https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.

Review article: using machine learning for snow remote sensing: trends and future directions for global snow measurements

Catherine Breen[1,2], Kehan Yang[1,2], Justin Pflug[1,3], Sujay Kumar[1], Nicoleta Cristea[4], Ibrahim Alabi[5], Carrie Vuyovich[1]

[1]NASA Goddard Space Flight Center, Greenbelt, MD, USA
[2]Science Systems Applications, Inc., Greenbelt, MD, USA
[3]University of Maryland, ESSIC, College Park, MD, USA
[4]University of Washington, Civil and Environmental Engineering, Seattle, WA, USA
[5]Department of Geosciences, Boise State University, Boise, ID, USA

Correspondence to: Catherine M. Breen (catherine.m.breen@nasa.gov)

Abstract. Snow covers 40% of Earth's northern hemisphere each year, playing an important role in regulating Earth's energy balance through its reflective properties and serving as the primary source of freshwater for one-sixth of the world's population. Remote sensing is a key technology for observing snow across large areas. Given the complexity of retrieving the snow signal from space, the snow community is increasingly using machine learning (ML) and deep learning (DL) approaches to derive and improve current spaceborne snow measurements. Here we summarize the research trends and applications of ML for snow retrievals, identifying best practices and the future direction of ML applications for multiple seasonal snow-related properties, in particular snow water equivalent (a measurement of the amount of water contained in the snow), snow depth, density, cover, and wet/dry conditions. Across our review, we find that most studies focus on extrapolating to new areas and time periods, with improved prediction after combining multiple sensors and referencing high-fidelity reference data. Gaps remain in generalizing across spatial domains, combining sensors at different spatial and temporal resolutions, and improving the ability of newer model architectures, such as transformers and foundation models, to support snow-related applications. ML/DL for snow remote sensing is an effective tool for integrating information across sensors, and we recommend the snow community continue to identify further use, thereby advancing towards more consistent and complete global snow monitoring that includes a range of snow types and climate conditions.

1 Introduction

Snow covers 40% of Earth's northern hemisphere and plays an important role in Earth's climate regulation through snow-albedo feedbacks and the global water cycle through seasonal water storage (Brown & Mote, 2009; Y. Hu et al., 2021). In addition, snow provides habitat for snow-adapted animals, water for more than one sixth of the world's population (Sturm et al., 2017), and water resources for agriculture, hydropower generation, and industry (Mankin et al., 2015). Snow is spatially and temporally variable at fine spatial scales (< 1 m and < daily; Miller et al., 2022), and while ground observations are the traditional, and oftentimes the most accurate method for measuring fine-scale snow properties, satellite-derived observations are critical to observe snow in remote regions throughout the winter season and to obtain basin-wide measurements for water resource applications.

Satellite-derived observations, namely from optical, microwave, and lidar platforms, have improved our ability to monitor snow properties (Frei et al., 2012; Liu et al., 2013). Optical satellites are often used for snow cover, by exploiting the difference between snow's reflectivity in the visible light (green band) and absorption in the shortwave-infrared (SWIR) band, in a relationship known

https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.

as the normalized difference snow index (NDSI) (Dozier, 1989), or more recently, by relying on blue bands (Thaler et al., 2023; K. Yang et al., 2023). Passive microwave (PM) has demonstrated sensitivity to snow mass as either depth or snow water equivalent (SWE) by using the brightness temperature difference between high-frequency channels (e.g., 37 GHz) that are sensitive to snowpack volume scattering and low-frequency channels (e.g., 19 GHz or 10 GHz) that primarily capture underlying soil emissions (Chang et al., 1987; Kunzi et al., 1982). Active radar (also referred to as active microwave) has indicated the potential ability to capture SWE and snow depth interferometric approaches (Tarricone et al., 2026) or a volume scattering approach (Tsang et al., 2022). Active radar transmits microwave pulses, resulting in high-resolution (~10s to 100s of meters depending on the sensor) retrievals. Spaceborne lidar observes snow depth by differencing snow-on and snow-off observations, a technique known as "differential altimetry" (Fair et al., 2025). Spaceborne platforms also provide full global coverage, an additional advantage for snow remote sensing.

However, optical, microwave, and lidar possess limitations for snow. Optical sensors do not penetrate through clouds and trees or observe at night (Dumont & Gascoin, 2016; Hall et al., 2019), and they do not provide information about the snow mass. Microwave offers advantages to optical because the microwave signals can penetrate through clouds and are not sensitive to nighttime conditions, but microwave retrievals are limited to dry snow and open, minimally forested areas (Dunmire et al., 2024). Furthermore, the coarse resolution of passive microwave (~ 25 km) limits applicability. Spaceborne lidar offers fine-scale snow depth observations (~40 m to 100 m) but is very limited in terms of spatial and temporal coverage from space (Fair et al., 2025). Lidar can observe at nighttime, but accuracy is sensitive to terrain, vegetation, and clouds, with previous studies identifying error greater than 40 cm unless ideal conditions (e.g., slope < 20 degrees; Deschamps-Berger et al., 2023; Fair et al., 2025). Furthermore, sensors present trade-offs in spatial and temporal resolution. Higher-resolution optical satellites (e.g., Landsat at 30-m and Sentinel 10-m) have repeat periods ranging between 5 to 16 days, and this gap can increase if the observable day is obstructed by clouds. Moderate-resolution optical satellites, such as VIIRS and MODIS, provide global coverage daily, but at the cost of resolution (Mahoney et al., 2018). Sentinel-1 C-band and the newly available NISAR L-band both offer 12-day repeats, but this temporal gap can still introduce uncertainty when using satellite observations to identify the snow peak (Tarricone et al., 2023). Thus, the varying structural properties of snow and need for observations in varying terrain reinforce that currently no single sensor captures all characteristics or can observe snow in all conditions, terrain, and spatial scales.

Current sensors are sensitive to snowpack properties, but given the lack of unique missions to observe snow mass (e.g., SWE) at high spatial resolution, the snow community has increasingly tested machine learning (ML) and deep learning (DL) approaches to facilitate using sensors for snowpack characterization (Palermo et al., 2023), gap-filling (e.g., Yatheendradas & Kumar, 2022), and downscaling (e.g., Mahanthege et al., 2024; Rittger et al., 2021). Machine learning approaches here encompass the broad array of models that learn relationships from data (Zhu et al., 2017). Machine learning, or ML, includes classical ML models that allow for nonlinear relationships among input variables, such as random forest, support vector machines, and gradient boosting (Hastie et al., 2017). Deep learning, or DL, includes the class of models with more hidden layers ("deeper" layers) with various neural network architectures, such as convolutional neural networks, U-Nets, transformers, and long short-term memory networks, among others. These larger models offer advantages for satellite image processing due to the ability to handle large amounts of data and to process information across multiple pixels simultaneously (Taylor et al., 2021). However, these advantages coincide with the major limitation that sufficient training and validation data must exist.

Advances in snow property retrievals from remotely sensed observations have been made through both classical machine learning and deep learning techniques; however, a consensus regarding the utility of ML/DL in snow remote sensing techniques remains to

https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.

be established. Past snow remote sensing reviews have focused on specific snowpack properties (e.g., for SWE, see Saberi et al., 2020; Schilling et al., 2024) or sensors (e.g., see L-band for SWE review as in Tarricone et al. 2023 and spaceborne lidar for snow depth review as in Fair et al. 2025) and do not focus on ML/DL approaches. Studies have also documented issues related to generalizability and uncertainty, suggesting a need to analyze multiple use cases to determine overall utility (Gascoin et al., 2024). ML/DL for earth science literature reviews exist, but they are not specific to snow (Krejcar & Namazi, 2026; Reichstein et al., 2019a; Zhu et al., 2017). Thus, the field lacks synthesis of the current models used, properties analyzed, and best practices related to data splits and error metrics. In this review, we summarize the recent literature on ML/DL approaches for remote sensing of snowpack properties, identifying trends and lessons learned to achieve strong accuracy and generalization. We first describe our methods to identify the current literature related to ML/DL for snow remote sensing, then proceed to discuss the common snowpack properties predicted, best practices, current challenges, and future directions. We intend for this work to guide researchers on utilizing ML/DL in their own work, while also directing the snow hydrology and computer science community on open areas of research to improve snow remote sensing globally.

2 Methods

We focus on all ML/DL use cases of spaceborne sensors (i.e., optical, passive microwave, active radar, and spaceborne lidar) for any seasonal snowpack property pertinent to terrestrial water from the recent literature (>1990). Relevant snowpack properties include snow depth, snow water equivalent (SWE), snow cover, and the dynamics related, such as snow melt timing, snow cover onset and disappearance, and liquid water presence in the snowpack. We acknowledge that this ignores snow properties related to sea ice, glaciers, and albedo. Due to the broad field of machine learning, we define machine learning here as a data-driven approach whereby the model learns a non-linear pattern from previously seen data (Mjolsness & DeCoste, 2001). This definition includes both classical machine learning (e.g., k-means clustering, random forests, and support vector machines), as well as more recently developed deep learning frameworks, such as all classes of neural networks (e.g., convolutional neural networks, long short-term memory networks, and transformers) for both supervised and unsupervised learning. We provide a table with a simple description of each method mentioned in this review, with citations to accompany in-depth descriptions for the interested reader (Table S1). We focus on spaceborne sensors given the global spatial coverage for snow and data accessibility compared to airborne and ground measurements.

Our review is based on a comprehensive literature search from Web of Science. We use the search terms (“machine learning” or “deep learning”), and (“snow density” or “snow depth” or “snow water equivalent” or “snow melt” or “snow cover” or “snow timing”), and (“remote sensing” or “InSAR” or “L-band” or “SAR” or “ICESat-2” or “passive microwave” or “optical”) and scanned for titles and abstracts from peer-reviewed journals that utilized machine learning and deep learning for snow remote sensing applications for each year since 1990. With papers that fit our scope, we subsequently added a snowball approach, whereby we reviewed sources cited for additional relevant literature that may not have been captured by our keyword searches. From the initial pool of 320 papers, we collected 107 papers. Papers discounted included papers where no spaceborne sensor was used, no form of machine learning used, no snow property analyzed, or some combination of those factors. The complete table of papers for this review is included as a spreadsheet in the code and data repository.

