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Remote sensing of mountain snow from space: status and recommendations

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The spatial and temporal variation of the seasonal snowpack in mountain regions is recognized as a clear knowledge gap for climate, ecology and water resources applications. Here, we identify three salient topics where recent developments in snow remote sensing and data assimilation can lead to significant progress: snow water equivalent, high resolution snow-covered area and long term snow cover observations including snow albedo. These topics can be addressed in the near future with institutional support.

KEYWORDS

snow, remote sensing, mountain, review, snow water equivalent, snow cover, snow hydrology, mountain ecology

Introduction

Every year, the seasonal snow covers up to 40% of the Earth's land surface, including 45% of the global mountain area (i.e. 21 millions km^2, Figure 1). As a result, the snow cover is a key driver of ecological, atmospheric, and hydrological processes in mountain environments. In addition, snowmelt from mountain regions represents an important contribution to river flow and groundwater recharge in many anthropized catchments, providing water resources to billions of humans (Mankin et al., 2015; Sturm et al., 2017; Qin et al., 2020). Consistent and reliable observations on the physical properties of the mountain snow cover are needed both for understanding mountain ecosystems but also in an operational context for water resources management and weather forecasting. Given the high spatial and temporal variability of seasonal snow in mountain regions, satellite observations have become an irreplaceable asset to monitor snow cover in complement to *in situ* observations and model simulations especially in data scarce regions (Fayad et al., 2017; Dong, 2018). In addition, long term observations of the seasonal snow cover are critically needed to evaluate the pace and the impact of climate change in mountain regions. Yet, the spatial and temporal variation of snow cover was listed as one of the clear knowledge gaps in the High Mountain Areas chapter of The Ocean and Cryosphere in a Changing Climate Special Report of the Intergovernmental Panel on Climate Change (2022). In NASA's Decadal Survey, "Quantify rates of snow accumulation,

