as surface temperature, is expected to remove this problem. Also next generation satellite products with better classification algorithms would perhaps overcome this.

Preliminary, the impact of the snow barrel pseudo-observations was compared with the impact of the CryoClim observations (Solberg et al., 2014) in a series of HARMONIE-AROME experiments conducted within the CARRA project (Schyberg et al., 2020) during 2017 over the CARRA Eastern domain. The validation used independent snow depth data from SYNOP stations along the Russian Arctic coast. Key findings highlighted that the satellite snow extent observations (both the snow barrels and CryoClim) influenced snow analysis only when the snow cover was thin, as the method prioritises conflicts between forecasts and observations. Snow depth observations from SYNOP stations had a stronger influence than satellite data where available, while the model snow field dominated in regions reliant solely on satellite inputs. Analysed snow fields with assimilated CryoClim and H SAF barrel data showed general agreement, although differences emerged in Arctic coastal areas, where inaccuracies in land-water distribution in the model poses challenges. Also, the usage of a satellite product in latitude-longitude coordinates (such as CryoClim and daily H32 snow extent) was recognised to be problematic over the polar latitudes.

The modelling platform SURFEX uses a so-called tiling approach, when different physical models run over different types of Earth's surface in each model grid box. Currently, "nature", "urban", "inland water" and "sea" surface types are distinguished in SURFEX. Each grid box of the atmospheric model grid is characterised by the percentage of each tile. However, the analysis system does not yet use the tiling approach. Only the land-sea mask is applied, where the surface is divided into "land" or "water" types, with the threshold of 50%. This causes errors in the analysis of surface fields in coastal regions. In particular, the snow analysis suffers from this problem because the snow errors accumulate during winter (not shown in the illustrations). Many of the potentially useful barrel observations are located close to the coastline, which calls for improving the algorithms and the code.

https://doi.org/10.5194/egusphere-2026-1408
Preprint. Discussion started: 2 June 2026