3 Overall trends in machine learning for snow remote sensing

https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.

The final collected papers (n = 107 papers) indicate that machine learning has seen a substantial rise in the field of snow remote sensing. Returns from our search suggest that ML applications for snow have doubled every 4-5 years since 2005, with a dramatic acceleration from 2021 to 2025 (68 papers) compared to pre-2020 (33 papers total spanning 20+ years; Figure 1). Random forests make up many of the frameworks (31%; Figure 2A) with simple feed-forward neural networks (e.g., ANNs) and convolutional neural networks (CNNs) comprising most of the remainder (17% and 14%, respectively). The applications of ML for snow properties roughly track what raw retrievals may be capable of seeing (Figure 2B). In other words, snow cover is the most studied application for ML for remote sensing (40% of papers), with snow depth and snow water equivalent as the second and third most (30% and 18% of papers, respectively; Figure 2B). Other properties include snow discrimination from clouds, wet snow, snow density, and snow clustering patterns (~10%).

Regarding trends in model architectures, earlier papers (published more than 10 years ago; before 2015) used simple feed-forward neural network models (e.g., ANNs) for supervised approaches of deriving SWE from passive microwave sensors (Dariane et al., 2014; Santi et al., 2022; Tabari et al., 2010; Tedesco & Narvekar, 2010), and more recent research (after 2015) broadened to other snow properties and sensors (Broxton et al., 2015; Nijhawan et al., 2019). Between 2015 and 2019, ensemble and kernel-based methods, namely, random forest models and support vector machines, as well as methods with learnable filters, such as simple convolutional neural networks (CNNs), began to appear in the literature, citing improved robustness to overfitting compared to the prior machine learning techniques and the ability to process high-dimensional image data (Bair et al., 2018; Varshney et al., 2018). Starting around 2020, coinciding with the publication and science adoption of software packages like TensorFlow (2015) and PyTorch (2017), the community saw adoption of neural network architectures (Brodylo et al., 2025; Cannistra et al., 2021; Elyoussfi et al., 2025; Guo et al., 2020; Kosmala et al., 2018). Random forests continued to dominate, and around 2020, papers focused on training and validating in larger, regional-sized domains (>400 km; Daudt et al., 2023) as well as globally. GPU-trained models also became more popular, with researchers usually training models on computer clusters available through Amazon, Microsoft, Google's Google Earth Engine, and university high-performance computer centers (Amani et al., 2022). Spatial transfer across different snow types remained a theme across much of the literature examined (Bair et al., 2018; Pflug et al., 2025; Santi et al., 2022; Tabari et al., 2010).

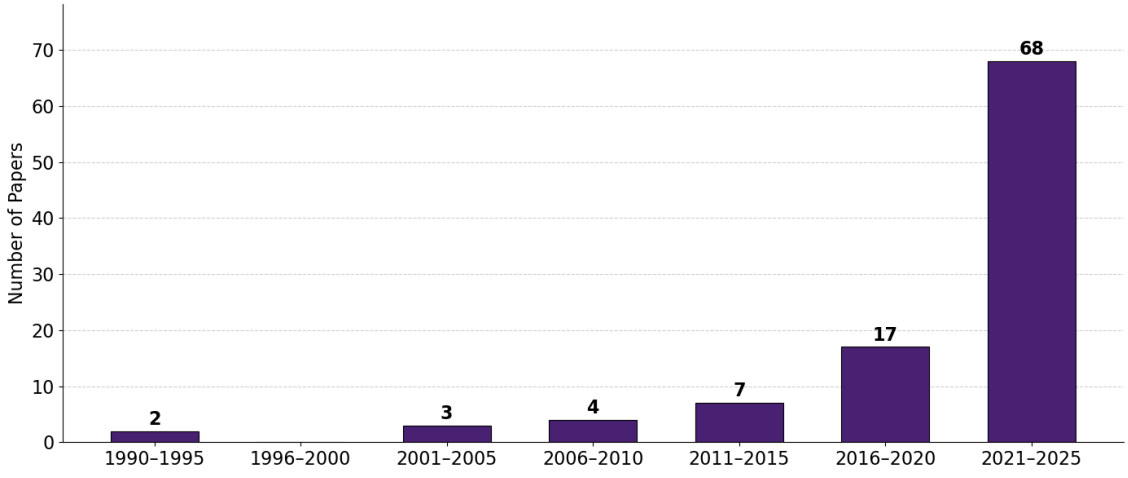


Figure 1: Publications on ML/DL for snow remote sensing from a comprehensive literature search starting in 1990. Results are separated into 5-year bins.

https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.

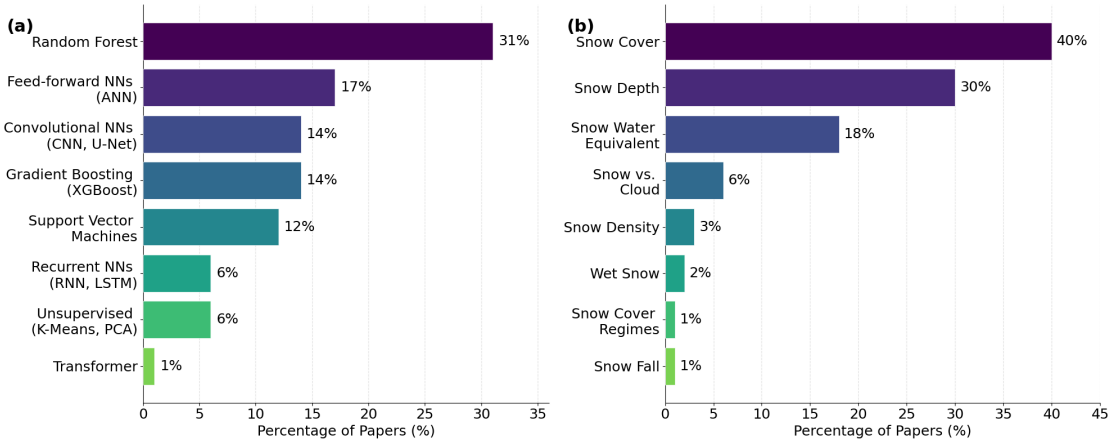


Figure 2: Summary of (a) model architectures used and (b) snow properties analyzed using machine learning. The specific papers used for constructing these tables are available in the code and data repository.

3.1 Machine learning for snow cover

The most dominant use case of ML for snow remote sensing is for monitoring snow cover, comprising 40% of all papers reviewed. Earliest use cases of using ML for snow cover involve simple feed-forward ANNs to derive fractional snow cover area (fSCA) maps from moderate-resolution MODIS sensors (~500 m), typically as a comparison to the MODIS NDSI snow cover product initially released in 2000 (Dobreva & Klein, 2011; Hall et al., 2019; J. Hou et al., 2019; Moosavi et al., 2014). One other early study used an ANN to derive fractional snow cover from Landsat (Czyzowska-Wisniewski et al., 2015). These early studies identified supporting factors for predicting fractional snow cover from NDSI, such as the normalized difference vegetation index (NDVI), land cover, and terrain. In the case of Dobreva & Klein (2011), they also found that including these predictions within a simple 1-hidden layer neural network framework matched NDSI-derived snow cover (R^2 = 0.90) and performed slightly better than NDSI-derived snow cover in forested areas (1-2%), due to the ability to inherently capture nonlinear relationships and relationships dependent on land features. Later studies such as De Gregorio et al. (2019) built upon this work by using a support vector machine (SVM) model to fuse MODIS NDSI snow cover with hydrological modeled values of SWE for 4-6% more spatially accurate timeseries (2012-2016) of snow cover maps in the Italian Dolomites. The model learned to default to the modeled values of SWE, particularly in forests, where NDSI snow cover values are less accurate. Similarly, Liu et al. (2020) found that SVMs successfully fused Sentinel-1 C Band SAR and MODIS NDSI to improve snow cover detection beneath clouds at 90% probability of detection, and Xiao et al. (2021) predicted snow cover beneath clouds using passive microwave and found that a fused passive microwave and optical product outperformed an optical product for snow cover by 18% for snow cover detection. Nijhawan et al. (2019) combined Sentinel-2 optical bands, Sentinel-1 SAR, and elevation with improved snow cover detection over a small area in northern India in a CNN framework and found that it improved snow cover detection by 2% compared to optical alone. The synthesis across this literature suggests that while snow cover demonstrates a strong raw retrieval, additional variables such as NDVI, land cover, elevation, and Sentinel-1 C Band information can facilitate detecting snow and the conversion from banded

https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.

retrievals and NDSI to fractional snow cover by accounting for forest impacts, cloud cover, and topographic features that impact the signal.

Over the last 10 years, researchers have also used machine learning to target coarse-resolution snow products for downscaling towards fine-scale snow cover observations. For example, training the daily but coarse (500-m) MODIS NDSI snow cover product against the infrequent (~16-day) but fine-scale (30-m) Landsat snow cover fraction maps with a random forest model provided a means for a daily 30-m snow cover fraction map, with an accuracy of 97% in the US Sierra Nevada and results consistent between seasons (Rittger et al., 2021). These results were expanded in a later study, which found multiple, spatially local, rather than a single random forest model improved the downscaling for the same region (Mahanthege et al., 2024). When additional variables are included, such as elevation, slope, aspect, average windspeed, and distance to the ocean, the model is 16% more accurate than the Rittger et al. (2021) study. Compared to snow depth and SWE, snow cover offers more opportunities for downscaling, as there are satellites at both moderate (>= 500 m) and fine-scale (< 100 m) resolutions capable of observing snow cover, therefore providing ample input and reference data for model training.