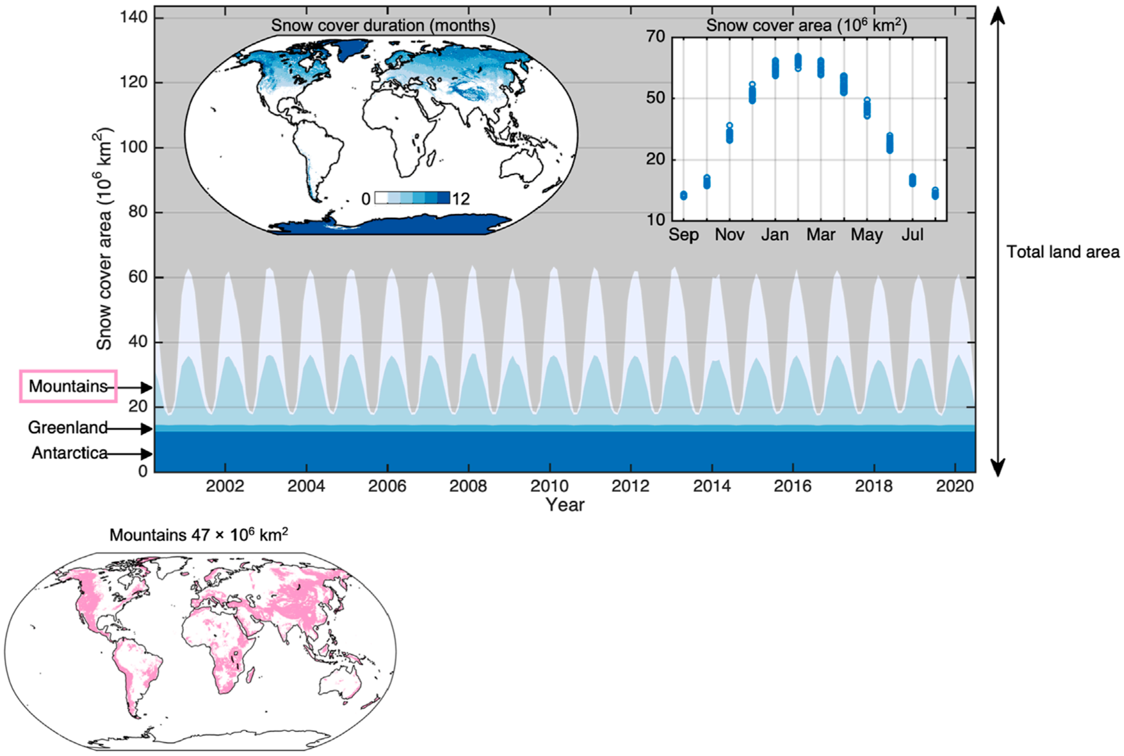

FIGURE 1
Spatial distribution of the snow cover duration and the evolution of the snow-covered area at global scale as observed from space over the past 2 decades. The snow cover area time series was computed in four land classes (Greenland, Antarctica, mountains regions and flat areas) to highlight the significance of the seasonal snow in mountain regions. The snow-covered area was obtained from MOD10C1 monthly products (Hall and Riggs, 2021) and post-processed to fill missing values using a linear interpolation in the time dimension. Mask of the mountain areas sourced from Viviroli et al. (2020). The snow cover area time series indicate that the interannual variability is low in comparison with the seasonal variability.

snowmelt, ice melt, and sublimation from snow and ice worldwide at scales driven by topographic variability" was prioritized as one of the most important objectives (National Academies of Sciences, Engineering, and Medicine, 2018). Snow-related variables in the Decadal Survey are "snow depth and snow water equivalent, including high spatial resolution in mountain areas," and "snow reflectivity" is also mentioned among the "surface biology and geology" observables.

Acknowledging the importance of monitoring the snow cover evolution across our planet, the Global Climate Observing System (GCOS) stated the snow-covered area, snow water equivalent and snow depth as essential climate variables (ECVs) for monitoring through satellite remote sensing, in alignment with Committee on Earth Observation Satellites (CEOS) agencies. Space agencies currently distribute a variety of datasets on the snow cover derived from remote sensing observations. CEOS maintains a list of operational snow products accompanied with their spatial and temporal coverage, spatial and temporal resolution and a link to validation information (CEOS, 2023). Some of them are already widely used for scientific studies and operational water resource management (Awasthi and Varade, 2021). Operational products currently belong mostly either to the category of optical remote sensing of the snow cover extent or to snow water equivalent products generated by assimilating *in situ* snow measurements with passive microwave satellite. Snow-covered area products can be either binary (snow cover absence or presence), or fractional (provides the fraction of a pixel which is covered by snow). Binary snow cover and fractional snow cover products are the only snow products to have reached validation stage 2 (CEOS, 2023). In particular, the collection of MODIS/VIIRS snow products distributed by the NASA since the early 2000's (Hall et al., 2002) offers the best tradeoff in terms of coverage (global), revisit (daily), resolution (500 m) and accessibility (open data policy) for mountain snow studies.

Other available operational products include snow-covered area from low resolution optical and microwave sensors aboard geostationary and polar-orbiting meteorological satellites (GOES, MSG, MetOp), wet/dry snow derived from passive microwave sensors (AMSR-E, SSM/I), snow albedo and grain size from MODIS, and high resolution snow-covered area from Landsat 8/9 and/or Sentinel-2 over specific regions (United States, Europe). However, as detailed below, this portfolio of products remains insufficient in the specific context of the mountain regions for three main reasons: 1) lack of snow water equivalent observations, 2) lack of systematic and regular high resolution observations and 3) lack of long term observations.

1. Operational satellite remote sensing approaches to retrieve the snow water equivalent (SWE) in mountain terrain at high spatial resolution are still lacking (Dozier et al., 2016;

Tsang et al., 2022). This constitutes a key shortcoming as an accurate knowledge of SWE spatial distribution is essential to predict streamflow in snow dominated mountain catchments (Freudiger et al., 2017). A possible approach to reconstruct high resolution SWE over large mountain regions relies on the assimilation of snow-covered area products in a snowpack model (Girotto et al., 2020; Liu et al., 2021). This approach enables to generate accurate snow reanalyses once the snow season is over, but is less suitable to retrieve SWE distribution in near real time. Direct methods based on active microwave remote sensing are being developed since the 2000's but more research is still needed to reach the user needs (Guneriussen et al., 2001; Tsang et al., 2022). Acknowledging the lack of an operational concept or sensor to measure the spatial distribution of SWE from space, NASA developed the airborne snow observatory using lidar to fulfill the need to estimate water resources in the western United States (Painter et al., 2016). Yet, lidar does not measure snow water equivalent but snow depth, so it can only fulfill this need in conjunction with modeled snow density.