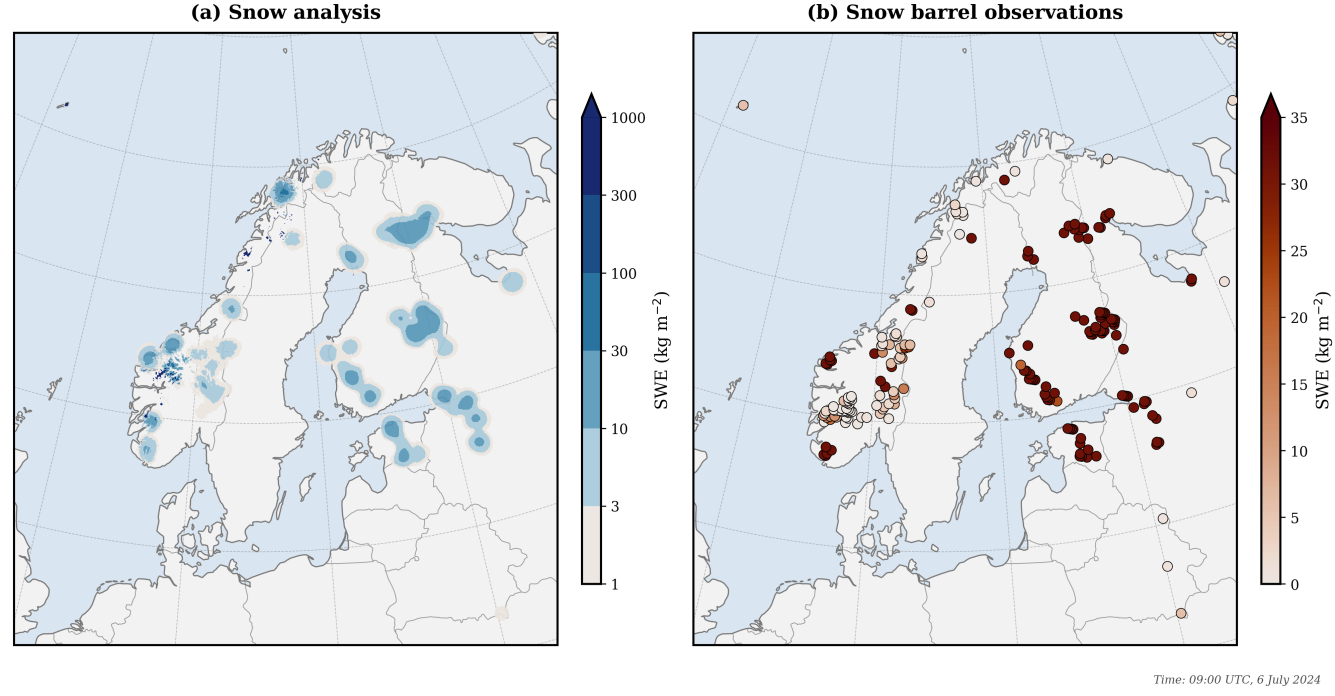


**Figure 8.** The 09 UTC SWE analysis for 6th of July illustrates a noticed summertime issue, where the H32 snow product misclassifies convective high clouds as snow, leading to spurious snow patches across the domain. In reality, snow is present only at the highest peaks of the Norwegian mountains.

At the moment, the snow barrel approach has been used only with the EUMETSAT's MetOp satellites on morning orbit. However, the barrel method can be applied to any satellite snow product which provides information about presence of snow. Employing barrel method to afternoon orbit products would also benefit snow analysis as they may provide more daylight observations particularly in the northern regions of the domain. Other option would be using geostationary satellite based snow extent products such as H SAF H31 and H34 for MSG/SEVIRI or H43 for MTG/FCI (Flexible Combined Imager), although polar-orbiting satellite data are better suited for snow barrel production.

To overcome limitations associated with visible-light observations, the assimilation of microwave radiance observations can provide an effective approach for snow monitoring, as microwave measurements are largely insensitive to cloud cover and illumination conditions. Nevertheless, microwave-based snow detection has important limitations. Passive microwave instruments offer broad spatial coverage but relatively coarse spatial resolution, whereas active microwave instruments (e.g., radar) provide much finer spatial resolution at the expense of more limited spatial coverage. Both passive and active microwave techniques exhibit reduced sensitivity to shallow snowpacks, particularly in the case of thin, dry snow (Takala et al., 2011; Nolin, 2010).

Remaining operational lifetime of the current MetOp satellites is another limitation of the snow barrel approach used in this study. The next-generation EUMETSAT satellite, MetOp-SG, was launched in August 2025. A similar snow extent product

https://doi.org/10.5194/egusphere-2026-1408
Preprint. Discussion started: 2 June 2026


(H SAF H85) is in development for MetOp-SG/Meteorological Imager (METimage) and will be suitable for snow barrel production once the product will reach the operational status.

In the coming MetCoOp model version, which is now undergoing pre-operational testing, the snow data assimilation is performed for snow depth rather than for SWE. This change eliminates the need to convert in-situ snow depth observations into SWE using climatological snow density values. Instead, the analysed snow depth field is converted to SWE using the model's own, spatially variable snow density. For this configuration, the observation error for snow barrel data is set to 3 cm, while the background and in-situ observation errors are set to 2.5 cm, preserving the same relative weighting as in the previous system. Preliminary tests show that assimilating satellite snow depth observations yields results comparable to the current SWE-based system, with the added benefit of more consistent and physically realistic treatment of snow density. As a result, snow barrel observations can provide more accurate corrections to the model's snow fields.

The snow barrel concept is applicable beyond the MetCoOp system. However, the conversion of the H SAF H32 intermediate product into snow barrels is carried out within our operational setup. Therefore, to apply this approach in other NWP use cases, users must create snow barrels from any available snow classification product that is provided in the original satellite grid.

In theory, the snow barrel method could also be applied to other satellite-derived parameters beyond the snow cover. However, for NWP applications, there are only a few satellite products that can be used with a classification approach similar to snow cover. Products like vegetation types and land use are currently static information within the NWP models, making them unsuitable for this method. One potential satellite parameter that could be updated using an approach similar to the snow barrel method is the inland water extent. This could improve model performance in capturing potential flood events and correcting evaporation. However, the benefits of applying the snow barrel method to other satellite products for NWP have not been explored yet.

In the future, objective analysis of snow cover on sea and lake ice will require more attention in the NWP models. Over ice, the only regular source of snow data are the satellite measurements. However, to our knowledge, methods to assimilate snow observations over ice are not yet developed. This remains a subject for future investigation.

## 6 Conclusions

This study introduced the snow barrel method, a new approach for integrating satellite-derived snow cover observations into the NWP model. By grouping satellite-pixel classifications into spatially coherent "barrels," the method effectively bridges the resolution gap between high-resolution satellite data and coarser NWP model grids. Its implementation within the MetCoOp operational MEPS system has demonstrated several key advantages.