More recently, a trend has emerged for using ML/DL approaches to derive snow cover maps from high-resolution optical images from commercial satellite providers, such as Planet (Cannistra et al., 2021; K. Yang et al., 2023) and Vantor (formerly Maxar) Worldview-2 and WorldView-3 (J. M. Hu & Shean, 2022). Although initial questions revolved around the ability to detect snow when the high-resolution satellites do not include a SWIR band, multiple studies documented the ability of models to learn snow-related relationships using the Red, Green, Blue, and near-infrared bands for detection for cloud-free images (Cannistra et al., 2021; John et al., 2022; K. Yang et al., 2023). Additionally, high-resolution imagery has the advantage of viewing snow cover in small forest clearings, improving the ability to monitor snow in areas with forest gaps (K. Yang et al., 2023). Temporal gap-filling for snow cover when clouds are present is another recent advancement for ML applications for snow cover, combining terrain information, temperature, solar radiation, and reanalysis products. Long short-term memory (LSTM) networks have proved advantageous for these applications, with the ability to learn relationships across time (C. Zhang et al., 2026).

3.2 Machine learning for SWE and snow depth

ML approaches are used less frequently for snow depth and SWE compared to snow cover. However, they document some of the earliest cases for ML for snow remote sensing, with multiple examples of ANNs to convert the 19 GHz and 37 GHz passive microwave channels to SWE as early as the 1990s (Chang & Tsang, 1992; Changyi Sun et al., 1995; Davis et al., 1993; Tsang et al., 1992), and similar approaches continuing into the 2000s and 2010s (Dariane et al., 2014; Tedesco et al., 2004; Zaerpour et al., 2020). This early work on SWE relative to snow cover matches the availability of passive microwave imagery relative to optical. Passive microwave scenes were freely available in the 1980s (e.g., SMMR, SSM/I), unlike optical scenes, which were not freely made available until 2008 (e.g., Landsat; Wulder et al., 2008). Furthermore, across these studies, the authors note the motivation of utilizing ML approaches to exploit the sensitivity of passive microwave to snow mass while overcoming the inherent complex, non-linear, and region-dependent phenomena that control the radiative transfer between passive microwave signals and snow properties (Davis et al., 1993; Tedesco et al., 2004). Even with these simple, early models applied to the passive microwave observations, the studies document the ability of the ANNs to capture nonlinear relationships but acknowledge accuracy varied widely based on snow conditions (~9% to 57% as in the case of Chang & Tsang, 1992) and topographic complexity (Tong, 2010).

https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.

Similar to snow cover, the last 20+ years reveal a building consensus that multiple variables perform better than a single variable for predicting SWE and snow depth. For both snow depth and SWE, multiple studies used 19 GHz and 37 GHz channels when utilizing AMSR2 passive microwave (H. Hou et al., 2024; Liu et al., 2024; Tanniru et al., 2025; G. Wang et al., 2025; Wei et al., 2022), and other studies add the 22 GHz channel (Zaerpour et al., 2020) or combine all frequencies for best results (Tanniru & Ramsankaran, 2023a). Topographic variables such as elevation, slope, aspect, forest fraction, and land cover continue to be an important factor (Bair et al., 2018; H. Hou et al., 2024; G. Wang et al., 2025; Wei et al., 2023; J. Yang et al., 2020; J. Zhang et al., 2021), and incorporating previous timesteps improves SWE and snow depth prediction from both passive microwave and optical (Elyoussfi et al., 2025; Pflug et al., 2024; Wei et al., 2022). The time component also allowed for temporal gap-filling for SWE from MODIS fSCA and SWE derived from reanalysis when the information was obstructed by clouds (Pflug et al., 2025). Climatological features also play an important role (e.g., precipitation and temperature; Guidicelli et al., 2024; Malygin et al., 2024; Yu et al., 2022).

The literature also trends toward higher resolution and using active radar. Wang et al. (2025) leveraged an XGBoost model to combine AMSR2 and MODIS to downscale snow depth to 500 m with an RMSE of 2.65 cm at weather stations and a 7.05 cm RMSE at independent field sites. Shaw et al. (2020) used meter-scale high-resolution retrievals from Planet along with information on wind and precipitation from regionally based physical models to derive snow depth using a random forest model with a RMSE of 0.30 m. For active radar, Dunmire et al. (2024) used ML and Sentinel-1 SAR along with snow cover fraction and elevation to perform the retrieval of snow depth from the complex radar signal in the European Alps, achieving Pearson's r value of 0.75 with cross-validated weather station sites, although error increased above 3 m snow depth (mean bias equal to -1.75 m vs. -0.08 m for snow depth < 3 m). As NISAR L-band images become available, recent papers have also documented L-band InSAR to perform at the same RMSE level for snow depth as lidar-derived snow depth (Alabi et al., 2025). The synthesized literature suggests that currently snow depth and SWE present a harder use case for machine learning, and more features and sensors are likely necessary to capture the variability. Overall, when inspecting the studies that either 1) reported RMSE binned by snow depth or 2) made snow depth predictions available via data availability statements, we found that generally RMSE increases with snow depth (Figure 3). This breakdown matches the error for shallow and deep snow with physics-based models (Clow et al., 2012; Stigter et al., 2017). We report in cm to stay aligned with how the papers reported results but acknowledge that RMSE at higher snow depths is typically reported as a percentage to reflect that the error is proportional to snow depth.

https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.

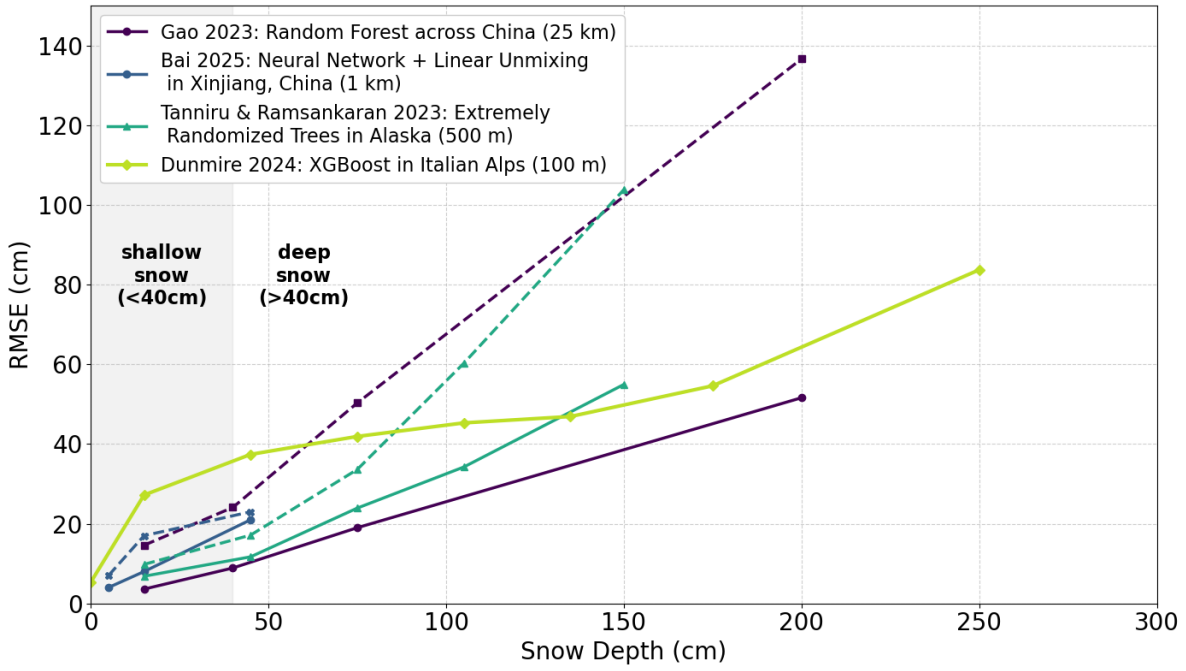


Figure 3. RMSE from four papers for snow depth. RMSE values were extracted from the results table or by pulling the data from the data availability statements (i.e., Dunmire et al. 2024) and binning the RMSE into multiple snow depth bins. The spatial resolution for the ML-derived product is shown in parentheses. Solid lines show the RMSE from the ML model, dashed lines show the RMSE when the authors compared the reference data to previously available products, such as the AMSR2 snow depth product in both cases (Gao et al., 2023; Tanniru & Ramsankaran, 2023a).

3.4 Machine learning for other snow properties

Our review documented other ML-derived snow properties such as snow density, snow wetness, snow class clustering, and snow vs. cloud discrimination. ML applications for snow density appeared in just 3 papers (~3% of papers). For density, the studies combined passive microwave information, such as the SWE-derived product from passive microwave (L. Jiang et al., 2022), along with elevation and outputs from reanalysis (ERA-5) data, including factors known to drive snow compaction, i.e., wind speed, air temperature, and relative humidity (Goodarzi et al., 2024; L. Sun et al., 2024). In the case of Sun et al., (2023), they achieved an overall R^2 of 0.67 compared to the reanalysis snow density information. Snow wetness studies used SAR-based sensors and random forest frameworks to predict wet or dry snow (Gallet et al., 2024; Kumar et al., 2022), citing ML as an advantage to capturing the multiple types of scattering behavior in polarimetric SAR.

Class clustering was the only example for unsupervised learning, but it proved useful for identifying patterns across different snow regions (Farmer et al., 2010; Johnston et al., 2024). For example, Farmer et al. (2010) illustrated clusters of snow wetness in central Canada using SSM/I passive microwave and hierarchical clustering approaches. The advantage of unsupervised behavior for this application is that it can override geographic biases and identify similarities in snow conditions that may not be immediately

https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.

obvious, such as similarities in snow timing in ephemeral snow regions at midlatitudes across the world (Johnston et al., 2024). Snow vs. cloud discrimination has also been a use case for ML/DL given the similarity in the optical bands without SWIR. In all papers identified, researchers used a subset of CNNs, namely U-Nets, ResNets, or larger CNNs such as DeepLab3+ (Barrou Dumont et al., 2024; Bloshchinskiy et al., 2020; Demil et al., 2025a; Jin et al., 2022; Yin et al., 2022; Zheng et al., 2021). The use of these models suggests that the neighboring spatial information incorporated during the convolutional step (the kernel) helps resolve the two classes, improving the accuracy for downstream snow property retrievals.