2. Near-daily observations of the snow-covered area are available but their spatial resolution can be too coarse for a range of studies in mountain hydrology and ecology, or even operational needs (Malnes et al., 2015). This is because the snow cover variability has a typical length scale on the order of 100 m in mountain regions (Blöschl, 1999). In particular, the widely-used MODIS snow products have a resolution of approximately 500 m which can fail to capture the spatial heterogeneity of snow cover induced by solar radiation in steep terrain (Bouamri et al., 2021). A high spatial resolution (~10 m) is also useful for ecologists to characterize habitats of mountain plants and animals (Dedieu et al., 2016; Alba et al., 2023; Niffenegger et al., 2023). Whereas a remotely sensed SWE is the holy grail of snow hydrology, ecologists have shown that the snow cover duration or melt out date are important predictors of alpine plants productivity, distribution and diversity (Galen and Stanton, 1995; Jonas et al., 2008; Carlson et al., 2015; Choler, 2015; Revuelto et al., 2022). These indicators can be easily derived from existing remote sensing technology, but the challenge is to get the information at high spatial and temporal resolutions to capture the snow cover phenology at the relevant scales and with sufficient precision.
3. Long term snow cover observations are necessary to characterize the impact of climate change on land-atmosphere feedbacks, water resources and ecosystems especially in mountain regions where the warming trend often exceeds the global average (Pepin et al., 2022). Existing long term (>30 years) remote sensing datasets are an invaluable source to study global or regional snow cover changes in the context of climate change (Hüsler et al., 2014) but may be inadequate in some cases due to their coarse resolution (Bormann et al., 2018). The MODIS dataset is increasingly used to determine trends in snow cover extent and duration (Saavedra et al., 2018; Notarnicola, 2020; Shi et al., 2022). Yet, its relatively short duration (23 years) makes it difficult to separate a long term trend from natural climate variability (Bormann et al., 2018; Fugazza et al., 2021). This is because snow cover changes not only reflect temperature changes but also precipitation variations which may be subject to multidecadal climatic oscillations (Monteiro and Morin, 2023; Gottlieb and Mankin, 2024).

The snow remote sensing community is actively working to adapt existing algorithms to new spaceborne sensors or to develop algorithms to retrieve new variables from space. A broad review of the remote sensing techniques for estimating the snow geophysical properties in mountain regions is already available (Awasthi and Varade, 2021), updating a previous review on a similar scope (Nolin, 2010). More specifically, a review of fundamental advances towards the global monitoring of SWE using high-frequency radar remote sensing has been published recently (Tsang et al., 2022). Complementary reviews of snow cover remote sensing methods using spaceborne synthetic aperture radar (SAR) (Tsai et al., 2019) or optical sensors (Dumont and Gascoin, 2016) are also available. New sensing concepts are supported by space agencies and may lead to solve the above issues in the long term (after 2030). A mission dedicated to snow depth and snow water equivalent, including high spatial resolution in mountain areas was listed as a priority for a new program element in the 2017 Decadal Survey and the Canadian Space Agency is developing the Terrestrial Snow Mass Mission for the same objective (Derksen et al., 2019; L. Wang et al., 2022). Here, we focus on recent advances that have the potential to specifically address the above three issues in the short term. First, we argue that progress can be made by applying existing algorithms to recent Earth Observation missions. Second, we highlight recent methodological progresses which have the potential to go beyond the current status. Then, we summarize current challenges to be addressed to go beyond the current status. We conclude by outlining a series of recommendations targeted at international organizations and space agencies. These recommendations are based on the consultation of a multi-national community of experts at the Mountain Snow Workshop held by the World Meteorological Organization and EUMETSAT in Darmstadt, Germany in 2023.

Recent advances

Application of existing algorithms to recent missions

The Copernicus Earth Observation programme offers the opportunity to monitor the snow cover at high resolution and global scale. Sentinel-1 and Sentinel-2 observations now span nearly a decade. The datasets are freely distributed and tools are available to process them. Following a method developed for ERS-1 data (Rott and Nagler, 1995; Nagler and Rott, 2000), wet snow can be detected from Sentinel-1 C-band backscatter (Nagler et al., 2016; Tsai et al., 2019). Similarly, early algorithms to map the snow-covered area developed for Landsat TM (Dozier, 1989) have been extended to Sentinel-2 multispectral imagery (Wayand et al., 2018; Gascoin et al., 2019). Both methods benefit from the enhanced spatial resolution and revisit times of Sentinel-1 and Sentinel-2 with respect to previous missions, allowing the development of a new generation of snow products at European scale (European Environment Agency, 2021). The combination of

Sentinel-1 wet snow-covered area and Sentinel-2 snow-covered area would increase the number of observations to estimate the area and duration of the snow cover at decametric resolution (Karbou et al., 2021).