First, snow barrels significantly improve the representation of snow cover in transitional regions, especially along the snowline during melting periods. By capturing local variations often missed by traditional SYNOP observations, the method improves the model description of patchy snow conditions, particularly in areas with sparse ground-based observations or rapidly changing snow cover.

https://doi.org/10.5194/egusphere-2026-1408
Preprint. Discussion started: 2 June 2026


Second, snow barrel observations are used selectively. They are applied in areas where they are inconsistent with the model background and where the snow cover is thin. This targeted use allows meaningful corrections without affecting solid snow cover. It also helps to overcome some limitations of optical satellite products while keeping most of their strengths.

Third, the method is computationally efficient, adding minimal processing time while improving snowfield accuracy. This favourable cost-benefit balance makes a practical enhancement for operational NWP systems.

Despite its benefits, the method has some limitations. As mentioned above, it relies on optical satellite data, making it sensitive to cloud cover and lighting conditions. This is especially problematic during midwinter at high latitudes. However, barrels are typically not used in areas with thick and solid snow cover, which is common in mid-winter. Therefore, this limitation is not considered critical.

Future improvements could include applying the snow barrel method to other satellite platforms, such as afternoon orbit or geostationary systems, to increase temporal coverage. Adding microwave observations may help address some of the limitations of optical sensors. However, challenges with resolution and the detection of thin snow layers remain. Refine the assimilation scheme for snow barrels by using spatially varying snow density instead of fixed climatological values may further improve accuracy.

The snow barrel method also shows promise beyond the MetCoOp system and could be adapted for use in other NWP frameworks worldwide.

*Code and data availability.* The HARMONIE-AROME model is developed using the same code structure as the ECMWF/IFS and MF/Arpege global models. Since these global models are not open source and a large part of the code is shared between them, we are not permitted to make the full model code publicly available. Access is restricted to ECMWF, Arpege, and ACCORD partners. However, the parts of the code developed specifically for this study can be shared and are available on Zenodo (https://doi.org/10.5281/zenodo.19001083; Hasu and Siljamo (2026)). The H32 intermediate snow product, which was used to produce snow barrel observations, is publicly available from the EUMETSAT H SAF archive at `https://hsaf.meteoam.it/Products/ProductsList?type=snow`.

*Author contributions.* The primary contributions to this paper were made by M.H. Significant input was also provided by N.S. in the Data section and by E.K. in the Model and Methods section. L.R. contributed to the discussion of previous studies. All authors were involved in reviewing and editing the manuscript. The algorithm of generating barrels from raw satellite data was developed by N.S., while the adaptation of barrel data for use in the NWP model and its subsequent testing were carried out by M.H., L.R., and E.K.

*Competing interests.* The authors declare that there are no conflicts of interest regarding the publication of this article.

https://doi.org/10.5194/egusphere-2026-1408
Preprint. Discussion started: 2 June 2026


*Acknowledgements.* We thank EUMETSAT and its Satellite Application Facilities (H SAF and LSA SAF) for providing the satellite products used in the snow barrel approach, and acknowledge our colleagues Mariken Homleid for her contributions to the development of satellite snow assimilation in HARMONIE-AROME system and Kalle Eerola for his work on the early developments of snow analysis. The scientific colour maps "roma" and "vik" from Crameri (2021) were selected to ensure that the results plots are accessible to readers with colour-vision deficiencies. (Crameri et al., 2020).

## Appendix A: Acronyms

| | |
|---|---|
| **ACCORD** | A Consortium for Convection-scale Modelling Research and Development |
| **ALADIN** | Aire Limitée Adaptation dynamique Développement International |
| **AVHRR** | Advanced Very High Resolution Radiometer |
| **CANARI** | Code for the Analysis Necessary for Arpege for its Rejects and its Initialization |
| **CARRA** | Copernicus Arctic Regional Reanalysis |
| **ECMWF** | European Centre for Medium-Range Weather Forecasts |
| **ESA** | European Space Agency |
| **ESTEA** | Estonian Environment Agency |
| **EUMETSAT** | European Organisation for the Exploitation of Meteorological Satellites |
| **FCI** | Flexible Combined Imager |
| **FMI** | Finnish Meteorological Institute |
| **GlobSnow** | Global Snow Monitoring for Climate Research |
| **H SAF** | EUMETSAT Satellite Application Facility on Support to Operational Hydrology and Water Management |
| **HARMONIE-AROME** | Hirlam Aladin Research towards Mesoscale Operational NWP in Europe |
| **HIRLAM** | High Resolution Limited Area Model |
| **IMS** | Interactive Multisensor Snow and Ice Mapping System |
| **ISBA** | Interaction between Soil Biosphere and Atmosphere |
| **LEGMC** | Latvian Environment, Geology and Meteorology Centre |