4 Best practices for machine learning and deep learning in snow remote sensing

Using the many use cases for ML/DL for seasonal snow properties, we now discuss the best practices for input data, reference data, data splits, model selection, and accuracy metrics.

4.1 Input data

Input data ranged from single to multiple satellites and varying combinations of topographical information, climate information, and reanalysis information, depending on the snow property analyzed (Figure 4A). Optical was the most common sensor utilized (26% of papers), predominantly for snow cover. Passive microwave was also predominantly used for snow mass properties (21% of papers). ML/DL frameworks have also enabled data fusion or combining multiple sensors to make a prediction. In papers that tested both single sensor and multi-sensor approaches, overwhelmingly, combinations of multiple sensors and features outperformed single sensor approaches, in some cases by as much as 40% (Bai et al., 2025; K. Yang et al., 2025). These fusion frameworks have improved the ability to detect snow beneath clouds and wet snow (Dunmire et al., 2024; Esmaeelzadeh et al., 2024; Liu et al., 2020; J. Yang et al., 2020). One study demonstrated that a random forest model with surface reflectance bands 1-7 from MODIS successfully retrieved 67% of forest snow pixels compared to just 8–14% using the standard MODIS NDSI threshold (Luo et al., 2022a).

However, given our review, we argue that the prevalence of the sensors used for model training does not necessarily correspond with best practices for future ML for snow remote sensing work and that current gaps still exist. For example, despite the prominence of optical for determining if a pixel was snow-covered, clouds and dense forest cover remained a key challenge even for ML models. Clouds limited training sample size (Cannistra et al., 2021; Dunmire et al., 2024; Yatheendradas & Kumar, 2022), and predictions in forests consistently had higher error, ranging between 6% to 96%. Overall, 12 papers (~10% of papers) explicitly listed the challenge of predictions in forests, demonstrating the universal challenge of predicting snow under canopy (Kumawat et al., 2025; Luo et al., 2022a; Santi et al., 2022; Wei et al., 2025; Xue & Forman, 2015; K. Yang et al., 2025; G. Yu et al., 2024). Similarly, passive microwave was used to predict snow depth and SWE, but this likely matches the long historical record rather than the optimal utility. Several studies noted higher model error in areas with deep snow (Y. Hu et al., 2023; Tanniru et al., 2025; Tedesco et al., 2004), wet snow (Xiao et al., 2018), and shallow snowpacks (< ~25 cm; J. Yang et al., 2020) likely due to the physical constraints of passive microwave and signal saturation in these conditions. Relationships for snow properties that the model learned only from passive microwave studies also failed to generalize spatially (e.g., R^2 decreased 0.69 to 0.21 as in Santi et al., 2012; see also Tong, 2010; Xiao et al., 2018), suggesting that coarseness and complexity of the brightness temperature signals can be difficult to match to snow even with the help of models. We recommend continued use of combining multiple

https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.

290 sensors as inputs for snow property prediction, but given the current sensors available, global snow monitoring, especially in forested areas, deep snow, wet snow, and at high resolutions, is challenging even with ML.

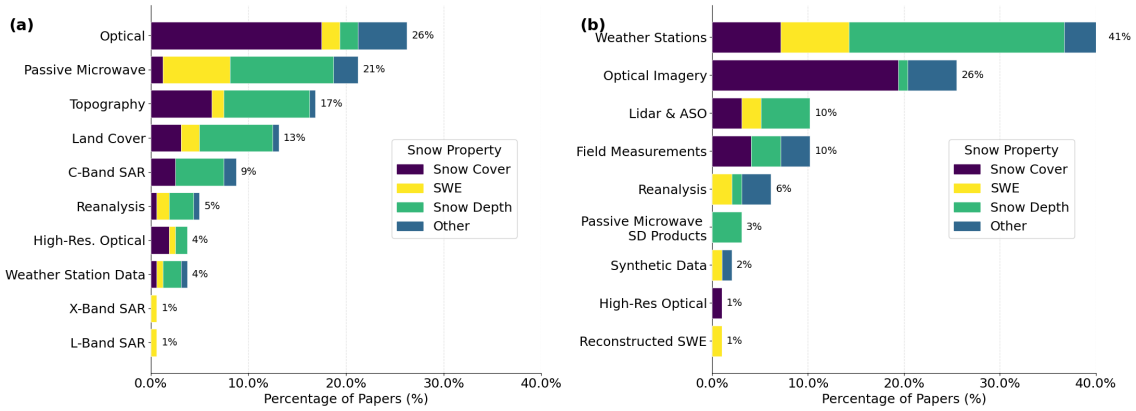


Figure 4. Summary of (a) input and (B) reference data used across literature search for use cases of ML/DL for snow 295 **remote sensing for the three dominant snow properties identified (snow cover, SWE, and snow depth). All other properties are grouped under "other." The papers assigned to each category are available in Table S2 and S3.**

4.2 Reference data

We use reference data here as the umbrella term for the data that the model compares its predicted outputs against during model 300 fitting and evaluation. As machine learning approaches are inherently data-driven, reference data plays an integral role in model training and evaluating (Bergen et al., 2019). Reference data across the literature reviewed largely ranged from ground-collected data, weather stations, airborne lidar, higher resolution satellite images, and reanalysis products (Figure 4B). We identified weather stations and optical satellite information (e.g., Landsat and Sentinel-2) as the most frequent reference datasets for models, representing 40% and 26% of papers, respectively. Reanalysis datasets, such as those from ERA-5 and CROCUS also serve as an 305 efficient form of validation for snow depth and SWE (7% of papers; Kumawat et al., 2025; Meloche et al., 2025). Multi-basin lidar flights, such as those provided by the Airborne Snow Observatory (ASO; Painter et al., 2016), have become more popular as reference data, with 11% of papers all within the last 5 years (P. Broxton et al., 2024; Cannistra et al., 2021b; Shaw et al., 2020; K. Yang et al., 2022, 2025). In one case, reconstructed SWE, where SWE derived from radiation information reanalysis datasets combined with fractional snow cover from MODIS was used to validate SWE predictions (Bair et al., 2018). Two other studies 310 used synthetic data for SWE and snow density derived from radiative transfer models to evaluate machine learning models trained on passive microwave (Chang & Tsang 1992; Tsang et al. 1992).

The diversity of datasets for reference suggests that no optimal reference snow dataset exists, and different trade-offs are inherent. For weather stations, authors cited the utility of weather stations for highly accurate observations, especially for downscaling coarse 315 (3 km +) satellite observations (Bai et al., 2025; Wei et al., 2025). However, weather station locations contain biases depending on the network, such as a focus on areas of higher snow and/or sparseness in mountainous areas (Broxton et al., 2019; Daudt et al., 2023; L. Sun et al., 2024). For example, J. Yang et al. (2020, 2021) found RMSE values doubled when extrapolating in space

https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.

versus time due to biases in the station network. Furthermore, due to the point-scale resolution, there can be misalignment with the observations and input data (Bai et al., 2025; Ni et al., 2024). Some of this misalignment and spatial transfer limitation can be accounted for through data split designs such as leave-one-out cross-validation, which blocks sampling design by geographic areas, ensuring overall error represents performance across all locations without spatial data leakage (see section 4.3 on data split strategies).

Contrastingly, lidar and reanalysis datasets are spatially complete, providing the ML models with gridded information on snow properties from which to learn. Cannistra et al., (2021) found that by presenting the model with an array of snow conditions for a model trained on high-resolution Planet snow cover and validated with airborne lidar, the model performed well on a climatically distinct out-of-sample (only 8% decrease in F-Score, their metric for accuracy), although the results did not hold well in regions with different canopy structures (~25% decrease in F-score). The results are more varied for snow depth and SWE, which are more spatially heterogeneous than snow cover (mean R^2 values ranging between 0.25 and 0.95; K. Yang et al., 2025). Lidar datasets also present limitations in temporal resolution and contain processing steps that can introduce uncertainty. For example, lidar flights are considered high-fidelity datasets for SWE at 50-m resolution, but other studies have identified that the snow density estimation is the largest source of uncertainty in these datasets (Raleigh & Small, 2017), and some ML-focused studies have identified processing artifacts in lidar-derived SWE datasets (Brencher et al., *in press*). As of date, we identified no study that accounted for this. Lidar flights for SWE also tend to focus on peak SWE to estimate snowmelt timing, but this can provide limitations to extrapolating to other time periods of the winter (P. Broxton et al., 2024).

Our summary of the reference datasets suggests that more work is needed to develop datasets that stratify snow conditions, time of year, and geographic locations to robustly train and evaluate model capabilities across spatiotemporally changing conditions. We recommend validation using multiple datasets when possible, such as lidar flights for spatial validation and weather stations for temporal analyses to further identify strengths and weaknesses of model performance. We also acknowledge that the dependency of ML models on reference data can be costly and time-intensive (Gascoin et al., 2024), and we recommend that the community continue to leverage publicly available datasets and community science opportunities for novel ground-truth data sources when appropriate (Breen et al., 2024; Kosmala et al., 2018; Luo et al., 2022b). Additionally, recent work has emphasized how strategically placed measurements can accurately measure snow depth and other snow properties across a basin (Oroza et al., 2016; Raleigh et al., 2025), and further work in this area could reduce labeling efforts in the future.

We also note that overwhelmingly, the studies identified focused on reference data for snow in the Northern Hemisphere, with just one study in the Southern Hemisphere (Shaw et al., 2020). This study focused on the Rio del Yeso basin in the Chilean Andes mountain range, a region classified as tundra snow, according to the recent map of snow classes (Sturm & Liston, 2021). While other studies in the Northern Hemisphere have also focused on tundra (Tanniru & Ramsankaran, 2023; J. Wang et al., 2020), the discrepancy between the number of studies in the Northern versus Southern Hemisphere suggests potential reference data gaps that may limit future global generalizability. Unlike physics-based snow models, ML models reflect the trained data, and any biases in the data will reflect in the predictions, whereas the physics-based models tend to have systematic biases (Sthapit et al., 2026).