Similarly, spectral unmixing methods developed for MODIS are being adapted to Landsat 8/9 and Sentinel-2 (Aalstad et al., 2020; Bair et al., 2020; Stillinger et al., 2023). Keuris et al. (2023) proposed a method for estimation fractional snow extent exploiting the full spectral capabilities of moderns satellite sensors such as Sentinel-2, Landsat-7/8/9 and Sentinel-3 SLSTR and OLCI, applying multispectral unmixing with local adaptive endmember selection and accounting for the high variable solar illumination in mountainous areas. These approaches take advantage of all available spectral information to retrieve fractional snow cover and other properties such as snow albedo, grain size or the presence of light absorbing particles (Nolin et al., 1993; Painter et al., 2009).

Recent methods applied to past and recent missions

In recent years, several methods were applied to retrieve snow depth from space. A mountain snow depth map obtained from satellite data only was generated by differencing digital elevation models from Pléiades stereoscopic imagery (Marti et al., 2016). The estimated random error was 0.6 m at a spatial resolution of 2 m. This method was refined and further evaluated against airborne lidar measurements showing that the accuracy of this method increases down to 0.3 m at 100 m resolution (Deschamps-Berger et al., 2020). It is limited by the swath width of Pléaides (or WorldView), which typically allows imaging a region of 400–1,000 km^2 in a single pass depending on the acquisition geometry, but it is a viable alternative to airborne campaigns (Eberhard et al., 2021). A conceptual method was proposed to retrieve mountain snow depth at northern hemisphere scale from Sentinel-1 polarimetric backscatter observations with a change detection technique (Lievens et al., 2019). Using a single global calibration factor this method yielded a mean absolute error of ~ 0.3 m at 1 km resolution, where regional calibration enabled improved performance (Lievens et al., 2022). With the 6–12 days revisit of Sentinel-1, this approach could provide useful frequent snow depth data. It is not applicable during the melt season when the radar signal is absorbed by the liquid water contained in the snowpack, and retrieval performance is reduced in regions with shallow or intermittent snow, and with dense vegetation. More recently, ICESat-2 land surface elevation retrievals were successfully used to retrieve snow depth in the Sierra Nevada (Deschamps-Berger et al., 2023). The method is not yet applicable at global scale as it requires an accurate snow-off digital terrain model. This is because ICESat-2 orbit is not repeated outside polar regions. Such reference elevation model could be obtained from VHR stereo imagery in areas where lidar surveys are not available. Last, machine/deep learning algorithms have also been successfully trained to infer snow depth in the Alps, either from AMSR-E at 10 km resolution (Santi et al., 2014) or from Sentinel-1/2 at 10 m resolution (Daudt et al., 2023). These methods rely on *in situ* or airborne data for model training, which prevents their application to other regions.

Machine learning algorithms are also increasingly used to detect the snow cover in high resolution satellite images, especially those devoid of shortwave infrared bands. This includes very high resolution imagery from commercial satellites operated by Maxar (Hu and Shean, 2022), Planet (Yang et al., 2023) or Venµs (Baba et al., 2020). These sensors offer the opportunity to map the snow cover at metric resolution, even in steep alpine terrain. Convolutional neural networks are efficient to perform the snow and cloud object segmentation as they account for the pixel neighborhood in addition to the pixel-wise spectral information (Lu et al., 2022). This approach is especially useful to extract the snow-covered area from historical satellite images with poor radiometric resolution and in the absence of a shortwave infrared band such as SPOT 1-4 and Landsat 1-4 (Barrou Dumont et al., 2023).

Methods to retrieve snow depth and snow-covered area can be used in combination with empirical snow density models to estimate catchment scale SWE. Error on snow density are rather low if the snow depth is known (Avanzi and De Michele, 2015). Jonas et al. (2009) reported an error of ±45 kg.m-3 (±1 standard deviation) on snow density using *in situ* snow depth data as predictor. In addition, land surface temperature monitoring open new research avenues on this topic. Indeed, the snow density could be estimated from Landsat with an RMSE of 82 kg m^{-3} (Colombo et al., 2023). A machine-learning approach enabled to estimate snow density from multiple MODIS and reanalyses datasets with an RMSE of 43 kg m^{-3} (H. Wang et al., 2023). However, as we argue below, a more optimal method to convert snow depth to SWE is through the assimilation in a snowpack model.