https://doi.org/10.5194/egusphere-2026-1408
Preprint. Discussion started: 2 June 2026


| | |
|---|---|
| **MEPS** | MetCoOp Ensemble Prediction System |
| **METimage** | Meteorological Imager |
| **MSG** | Meteosat Second Generation |
| **MTG** | Meteosat Third Generation |
| **Met Norway** | Norwegian Meteorological Institute |
| **MetCoOp** | Meteorological Cooperation on Operational Numerical Weather Prediction |
| **MetOp-SG** | Meteorological Operational Satellite - Second Generation |
| **MetOp** | Meteorological Operational satellite |
| **NWP** | Numerical Weather Prediction |
| **OI** | Optimal Interpolation |
| **PDU** | Product Dissemination Unit |
| **RMSE** | root mean square error |
| **SEVIRI** | Spinning Enhanced Visible Infra-Red Imager |
| **SMHI** | Swedish Meteorological and Hydrological Institute |
| **SURFEX** | Surface externalis´ee |
| **SWE** | Snow Water Equivalent |
| **SYNOP** | Surface Synoptic Observation |
| **VIIRS** | Visible Infrared Imaging Radiometer Suite |

https://doi.org/10.5194/egusphere-2026-1408
Preprint. Discussion started: 2 June 2026


## References

Cansado, A. and Navascues, B.: Optimum Interpolation Analysis Method for Snow Depth, HIRLAM Newsletter 43, pp. 58–64, 2003.

Copernicus Land Monitoring Service: Snow Water Equivalent (SWE) v1.0, 5km – Copernicus Land Monitoring Service, https://land.copernicus.eu/en/products/snow/snow-water-equivalent-v1-0-5km, accessed: 2025-04-16, 2024.

Crameri, F., Shaphard, G. E., and Heron, P. J.: The misuse of colour in science communication., Nature Communications, 11, https://doi.org/10.1038/s41467-020-19160-7, 2020.

Cressman, G. P.: AN OPERATIONAL OBJECTIVE ANALYSIS SYSTEM, Monthly Weather Review, 87, 367 – 374, https://doi.org/10.1175/1520-0493(1959)087<0367:AOOAS>2.0.CO;2, 1959.

de Rosnay, P., Isaksen, L., and Dahoui, M.: Snow data assimilation at ECMWF, https://doi.org/10.21957/lkpxq6x5, 2015.

Douville, H., Royer, J., and Mahfouf, J.: A NEW SNOW PARAMETERIZATION FOR THE METEO-FRANCE CLIMATE MODEL .1. VALIDATION IN STAND-ALONE EXPERIMENTS, CLIMATE DYNAMICS, 12, 21–35, https://doi.org/10.1007/BF00208761, 1995.

Drusch, M., Vasiljevic, D., and Viterbo, P.: ECMWF's global snow analysis: Assessment and revision based on satellite observations., https://doi.org/10.21957/xe9n9n2fh, 2004.

Eerola, K.: Experiences with the analysis of sea surface temperature, ice coverage and snow depth, Proceedings of the HIRLAM3 Workshop on soil processes and soil/surface data assimilation, 27-29 November 1995, pp. 33–37, 1995.

Gandin, L.: Objective analysis of meteorological fields, Gidrometeorologichoskoe Isdatel'stvo, Leningrad, israel Program for Scientific Translation, Jerusalem, 1965.

Gaytandjieva, L., Gerard, E., and Bouyssel, F.: Validation of the snow analysis in CANARI/ALADIN, https://www.umr-cnrm.fr/aladin/IMG/pdf/REPORT_snow2000b_L.pdf, 2000.

Gichamo, T. Z., Draper, C. S., and Barlage, M.: Improving NOAA's global NWP snow data assimilation by updating to an Ensemble Kalman Filter, Journal of Hydrology, 660, 133 301, https://doi.org/https://doi.org/10.1016/j.jhydrol.2025.133301, 2025.