4.3 Data split strategies

Data splits determine how the reference data is split between training and testing of the model. This has important implications for how well the model generalizes. For snow applications, we identify that most data splits avoid random splits and instead conduct

https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.

spatial splits (Cannistra et al., 2021; John et al., 2022; Pflug et al., 2024; Santi et al., 2022; K. Yang et al., 2023), whereby the researchers hold out an area from training and test on a new area, or temporal splits (Bair et al., 2018; Tong, 2010), which implies holding out one or more water years and testing on the unseen time period. Alternatively, some researchers conducted a spatiotemporal split, which is a combination of both new space and time periods in the test set (Wei et al., 2026). In some cases, studies conducted cross-block validations (e.g., holding out a year for each year or holding out a region for all regions), which is the most rigorous, although most computationally intensive, data split design (L. Sun et al., 2024; Tanniru & Ramsankaran, 2023a; K. Yang et al., 2025).

The data split selection will depend on the task at hand and the data available, and performance will also depend on those factors. In papers that conducted both temporal and spatial splits, the temporally trained model outperformed the spatially trained model (see Tong et al. 2010; Bair et al. 2018). However, the outperformance of temporal splits is likely a result of the availability of temporally consistent snow information, as we generally have more continuous data temporally (e.g., from weather stations) than spatial datasets. Some outperformance may, in part, be due to repeatable spatial patterns annually (Pflug et al., 2022), although this advantage may change under future conditions. Cross block designs are advantageous for small training datasets by ensuring that all samples contribute to both training and evaluation, but some caution should be used as snow is spatially autocorrelated (Reinking et al., 2022), and sites close to each other will inherently leak information between training and evaluation (Tanniru & Ramsankaran, 2023). In these cases, however, authors achieve results robust to new locations in time and space (K. Yang et al., 2025). Therefore, we recommend that, regardless of split, authors remain transparent about possible spatial or temporal autocorrelation that may inflate transfer metrics. We also recommend that, when possible, authors present both spatial and temporal splits so that future users can understand replicability in both time and geographic regions.

An additional consideration during a split is class balance, or ensuring that snow conditions, geographic diversity, and value ranges are proportionally represented across training and evaluation sets. For snow specifically, zero snow depth (or zero SWE or snow cover) values are often overrepresented in training relative to high amounts, which are rarer but critical for water resource applications. Under-sampling zero or near-zero values and oversampling high snow values can help the model learn the full range of snowpack states, improving predictions at both extremes (Dunmire et al., 2024).

4.4 Model selection

As mentioned in section 3, random forests dominated the ML frameworks (40%), with varieties of neural networks as the second and third most common (17% and 14%) (see Figure 2A). Upon inspection of the model choices, authors cited random forests for quick model fits without a GPU and ability for interpretation via feature importance analyses. ANNs were also successful for small sample sizes without a GPU, although they were sensitive to outliers (Palermo et al., 2023; Ying et al., 2025). Larger models, namely CNNs, required a GPU to handle the matrix multiplication at large sample sizes but contained the ability to implicitly learn location and neighborhood information (Demil et al., 2025b; Yatheendradas & Kumar, 2022). Understanding feature importance in CNNs was difficult, however, due to the complexity of the models (Elyoussfi et al., 2025). LSTM models provided a means to make predictions leveraging time-series information (Bai et al., 2026; Daudt et al., 2023).

The trade-offs in model selection reinforce that model selection depends on the size and type of the dataset, the variable to predict, and access to computational resources. In some cases, authors trained multiple models and conducted a model comparison, presenting opportunities to understand how some model frameworks present advantages for certain snow applications. For

https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.

example, in direct comparisons, CNNs and U-Nets outperformed random forests for snow cover mapping where spatial context mattered (Wang et al. 2022; John et al. 2022), while the advantage was less consistent for regression tasks such as SWE or snow depth where tabular passive microwave or reanalysis inputs dominate (Bair et al., 2018). Complexity is not always better, however, as Yang et al. (2022) fit a linear model for snow cover using historical SWE, daily mean fractional snow cover area, and 18 topographic variables and achieved an R^2 of 0.60, demonstrating that when meaningful variables are incorporated, simpler models can perform as accurately. Additionally, smaller models, such as RFs and feed-forward neural networks, offer fast training times and are more robust to overfitting on small datasets relative to larger models (Gregorio et al., 2018; Kuter, 2021; Nijhawan et al., 2019). Overall, more work is needed to understand the best model, especially for snow properties without a dedicated sensor, such as SWE, with more model comparison studies using benchmark datasets.

4.5 Physics-informed machine learning

Incorporating physical knowledge has been recommended to aid model interpretability (Reichstein et al., 2019b; Schneider et al., 2022) and to ensure physical accuracy. The simplest way to provide physical knowledge for snow predictions from ML/DL approaches is to control the prediction to physically realistic values as a post-processing step. For example, Tong et al. (2010) limited model predictions for SWE to only the physically plausible range (no negative values) after model prediction, while Shaw et al. (2020) produced negative snow depth values in shallow snow, demonstrating the consequence of omitting physical constraints. We also found cases where researchers first corrected inputs using radiative transfer models and found that the corrected inputs performed better than uncorrected, as it enabled the model to learn from the isolated information of interest (Wei et al., 2025). For example, Yang et al. (2021) predicted snow depth by training a random forest model on AMSR2 observations along with snow grain size estimates from a radiative transfer model and decreased the unbiased RMSE from 7.5 to 3.5 cm (i.e., ~50%) across China.

A more advanced approach of incorporating physical knowledge might include penalizing the model for making unrealistic predictions in the loss function for models that make multiple passes through the data (i.e., neural networks), as it ensures no post-processing is required and that the model has internalized physical relationships. A simple addition such as ensuring non-negative snow prediction values is one improvement to a custom loss function for snow. More complex loss functions might include conditional relationships that depend on the inputs. For example, if precipitation is an input, SWE should only increase following snowfall precipitation events, as is the protocol by other snow products like GlobSnow (Pulliainen et al., 2020). Evidence of this approach exists in other earth science disciplines (Daw et al., 2021; Shen et al., 2023), and we recommend that this continue to be an active area of research. We also recommend exploration of replacing the physical governing equation with ML/DL as done in modeling with emulators (Tang et al., 2025). In remote sensing of snow, this appears less common but holds potential for radiative transfer modeling.

4.6 Accuracy metrics and reporting

The most common reported metric for regression tasks across all papers was RMSE, while R^2, MSE, MAE, and percentage biases were also common. For classification tasks, F-1 score was the most common metric. However, there was no consistent report metric used in all papers. This result made it difficult to compare results across papers and aggregate an overall ML/DL accuracy for snow. As a case study, we inspected papers that reported RMSE for SWE derivation across for the last 15 years (n = 8 papers) and found that our overall ability to retrieve SWE using ML/DL has generally stayed below RMSE = 20 cm (Figure 5), although

https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.

it was difficult to identify a trend across studies as sample size varied, validation source varied, and RMSE varied with snowpack depth. For example, some earlier studies performed better than recent studies (see Tedesco et al. 2005), however this study was conducted in shallower snowpacks (snow depth < 1.5 m), compared to later studies with deeper snowpacks (SWE up to 2 m; Yang et al. 2022) where errors are larger but proportional to snow depth.

Moving forward, we recommend the continued use of multiple metrics that capture both the magnitude of error as well as the variance of error (e.g., RMSE and R^2). However, particularly for SWE, we recommend additional reporting accuracy as a percentage. The NASA Decadal Survey identifies SWE as a "Most Important" targeted observable from space and sets a target of 10% accuracy (Committee on the Decadal Survey for Earth Science and Applications from Space et al., 2018), and we encourage researchers to incorporate the use of percentages for accuracies, particularly for SWE-focused studies to stay accountable towards larger community goals. For example, normalized RMSE (nRMSE), where the RMSE is divided by the mean of the observed values, can be multiplied by 100 to present the error as a percent. Additionally, we also recommend stratifying error by time of year and region when appropriate, to generate a complete picture of performance.

In addition to reporting overall model accuracy relative to reference data, we also recommend evaluating performance relative to existing physical and statistical benchmarks and reporting the training time. Several papers compared against baseline physical models or physical retrievals (Cui et al., 2023; Kumawat et al., 2025; K. Yang et al., 2022). Similar to model selection, accuracy relative to simple models (e.g., linear models or random forests in the case of deep learning) can provide indications of trade-offs in computation, speed, and inference accuracy (Brodylo et al., 2025; John et al., 2022). Including training time, such as in the case of John et al. (2022), where a model with more features took five times longer (total 20 hours), allows the reader to evaluate for added accuracy while considering computation load. These are generally the best practices for ML for earth sciences (Reichstein et al., 2019), and we encourage continued adoption here.

https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.

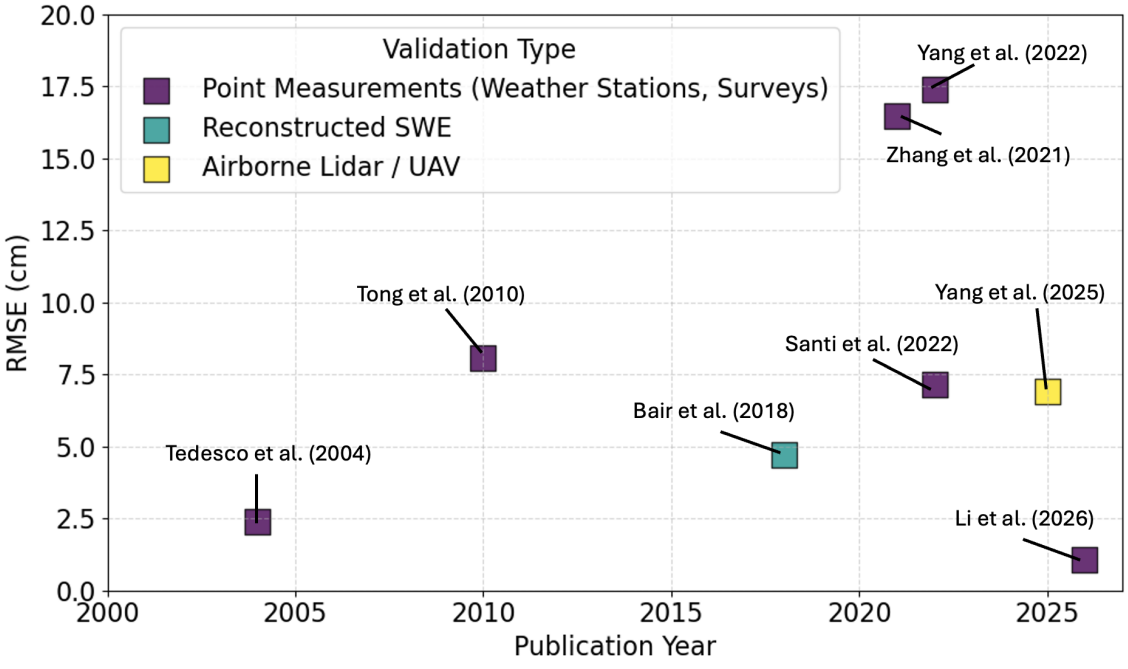


Figure 5. RMSE across studies and year for SWE shows RMSE falls below 20 cm. We only include the studies that report accuracy in RMSE.