The above satellite methods provide incomplete information due to orbital constraints, sensor geometry, cloud cover and applicability domain of the retrieval algorithm. Indeed, most approaches do not work well in all snow climate and/or environmental conditions (e.g., deep vs. shallow snowpack). Microwave approaches are generally more uncertain in case of wet snow or dense forest cover. Data assimilation enables to merge different types of satellite observations accounting for the retrieval uncertainty to generate physically consistent, *spatially and temporally* continuous datasets of the snow cover properties, including SWE, snow depth, etc. (Girotto et al., 2020; Largeron et al., 2020). Previous studies have shown the value of data assimilation for water resources studies (Margulis et al., 2015), operational near real time applications (Cluzet et al., 2021), climate reanalysis (Hersbach et al., 2020), numerical weather prediction (de Rosnay et al., 2015, 2022), and seasonal prediction (Orsolini et al., 2019). The recent release of the Multiple Snow data Assimilation System (MuSA) (Alonso-González et al., 2022b) should facilitate the development of data assimilation experiments and the generation of snow datasets in mountain regions taking advantage of various remote sensing products. Data assimilation studies would also benefit from radiative transfer models like the Snow Microwave Radiative Transfer model (SMRT), which enables to compute backscattering and brightness temperature in active and passive mode from multilayered snowpack (Picard et al., 2018). SMRT enables to test the assimilation of low level satellite measurements (e.g., radiance) as it is typically done in numerical weather prediction.

Challenges

As briefly discussed above, the availability of petabytes of satellite data enables the observation of multiple snow variables with ever-increasing temporal and spatial precision at the scale of entire mountain ranges (Lievens et al., 2019; Liu et al., 2021). However, to fully harness the wealth of satellites, there remain challenges in accessing, processing and interpreting results from large datasets. This is especially the case with the Sentinel-1, Sentinel-2 and Landsat datasets, but it will be the case with upcoming missions like NISAR. Snow scientists increasingly rely on commercial cloud geoprocessing platforms such as Google Earth Engine and Microsoft Planetary Computer to process remote sensing datasets (Crumley et al., 2020; Notarnicola, 2020; Gascoin et al., 2022; Gagliano et al., 2023). High performance and cloud computing is also becoming critical to perform intensive computations for machine and deep learning and ensemble-based data assimilation.

In addition to the computing resources issue, the scarcity of snow-specific data assimilation software has hindered the adoption of data assimilation in snow science. Data assimilation algorithms can be complex and sometimes require advanced knowledge in applied mathematics. Several well-documented open source snow models with different levels of complexity are now available, but, in contrast, there is only one open source snow model including data assimilation tools to our best knowledge (Alonso-González et al., 2022a). The open-source NASA Land Information System software also embeds land surface models including snow modules and data assimilation code (Kumar et al., 2006). Another key challenge that should be addressed to facilitate data assimilation is the quantification of remote sensing data accuracy in various conditions, because a good knowledge of the observation error is needed to balance the weight of the observations in the model analysis.

From the numerical weather prediction and climate reanalysis perspectives, the main challenges are (i) the availability and sustainability of relevant operational satellites sensitive to snow properties, (ii) the complexity of the radiative transfer processes that link snow properties to the signal that the satellite measures. Radiative transfer models are required to optimally use satellite observations to analyze snow.

Despite several decades of research in optical remote sensing of the snow cover, there remain some challenges. Cloud cover hinders our capacity to observe basic variables such as snow cover. This issue is particularly pronounced in key regions like the Eastern Himalaya and the Pacific Northwest of North America. Moreover, the confusion between clouds and snow cover in optical images classification is an issue that is often underestimated (Stillinger et al., 2019). Evaluation studies have typically focused on clear-sky images whereas cloud cover can mask over 50% of observations in temperate mountain ranges (Rittger et al., 2013; Masson et al., 2018). The issue of snow-cloud discrimination is also largely unaddressed in studies using commercial very high resolution imagery, which prevents their more systematic use on a large scale. Even a very accurate snow detection algorithm is of limited utility if the associated cloud and cloud shadow detection algorithm is too conservative and masks most of the snow pixels. Another important challenge is that optical methods are very uncertain in forested areas (Xin et al., 2012; Muhuri et al., 2021). This is also true for microwave methods. As a result, our ability to characterize the snow-covered area, snow depth or snow albedo from remote sensing is very limited in forested area.