Gleeson, E., Kurzeneva, E., de Rooy, W., Rontu, L., Martín Pérez, D., Clancy, C., Ivarsson, K.-I., Engdahl, B. J., Tijm, S., Nielsen, K. P., Shapkalijevski, M., Maalampi, P., Ukkonen, P., Batrak, Y., Kähnert, M., Kettler, T., van den Brekel, S. M. E., Adriaens, M. R., Theeuwes, N., Pálmason, B., Rieutord, T., Fannon, J., Whelan, E., Viana, S., Homleid, M., Bessardon, G., Onvlee, J., Samuelsson, P., Santos-Muñoz, D., Vignes, O. N., and Stappers, R.: The Cycle 46 Configuration of the HARMONIE-AROME Forecast Model, Meteorology, 3, 354–390, https://doi.org/10.3390/meteorology3040018, 2024.

Hasu, M. and Siljamo, N.: Snow Barrels model code (Version v1.0), https://doi.org/10.5281/zenodo.19001083, 2026.

Helfrich, S. R., McNamara, D., Ramsay, B. H., Baldwin, T., and Kasheta, T.: Enhancements to, and forthcoming developments in the Interactive Multisensor Snow and Ice Mapping System (IMS), Hydrological Processes, 21, 1576–1586, https://doi.org/https://doi.org/10.1002/hyp.6720, 2007.

Homleid, M. and Killie, M. A.: HARMONIE snow analysis experiments with additional observations, Meteorology Report 5-2013, https://www.met.no/publikasjoner/met-report/met-report-2013/_/attachment/download/803a5265-6fe7-4782-95df-963ebf948bd2:0a6e79d932bb5437040ce6c706e0bfed3d886eb8/MET-report-06-2013.pdf, 2013.

Järvenoja, S.: Missing snow cover in the HIRLAM system in winter - a catastrophe or not?, HIRLAM Newsletter 35, pp. 49–56, 2000.

Le Moigne, P.: Surfex scientific documentation, Météo-France, 2018.

Li, W., Chen, J., Li, L., Orsolini, Y. J., Xiang, Y., Senan, R., and de Rosnay, P.: Impacts of snow assimilation on seasonal snow and meteorological forecasts for the Tibetan Plateau, The Cryosphere, 16, 4985–5000, https://doi.org/10.5194/tc-16-4985-2022, 2022.

https://doi.org/10.5194/egusphere-2026-1408
Preprint. Discussion started: 2 June 2026


Luojus, K., Pulliainen, J., Takala, M., Lemmetyinen, J., and Moisander, M.: GlobSnow v3.0 snow water equivalent (SWE), https://doi.org/10.1594/PANGAEA.911944, 2020.

Marsh, P., Pomeroy, J. W., and Neumann, N.: Sensible heat flux and local advection over a heterogeneous landscape at an Arctic tundra site during snowmelt, Annals of Glaciology, 25, 132–136, https://doi.org/10.3189/S0260305500013926, 1997.

Müller, M., Homleid, M., Ivarsson, K.-I., Køltzow, M. A. Ø., Lindskog, M., Midtbø, K. H., Andrae, U., Aspelien, T., Berggren, L., Bjørge, D., Dahlgren, P., Kristiansen, J., Randriamampianina, R., Ridal, M., and Vignes, O.: AROME-MetCoOp: A Nordic Convective-Scale Operational Weather Prediction Model, Weather and Forecasting, 32, 609 – 627, https://doi.org/10.1175/WAF-D-16-0099.1, 2017.

NASA Earthdata: Worldview, https://worldview.earthdata.nasa.gov/, we acknowledge the use of imagery from the NASA Worldview application, part of the NASA Earth Science Data and Information System (ESDIS). Accessed: 2025-08-13.

Nolin, A. W.: Recent advances in remote sensing of seasonal snow, Journal of Glaciology, 56, 1141–1150, https://doi.org/10.3189/002214311796406077, 2010.

Pulliainen, J.: Mapping of snow water equivalent and snow depth in boreal and sub-arctic zones by assimilating space-borne microwave radiometer data and ground-based observations, Remote Sensing of Environment, 101, 257–269, https://doi.org/https://doi.org/10.1016/j.rse.2006.01.002, 2006.

Ramsay, B. H.: The interactive multisensor snow and ice mapping system, Hydrological Processes, 12, 1537–1546, https://doi.org/https://doi.org/10.1002/(SICI)1099-1085(199808/09)12:10/11<1537::AID-HYP679>3.0.CO;2-A, 1998.