5 Future directions

After synthesizing the research, we present four core areas of future work for the snow community in the realm of new 1) models, 2) datasets, 3) benchmarking, 4) applications, and 5) capacity building.

5.1 Models

The recent literature indicates that random forests and neural networks are the dominant methods used in remote sensing for snow applications, with just one paper utilizing a transformer (Kumawat et al., 2025). However, in Earth Science, transformer models are generating momentum due to the ability to capture long-range spatial dependencies and attention mechanisms sensitive to multi-modal inputs (Xu et al., 2026; T. Zhao et al., 2024). Additionally, foundation models, such as NASA and IBM's Prithvi-EO-2.0, Google's AlphaEarth, among others, are a subset of transformer models that self-supervise on large amounts of imagery that can either be fine-tuned for specific tasks (e.g., Prithvi) or produce embeddings (e.g., AlphaEarth) to be used downstream as inputs in other models. In remote sensing applications, embeddings are a way of representing a subset of an image (sometimes referred to as an "image patch" or "chip") as a numerical vector, such that the information can be fed into transformer models (Dosovitskiy et al., 2021). As of publication, no foundation model has tested applications for sub-seasonal snow measurements, and applications for snow remain largely unknown. Many of the current available models include optical bands, which may be suitable for snow cover applications, but few contain active radar bands and passive microwave information for snow mass applications (Brown et al., 2025; Szwarcman et al., 2025). Some also contain architectures that take in single vs. multiple outputs or are optimized for

https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.

daily or monthly timesteps, which present pros and cons for snow monitoring (Guo et al., 2024). The difference across these models results in foundation model performance that depends on the task at hand (Marsocci et al., 2025). So, while we recommend the community test state-of-the-art transformer architectures for snow applications, we impress upon the community that the best model for a specific snow application will depend on the task and dataset.

5.2 Optimal remote sensing datasets for snow

Our review identified that combining sensors for snow improved results, but gaps remain in our ability to retrieve snow from space with current sensors available. Ideally, the snow remote sensing community would have a snow-focused satellite mission instead of utilizing machine learning to mitigate current sensor limitations for snow applicability. Spaceborne L-band information and lidar information present new opportunities for snow (Alabi et al., 2025; Fair et al., 2025), and current sensors on airborne platforms, such as X-band radar, also present opportunities for SWE estimation, although as of date there are no publicly available X-band spaceborne platforms (Santi et al., 2022).

In addition to exploring ML-derived snow retrievals from new platforms, future work should also focus on integration across datasets with varying spatial and temporal resolutions, as we currently do not have spatially complete snow information at fine scales. Regardless of the model architecture, effective data integration methods, such as separate model encoders for each input dataset or additional channels for missing data and temporal lags (Tseng et al., 2024; Brown et al., 2025, Bodnar et al. 2024) may facilitate data integration and the addition of new datasets. We encourage the community to explore not just additional inputs but additional data fusion architectures, with our suggestion to investigate transformer backbones (see 5.1), encoders for sensors, and additional channels for missing information as promising near-term directions.

5.3 Benchmarking datasets and models

Benchmarking for snow retrievals is typically conducted with current products available for snow cover, depth, or SWE, but as demonstrated in Figure 4B, a variety of validation datasets exist. We encourage community consensus around benchmark datasets, which could be facilitated in part by a dedicated snow mission. Benchmarked datasets can also serve as baselines for Earth Science Hackathon competitions, where participants can compare competing models on the same reference target. When developing benchmarking datasets, the SpatioTemporal Asset Catalog (STAC), a framework for structuring satellite metadata, allows for efficient retrieval, particularly for ML, and could be adopted for further systematic model integration (Y. Zhao et al., 2021). Beyond benchmark dataset development, we encourage future work to benchmark models through model intercomparison studies, which indicate performance variations driven by model selection. Models should be made available on public platforms, like Hugging Face and Zenodo, with installation instructions for popular coding environments including Python, to encourage model benchmarking across studies.

5.4 Applications

We suggest continued work to refine ML/DL approaches as complements or replacements for retrieval algorithms for the snow properties discussed here. Future work should continue to explore applications that improve predictions in deep snow, shallow snow, and snow in forests, as these regions presented challenges across many of the papers reviewed. Topics beyond this review may also be future applications. For example, real-time anomaly detection, where an ML/DL model detects natural or human-induced disruptions on the Earth's surface during the observation, also presents opportunities for the snow community (Yan et al.,

https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.

2025), although the technique is not currently integrated at scale. If applied to snow, anomaly detection integrated into satellite platforms could help detect storms, extreme SWE, rain-on-snow melt-out, and other events that carry implications for human and ecological communities. More work is needed to determine real-time processing technologies (e.g., atmospheric correction) and proper energy and memory efficiency constraints while maintaining model accuracy (L. Sun et al., 2024; Yan et al., 2025), but it carries implications for many real-world remote sensing and hydrology needs.

5.5 Capacity building

Finally, training the next generation of snow researchers capable of developing and using ML/DL approaches is essential for new innovations and continuing efforts for effective water monitoring and management. In-person and hybrid "hackweeks" for snow have been successful for teaching advanced computer science techniques (Arendt et al., 2022; Henderson et al., 2021; Pestana et al., 2024), and online content such as GeoScience MAchine Learning Resources and Training (GeoSMART) provides curriculum and workflow pipeline examples for encouraging adoption of ML techniques when appropriate (Cristea et al., 2022). As generative Artificial Intelligence (AI) tools (e.g., ChatGPT, Claude, and others) increase in popularity, more ML adoption potentially increases due to lowering coding barriers (Q. Jiang et al., 2025; Smith et al., 2024). While some might argue that large language models (LLMs) reduce the necessity for ML capacity building, we contend that in-person and virtual trainings remain essential. Capacity building should evolve to help scientists responsibly integrate AI into their ML workflows, ensuring they maintain oversight of model design and adhere to FAIR (Findable, Accessible, Interoperable, and Reusable) principles when utilizing these tools (Z. Sun et al., 2024).

6 Conclusion

The snow community has used ML/DL for the last 20+ years and rapidly adopted ML/DL methods in the last five years. The synthesis of the use cases demonstrates that ML/DL methods are largely successful for snow cover, SWE, and snow depth, and leverage information from passive microwave, optical, and radar, among other environmental and meteorological variables, such as elevation, air temperature, and precipitation. Snow remains uniquely hard for ML/DL approaches due to the fine-scale temporal and spatial variability, and clouds, nighttime, deep snow, and forested areas prove challenging for models. The snow community should continue to explore ML/DL applications for snow, and recognize that ML is a tool for extending or enhancing information, not a substitute for observing it. As the volume and diversity of satellite observations sensitive to snow continues to expand and the ML/DL research continues to evolve, systematic evaluation of how the two can be used in tandem is essential for advancing global snow monitoring. Given the work accomplished over the last several decades, we believe the community is well-positioned for significant ML/DL advances in snow monitoring and will continue to be a leader for highly heterogeneous physical ML/DL applications broadly.

Code and data availability

The exported paper metadata from the Web of Science search, the additional information extracted from papers, and the code to make the summary plots is available at the following GitHub repository: https://github.com/catherine-m-breen/ml_for_snow_remote_sensing_review.

https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.

Author contributions

CB: conceptualization, data curation, formal analysis, investigation, writing (review and editing). KY: Writing (review and editing). JP: Writing (review and editing). NC: Writing (review and editing). SK: Writing (review and editing). NC: Writing (review and editing). IA: Writing (review and editing). CV: Conceptualization, writing (review and editing), funding acquisition. CB prepared the manuscript with contributions from all co-authors.

Competing interests

At least one of the (co-)authors is a member of the editorial board of The Cryosphere.

Disclaimer

Copernicus Publications remains neutral with regard to jurisdictional claims made in the text, published maps, institutional affiliations, or any other geographical representation in this paper. While Copernicus Publications makes every effort to include appropriate place names, the final responsibility lies with the authors. Views expressed in the text are those of the authors and do not necessarily reflect the views of the publisher.

Acknowledgements

In preparation of this work, the authors used NASA's internal chatbot, ChatGSFC (Claude 4.6 Sonnet) as a supplementary tool to assist in language editing, organization, consistency checks, and code drafting for selected preprocessing and visualization scripts. However, any information identified or code written was carefully reviewed, revised, and evaluated prior to inclusion in the manuscript, and the authors made all decisions regarding analysis, interpretation, and presentation. The authors take full responsibility for the content of the publication.

Financial Support

This work was supported by a NASA Advanced Information Systems Technology (AIST) project titled, A New Snow Observing Strategy in Support of Hydrological Science and Applications. This work was also supported by a NASA User-Centered Applications with Large Earth Foundation Models (EA FM) project, titled, Prithvi-EO-Enabled High Resolution Snow Load Mapping in Support of ASCE Structural Design Standards in Colorado and Beyond.