Although this is a long standing issue in remote sensing, there often remains a scale gap between remote sensing retrievals, *in situ* measurements and model outputs (Blöschl, 1999). This can lead to systematic differences between these quantities. For example, the intrinsic snow albedo that can be measured *in situ* or simulated by snowpack models differs from the apparent (or effective) albedo retrieved from space due to snow surface microtopography (Bair et al., 2022). The scale mismatch with *in situ* measurements similarly impedes the evaluation of many remote sensing products like snow depth and SWE.

Recommendations

After the workshop, the experts agreed on a list of recommendations to go beyond the current status in mountain snow remote sensing. This document is provided in Supplementary Appendix. We highlight and develop here the key points to address the three key issues that were highlighted in the introduction (#1. lack of representative snow water equivalent observations, #2. lack of systematic and regular high resolution observations and #3. lack of long term observations).

First, we consider that a range of satellite snow products and methods are already available to go beyond the *status quo* in the short term. Global scale, high resolution (10–30 m) monitoring of the snow-covered area can be achieved using Sentinel-2 and Landsat-8/9 observations with a revisit lower than 5 days (cloud permitting). Although snow and cloud flags are already included in standard level 2 Sentinel-2 and Landsat products distributed by ESA and USGS, they can be improved using existing algorithms tailored to snow cover mapping. Open source software is available to generate fractional snow cover maps at continental scale from Sentinel-2 and is already operated in Europe (European Environment Agency, 2020). In addition, Sentinel-1 data are now used by the same agency to increase the effective observation frequency of the snow-covered area when the snowpack contains liquid water. Similarly, the USGS distributes Landsat fractional snow cover products over the United States. Such datasets if available globally would enable to address key issue #2, enabling many applications in mountain ecology.

Secondly, while there is currently no operational method to retrieve mountain SWE from space, we argue that the SWE question (key issue #1) can be tackled by the assimilation of multiple remote sensing observations in a distributed snowpack model. Recent advances in snow depth remote sensing with Sentinel-1, ICESat-2 are promising as the snow depth is the main driver of SWE variability. More systematic repeat-track ICESat-2 campaigns over non-polar, snow-covered mountain regions would enable to retrieve snow depth from ICESat-2 data only (Besso et al., 2024). This would be especially useful to better estimate snow depth in forested areas thanks to the unique ability of ICESat-2 to measure surface elevation below the forest canopy, where other optical and microwave sensors provide limited information. In the meantime, merging satellite snow depth from Sentinel-1 and snow-covered area from Sentinel-2 should be tested. While Sentinel-1 snow depth algorithm is not applicable during the melt season, Sentinel-2 provides frequent observations of the snow-covered area during spring and summer, an additional constraint to estimate SWE (Figure 2). Further research is required to take full advantage of those observations. In particular it is essential to characterize their uncertainty, as it is a key input for data assimilation. To go forward in this topic, we need accurate benchmarking datasets in pilot sites. An outstanding example is the Tuolumne river basin in California Sierra Nevada, where snow depth is frequently monitored by airborne lidar since 2012, including very dry and very wet years. Several instrumented sites are available in other mountain ranges. A recent compilation of research catchments is available from the International Network for Alpine Research Catchment Hydrology (INARCH) website (Pomeroy et al., 2015). However, each site includes different types of observations with varying spatio-temporal resolutions, etc. Assimilating these observations into processed-based snow models would allow assembling benchmarking datasets that are physically consistent and complete in space and time. The development of such benchmarking datasets would help maximize the usage of *in situ* observations for the evaluation of remote sensing products. Regarding the assimilation method itself, previous studies recommend the use of ensemble approaches (in contrast with variational approaches) because they make it possible to use off-the-shelf nonlinear snowpack models, without the need to implement an adjoint model (Helmert et al., 2018; Largeron et al., 2020; Alonso-González et al., 2022b). We note however that this status may change soon in the future with the adoption of automatic differentiation tools in the Earth science modeling community.