Rodriguez, E., Navascués, B., Ayuso, J., and Järvenoja, S.: Analysis of surface variables and parameterization of surface processes in HIRLAM. Part I: Approach and verification by parallel runs., HIRLAM Technical report 58, 2003.

Rudjord, Ø., Salberg, A.-B., and Solberg, R.: Global snow cover mapping using a multi-temporal multi-sensor approach, in: 2015 8th International Workshop on the Analysis of Multitemporal Remote Sensing Images (Multi-Temp), pp. 1–4, https://doi.org/10.1109/Multi-Temp.2015.7245775, 2015.

Schyberg, H., Yang, X., Køltzow, M., Amstrup, B., Bakketun, Å., Bazile, E., Bojarova, J., Box, J. E., Dahlgren, P., Hagelin, S., Homleid, M., Horányi, A., Høyer, J., Johansson, Å., Killie, M., Körnich, H., Le Moigne, P., Lindskog, M., Manninen, T., Nielsen Englyst, P., Nielsen, K., Olsson, E., Palmason, B., Peralta Aros, C., Randriamampianina, R., Samuelsson, P., Stappers, R., Støylen, E., Thorsteinsson, S., Valkonen, T., and Wang, Z.: Arctic regional reanalysis on single levels from 1991 to present, https://doi.org/10.24381/cds.713858f6, accessed on January 1 2025, 2020.

Siljamo, N. and Hyvärinen, O.: New Geostationary Satellite–Based Snow-Cover Algorithm, Journal of Applied Meteorology and Climatology, 50, 1275 – 1290, https://doi.org/10.1175/2010JAMC2568.1, 2011.

Siljamo, N., Hyvärinen, O., Riihelä, A., and Suomalainen, M.: MetOp/AVHRR Snow Detection Method for Meteorological Applications, Journal of Applied Meteorology and Climatology, 59, 2001 – 2019, https://doi.org/10.1175/JAMC-D-20-0032.1, 2020.

Solberg, R., Killie, M. A., Andreassen, L. M., and König, M.: CryoClim: A new system and service for climate monitoring of the cryosphere, IOP Conference Series: Earth and Environmental Science, 17, 012 008, https://doi.org/10.1088/1755-1315/17/1/012008, 2014.

Taillefer, F.: CANARI (Code for the Analysis Necessary for Arpege for its Rejects and its Initialization): Technical documentation, http://www.cnrm.meteo.fr/gmapdoc/spip.php?article3, 2002.

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/https://doi.org/10.1016/j.rse.2011.08.014, 2011.

https://doi.org/10.5194/egusphere-2026-1408
Preprint. Discussion started: 2 June 2026


Termonia, P., Fischer, C., Bazile, E., Bouyssel, F., Brožková, R., Bénard, P., Bochenek, B., Degrauwe, D., Derková, M., El Khatib, R., Hamdi, R., Mašek, J., Pottier, P., Pristov, N., Seity, Y., Smolíková, P., Španiel, O., Tudor, M., Wang, Y., Wittmann, C., and Joly, A.: The ALADIN System and its canonical model configurations AROME CY41T1 and ALARO CY40T1, Geoscientific Model Development, 11, 257–281, https://doi.org/10.5194/gmd-11-257-2018, 2018.

Undén, P., Rontu, L., Järvinen, H., Lynch, P., Sánchez, F. J. C., Cats, G., Cuxart, J., Eerola, K., Fortelius, C., García-Moya, J. A., Jones, C., Lenderink, G., McDonald, A., McGrath, R., Navascués, B., Woetman-Nielsen, N., Odegaard, V., Camino, E. R., Rummukainen, M., Room, R., Sattler, K., Sass, B. H., Savijärvi, H., Schreur, B. W., Sigg, R., and Tijm, A.: HIRLAM-5 Scientific documentation, 2002.

Wang, S., Yang, Y., and Che, Y.: Global Snow- and Ice-Related Disaster Risk: A Review, Natural Hazards Review, 23, 03122 002, https://doi.org/10.1061/(ASCE)NH.1527-6996.0000584, 2022.

Zhang, T.: Influence of the seasonal snow cover on the ground thermal regime: An overview, Reviews of Geophysics, 43, https://doi.org/https://doi.org/10.1029/2004RG000157, 2005.