References

Alabi, I. O., Marshall, H.-P., Mead, J., & Trujillo, E. (2025). Advancing terrestrial snow depth monitoring with machine learning and L-band InSAR data: A case study using NASA's SnowEx 2017 data. *Frontiers in Remote Sensing*, *5*. https://doi.org/10.3389/frsen.2024.1481848

Amani, M., Mehravar, S., Asiyabi, R. M., Moghimi, A., Ghorbanian, A., Ahmadi, S. A., Ebrahimy, H., Moghaddam, S. H. A., Naboureh, A., Ranjgar, B., Mohseni, F., Nazari, M. E., Mahdavi, S., Mirmazloumi, S. M., Ojaghi, S., & Jin, S. (2022). Ocean Remote Sensing Techniques and Applications: A Review (Part II). *Water*, *14*(21), 3401. https://doi.org/10.3390/w14213401

Arendt, A. A., Marshall, H.-P., Henderson, S. T., Vuyovich, C., Haley, C., Reckase, G., Scheick, J., Setiawan, L., Alterman, N., Ofekeze, E., Boyd, D., Osmanoglu, B., Piunno, R., Holmes, E. E., Sandusky, M., Ackroyd, C., Adebisi, N., Mason, M.,

https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.

Tarricone, J., … Meyer, J. (2022). *Lessons Learned from SnowEx 2022 Hackweek for Fostering Open Science Communities*. *2022*, ED16B-04. https://ui.adsabs.harvard.edu/abs/2022AGUFMED16B..04A

Bai, Y., Li, Z., Zhang, P., Huang, L., Gao, S., Qiao, H., Liu, C., Liang, S., & Hu, H. (2025). High-resolution snow depth retrieval by passive microwave based on linear unmixing and machine learning stacking technique. *International Journal of Applied Earth Observation and Geoinformation*, *138*, 104467. https://doi.org/10.1016/j.jag.2025.104467

Bai, Y., Li, Z., Zhang, P., Zeng, J., Huang, L., Qiao, H., Gao, S., & Hu, H. (2026). A Snow Depth Retrieval Method Based on Super-Resolution Brightness Temperature Reconstruction and Multimodal Feature Synergy. *IEEE Transactions on Geoscience and Remote Sensing*, *64*, 1–15. https://doi.org/10.1109/TGRS.2026.3653456

Bair, E. H., Abreu Calfa, A., Rittger, K., & Dozier, J. (2018). Using machine learning for real-time estimates of snow water equivalent in the watersheds of Afghanistan. *The Cryosphere*, *12*(5), 1579–1594. https://doi.org/10.5194/tc-12-1579-2018

Barrou Dumont, Z., Gascoin, S., & Inglada, J. (2024). Snow and Cloud Classification in Historical SPOT Images: An Image Emulation Approach for Training a Deep Learning Model Without Reference Data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *17*, 5541–5552. https://doi.org/10.1109/JSTARS.2024.3361838

Bergen, K. J., Johnson, P. A., De Hoop, M. V., & Beroza, G. C. (2019). Machine learning for data-driven discovery in solid Earth geoscience. *Science*, *363*(6433), eaau0323. https://doi.org/10.1126/science.aau0323

Bloshchinskiy, V. D., Kuchma, M. O., Andreev, A. I., & Sorokin, A. A. (2020). Snow and cloud detection using a convolutional neural network and low-resolution data from the Electro-L No. 2 Satellite. *Journal of Applied Remote Sensing*, *14*(03), 1. https://doi.org/10.1117/1.JRS.14.034506

Breen, C. M., Currier, W. R., Vuyovich, C., Miao, Z., & Prugh, L. R. (2024). Snow Depth Extraction From Time-Lapse Imagery Using a Keypoint Deep Learning Model. *Water Resources Research*, *60*(7), e2023WR036682. https://doi.org/10.1029/2023WR036682

Brodylo, D., Bosche, L. V., Busby, R. R., Deeb, E. J., Douglas, T. A., & Lemmetyinen, J. (2025). Object-based ensemble estimation of snow depth and snow water equivalent over multiple months in Sodankylä, Finland. *The Cryosphere*, *19*(11), 6127–6148. https://doi.org/10.5194/tc-19-6127-2025

Brown, C. F., Kazmierski, M. R., Pasquarella, V. J., Rucklidge, W. J., Samsikova, M., Zhang, C., Shelhamer, E., Lahera, E., Wiles, O., Ilyushchenko, S., Gorelick, N., Zhang, L. L., Alj, S., Schechter, E., Askay, S., Guinan, O., Moore, R., Boukouvalas, A., & Kohli, P. (2025). *AlphaEarth Foundations: An embedding field model for accurate and efficient global mapping from sparse label data* (arXiv:2507.22291). arXiv. https://doi.org/10.48550/arXiv.2507.22291

Broxton, P. D., Harpold, A. A., Biederman, J. A., Troch, P. A., Molotch, N. P., & Brooks, P. D. (2015). Quantifying the effects of vegetation structure on snow accumulation and ablation in mixed-conifer forests. *Ecohydrology*, *8*(6), 1073–1094. https://doi.org/10.1002/eco.1565

Broxton, P. D., Leeuwen, W. J. D., & Biederman, J. A. (2019). Improving Snow Water Equivalent Maps With Machine Learning of Snow Survey and Lidar Measurements. *Water Resources Research*, *55*(5), 3739–3757. https://doi.org/10.1029/2018WR024146

Cannistra, A. F., Shean, D. E., & Cristea, N. C. (2021). High-resolution CubeSat imagery and machine learning for detailed snow-covered area. *Remote Sensing of Environment*, *258*, 112399. https://doi.org/10.1016/j.rse.2021.112399

Chang, A. T. C., Foster, J. L., & Hall, D. K. (1987). Nimbus-7 SMMR Derived Global Snow Cover Parameters. *Annals of Glaciology*, *9*, 39–44. https://doi.org/10.3189/S0260305500200736

Chang, A. T. C., & Tsang, L. (1992). A Neural Network Approach to Inversion of Snow Water Equivalent from Passive Microwave Measurements. *Hydrology Research*, *23*(3), 173–182. https://doi.org/10.2166/nh.1992.0012

Changyi Sun, Heng-Da Cheng, McDonnell, J. J., & Neale, C. M. U. (1995). Identification of mountain snow cover using SSM/I and artificial neural network. *1995 International Conference on Acoustics, Speech, and Signal Processing*, *5*, 3451–3454. https://doi.org/10.1109/ICASSP.1995.479728

Clow, D. W., Nanus, L., Verdin, K. L., & Schmidt, J. (2012). Evaluation of SNODAS snow depth and snow water equivalent estimates for the Colorado Rocky Mountains, USA. *Hydrological Processes*, *26*(17), 2583–2591. https://doi.org/10.1002/hyp.9385

Committee on the Decadal Survey for Earth Science and Applications from Space, Space Studies Board, Division on Engineering and Physical Sciences, & National Academies of Sciences, Engineering, and Medicine. (2018). *Thriving on Our Changing Planet: A Decadal Strategy for Earth Observation from Space* (p. 24938). National Academies Press. https://doi.org/10.17226/24938

https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.

Cristea, N. C., Sun, Z., Arendt, A. A., Henderson, S. T., Denolle, M., & Burgess, A. (2022). *GeoSMART: Machine Learning Training and Curriculum Development for Earth Science Studies*. *2022*, ED22B-0550. https://ui.adsabs.harvard.edu/abs/2022AGUFMED22B0550C

Cui, G., Anderson, M., & Bales, R. (2023). Mapping of snow water equivalent by a deep-learning model assimilating snow observations. *Journal of Hydrology*, *616*, 128835. https://doi.org/10.1016/j.jhydrol.2022.128835

Czyzowska-Wisniewski, E. H., Van Leeuwen, W. J. D., Hirschboeck, K. K., Marsh, S. E., & Wisniewski, W. T. (2015). Fractional snow cover estimation in complex alpine-forested environments using an artificial neural network. *Remote Sensing of Environment*, *156*, 403–417. https://doi.org/10.1016/j.rse.2014.09.026

Dariane, A. B., Azimi, S., & Zakerinejad, A. (2014). Artificial neural network coupled with wavelet transform for estimating snow water equivalent using passive microwave data. *Journal of Earth System Science*, *123*(7), 1591–1601. https://doi.org/10.1007/s12040-014-0485-1

Daudt, R. C., Wulf, H., Hafner, E. D., Bühler, Y., Schindler, K., & Wegner, J. D. (2023). Snow depth estimation at country-scale with high spatial and temporal resolution. *ISPRS Journal of Photogrammetry and Remote Sensing*, *197*, 105–121. https://doi.org/10.1016/j.isprsjprs.2023.01.017

Davis, D. T., Chen, Z., Tsang, L., Hwang, J.-N., & Chang, A. T. C. (1993). Retrieval of snow parameters by iterative inversion of a neural network. *IEEE Transactions on Geoscience and Remote Sensing*, *31*(4), 842–852. https://doi.org/10.1109/36.239907

Daw, A., Karpatne, A., Watkins, W., Read, J., & Kumar, V. (2021). *Physics-guided Neural Networks (PGNN): An Application in Lake Temperature Modeling* (arXiv:1710.11431). arXiv. https://doi.org/10.48550/arXiv.1710.11431

De Gregorio, L., Callegari, M., Marin, C., Zebisch, M., Bruzzone, L., Demir, B., Strasser, U., Marke, T., Gunther, D., Nadalet, R., & Notarnicola, C. (2019). A Novel Data Fusion Technique for Snow Cover Retrieval. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *12*(8), 2862–2877. https://doi.org/10.1109/JSTARS.2019.2920676

Demil, G., Haghighi, A. T., Klöve, B., & Oussalah, M. (2025a). Advances in image-based estimation of snow variable: A systematic literature review on recent studies. *Journal of Hydrology*, *654*, 132855. https://doi.org/10.1016/j.jhydrol.2025.132855

Demil, G., Haghighi, A. T., Klöve, B., & Oussalah, M. (2025b). Seeing through the clouds: Enhanced snow and cloud segmentation in sentinel-2 imagery with mDeepLabV3+. *Earth Science Informatics*, *18*(3), 477. https://doi.org/10.1007/s12145-025-01950-6