Third, data assimilation is also a way to address the lack of long term observations (key issue #3), as it allows merging multiple discontinuous satellite time series and different variables of interest. In this case, the batch smoothing approach is well suited (in contrast with a filtering algorithm) since it assimilates simultaneously all available observations over a time window so that late snow season observations are used to update the early snow season parameters distribution and reciprocally (Durand et al., 2008). Again, this requires a good knowledge of the data uncertainties especially if the objective is to study trends due to climate change. A detailed intercomparison of global to northern hemispheric daily snow extent products is being carried out in the Satellite Snow Product Intercomparison and Evaluation Exercise (SnowPEx and SnowPEx+). A national program led by China National Satellite Meteorological Center called RetrospectIve Calibration of Historical Chinese Earth Observation Satellite data (RICH-CEOS) aims to cross-calibrate historical datasets from multiple satellites operated by China. The multispectral data provided by HJ-1A and HJ-1B missions should be of particular interest for the snow community due to their high spatial resolution (30–150 m) and 4 days revisit period. To facilitate the fusion of multiple remote sensing datasets, we encourage data providers to adopt standardized data and meta-data formats and we recommend to provide uncertainty estimates on a pixel-by-pixel basis. Machine-learning products should also include their uncertainty and domain of applicability.

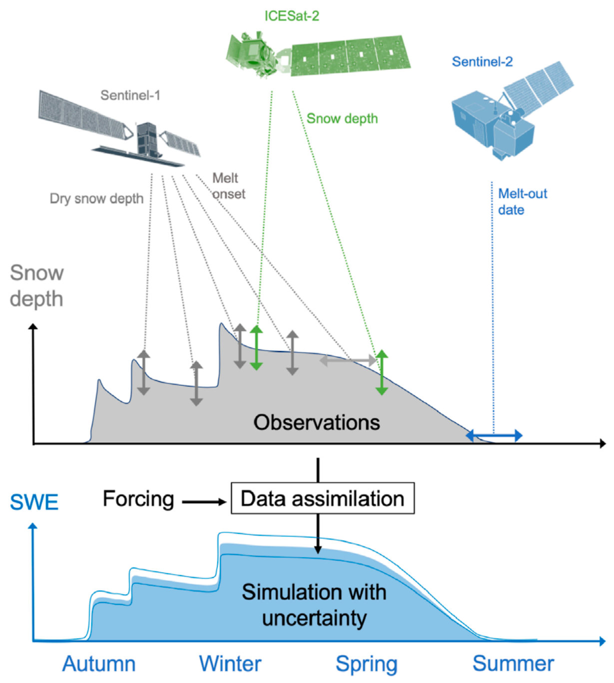

FIGURE 2
Schematic representation of how various remote sensing data can be used to estimate the snow water equivalent in mountain regions by data assimilation in a snowpack model. Remote sensing observations and model forcing come with errors (top diagram) that are reflected in the posterior model uncertainties (bottom diagram). The blue lines in the bottom diagram represent the bounds of uncertainty of the simulated SWE.

Finally, we expect that upcoming Earth observation missions will create new opportunities to improve our knowledge of the mountain snow. L-band SAR missions (ROSE-L, NISAR, ALOS-4) should open the door to InSAR retrieval of the SWE changes in complex terrain (Tarricone et al., 2023). Thermal infrared missions (TRISHNA, LSTM, SBG) will allow the assimilation of near daily surface temperature to improve SWE simulations (Alonso-González et al., 2023). These missions will also allow the retrieval of snow albedo at finer resolution than the current products from Sentinel-3 or VIIRS thanks to their multispectral and multiangle imaging capabilities. To foster the development of new algorithms and prepare future missions, we recommend a better coordination of on-demand satellite data acquisitions (e.g., very high resolution SAR and optical stereoscopic images) over pilot mountain sites by space agencies and commercial providers following the example of NASA SnowEx campaigns.

Author contributions

SG: Visualization, Writing–original draft. KL: Conceptualization, Writing–review and editing. TN: Writing–review and editing. HL: Writing–review and editing. MM: Writing–review and editing. TJ:

Writing–review and editing. ZZ: Writing–review and editing. PD: Writing–review and editing.

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Conflict of interest

Authors KL and HL were employed by Snowcap BV, a start-up based on scientific research at KU Leuven. Author TN was employed by ENVEO Environmental Earth Observation IT GmbH.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feart.2024.1381323/full#supplementary-material

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