Deschamps-Berger, C., Gascoin, S., Shean, D., Besso, H., Guiot, A., & López-Moreno, J. I. (2023). Evaluation of snow depth retrievals from ICESat-2 using airborne laser-scanning data. *The Cryosphere*, *17*(7), 2779–2792. https://doi.org/10.5194/tc-17-2779-2023

Dobreva, I. D., & Klein, A. G. (2011). Fractional snow cover mapping through artificial neural network analysis of MODIS surface reflectance. *Remote Sensing of Environment*, *115*(12), 3355–3366. https://doi.org/10.1016/j.rse.2011.07.018

Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., Dehghani, M., Minderer, M., Heigold, G., Gelly, S., Uszkoreit, J., & Houlsby, N. (2021). *An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale* (arXiv:2010.11929). arXiv. https://doi.org/10.48550/arXiv.2010.11929

Dozier, J. (1989). Spectral signature of alpine snow cover from the landsat thematic mapper. *Remote Sensing of Environment*, *28*, 9–22. https://doi.org/10.1016/0034-4257(89)90101-6

Dumont, M., & Gascoin, S. (2016). Optical Remote Sensing of Snow Cover. In *Land Surface Remote Sensing in Continental Hydrology* (pp. 115–137). Elsevier. https://doi.org/10.1016/B978-1-78548-104-8.50004-8

Dunmire, D., Lievens, H., Boeykens, L., & De Lannoy, G. J. M. (2024). A machine learning approach for estimating snow depth across the European Alps from Sentinel-1 imagery. *Remote Sensing of Environment*, *314*, 114369. https://doi.org/10.1016/j.rse.2024.114369

Elyoussfi, H., Boudhar, A., Belaqziz, S., Bousbaa, M., Nifa, K., Bargam, B., & Chehbouni, A. (2025). Leveraging advanced deep learning and machine learning approaches for snow depth prediction using remote sensing and ground data. *Journal of Hydrology: Regional Studies*, *57*, 102085. https://doi.org/10.1016/j.ejrh.2024.102085

Esmaeelzadeh, R., Emamgholizadeh, S., & Bigdeli, B. (2024). Improvement on the Effective Snow Cover Extraction Using Fusion Satellite Images Approach. *Journal of the Indian Society of Remote Sensing*, *52*(2), 449–462. https://doi.org/10.1007/s12524-024-01828-y

Fair, Z., Vuyovich, C., Neumann, T., Pflug, J., Shean, D., Enderlin, E. M., Zikan, K., Besso, H., Lundquist, J., Deschamps-Berger, C., & Treichler, D. (2025). Review article: Using spaceborne lidar for snow depth retrievals: recent findings and utility for hydrologic applications. *The Cryosphere*, *19*(11), 5671–5691. https://doi.org/10.5194/tc-19-5671-2025

https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.

Farmer, C. J. Q., Nelson, T. A., Wulder, M. A., & Derksen, C. (2010). Identification of snow cover regimes through spatial and temporal clustering of satellite microwave brightness temperatures. *Remote Sensing of Environment*, *114*(1), 199–210. https://doi.org/10.1016/j.rse.2009.09.002

Frei, A., Tedesco, M., Lee, S., Foster, J., Hall, D. K., Kelly, R., & Robinson, D. A. (2012). A review of global satellite-derived snow products. *Advances in Space Research*, *50*(8), 1007–1029. https://doi.org/10.1016/j.asr.2011.12.021

Gallet, M., Atto, A., Karbou, F., & Trouvé, E. (2024). Wet Snow Detection From Satellite SAR Images by Machine Learning With Physical Snowpack Model Labeling. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *17*, 2901–2917. https://doi.org/10.1109/JSTARS.2023.3342990

Gao, S., Li, Z., Zhang, P., Chen, Q., Huang, L., Zhou, J., Zhao, C., Qiao, H., & Zheng, Z. (2023). A novel global snow depth retrieval method considering snow metamorphism and forest influence. *Remote Sensing of Environment*, *295*, 113712. https://doi.org/10.1016/j.rse.2023.113712

Gascoin, S., Luojus, K., Nagler, T., Lievens, H., Masiokas, M., Jonas, T., Zheng, Z., & De Rosnay, P. (2024). Remote sensing of mountain snow from space: Status and recommendations. *Frontiers in Earth Science*, *12*, 1381323. https://doi.org/10.3389/feart.2024.1381323

Goodarzi, M. R., Sabaghzadeh, M., Barzkar, A., Niazkar, M., & Saghafi, M. (2024). A comparison of machine learning methods for estimation of snow density using satellite images. *Water and Environment Journal*, *38*(3), 437–449. https://doi.org/10.1111/wej.12939

Gregorio, L. D., Callegari, M., Marin, C., Zebisch, M., Bruzzone, L., Demir, B., Strasser, U., Marke, T., Günther, D., Nadalet, R., & Notarnicola, C. (2018). *Improved snow parameters estimation through integration of simulated and remotely sensed snow cover information*.

Guidicelli, M., Aalstad, K., Treichler, D., & Salzmann, N. (2024). A combined data assimilation and deep learning approach for continuous spatio-temporal SWE reconstruction from sparse ground tracks. *Journal of Hydrology X*, *25*, 100190. https://doi.org/10.1016/j.hydroa.2024.100190

Guo, X., Chen, Y., Liu, X., & Zhao, Y. (2020). Extraction of snow cover from high-resolution remote sensing imagery using deep learning on a small dataset. *Remote Sensing Letters*, *11*(1), 66–75. https://doi.org/10.1080/2150704X.2019.1686548

Guo, X., Lao, J., Dang, B., Zhang, Y., Yu, L., Ru, L., Zhong, L., Huang, Z., Wu, K., Hu, D., He, H., Wang, J., Chen, J., Yang, M., Zhang, Y., & Li, Y. (2024). *SkySense: A Multi-Modal Remote Sensing Foundation Model Towards Universal Interpretation for Earth Observation Imagery* (arXiv:2312.10115). arXiv. https://doi.org/10.48550/arXiv.2312.10115

Hall, D. K., Riggs, G. A., DiGirolamo, N. E., & Román, M. O. (2019). Evaluation of MODIS and VIIRS cloud-gap-filled snow-cover products for production of an Earth science data record. *Hydrology and Earth System Sciences*, *23*(12), 5227–5241. https://doi.org/10.5194/hess-23-5227-2019

Hastie, T., Tibshirani, R., & Friedman, J. H. (2017). *The elements of statistical learning: Data mining, inference, and prediction* (Second edition). Springer.

Henderson, S., Arendt, A., Meyer, J., Breen, C., Johnson, M., Lundquist, J., Pestana, S., Marshall, H.-P., Webster, C., Wrzesien, M., Vuyovich, C., & Scheick, J. (2021). *Lessons learned from NASA SnowEx Hackweek 2021 for fostering open science communities*. *2021*, U51B-23. https://ui.adsabs.harvard.edu/abs/2021AGUFM.U51B..23H

Hou, H., Hu, G., Chu, N., You, Y., Gao, M., Li, M., & Hu, Z. (2024). Snow depth retrieval from microwave remote sensing by combining wavelet transform and machine learning models in Northern Xinjiang, China. *Journal of Applied Remote Sensing*, *18*(02). https://doi.org/10.1117/1.JRS.18.024517

Hou, J., Huang, C., Zhang, Y., Guo, J., & Gu, J. (2019). Gap-Filling of MODIS Fractional Snow Cover Products via Non-Local Spatio-Temporal Filtering Based on Machine Learning Techniques. *Remote Sensing*, *11*(1), 90. https://doi.org/10.3390/rs11010090

Hu, J. M., & Shean, D. (2022). Improving Mountain Snow and Land Cover Mapping Using Very-High-Resolution (VHR) Optical Satellite Images and Random Forest Machine Learning Models. *Remote Sensing*, *14*(17), 4227. https://doi.org/10.3390/rs14174227

Hu, Y., Che, T., Dai, L., Zhu, Y., Xiao, L., Deng, J., & Li, X. (2023). A long-term daily gridded snow depth dataset for the Northern Hemisphere from 1980 to 2019 based on machine learning. *Big Earth Data*, 1–28. https://doi.org/10.1080/20964471.2023.2177435

Jiang, L., Yang, J., Zhang, C., Wu, S., Li, Z., Dai, L., Li, X., & Qiu, Y. (2022). Daily snow water equivalent product with SMMR, SSM/I and SSMIS from 1980 to 2020 over China. *Big Earth Data*, *6*(4), 420–434. https://doi.org/10.1080/20964471.2022.2032998

https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.

Jiang, Q., Gao, Z., & Karniadakis, G. E. (2025). DeepSeek vs. ChatGPT vs. Claude: A comparative study for scientific computing and scientific machine learning tasks. *Theoretical and Applied Mechanics Letters*, *15*(3), 100583. https://doi.org/10.1016/j.taml.2025.100583

Jin, D., Lee, K.-S., Choi, S., Seong, N.-H., Jung, D., Sim, S., Woo, J., Jeon, U., Byeon, Y., & Han, K.-S. (2022). An improvement of snow/cloud discrimination from machine learning using geostationary satellite data. *International Journal of Digital Earth*, *15*(1), 2355–2375. https://doi.org/10.1080/17538947.2022.2152886

John, A., Cannistra, A. F., Yang, K., Tan, A., Shean, D., Hille Ris Lambers, J., & Cristea, N. (2022). High-Resolution Snow-Covered Area Mapping in Forested Mountain Ecosystems Using PlanetScope Imagery. *Remote Sensing*, *14*(14), 3409. https://doi.org/10.3390/rs14143409

Johnston, J., Jacobs, J. M., & Cho, E. (2024). Global Snow Seasonality Regimes from Satellite Records of Snow Cover. *Journal of Hydrometeorology*, *25*(1), 65–88. https://doi.org/10.1175/JHM-D-23-0047.1

Kosmala, M., Hufkens, K., & Richardson, A. D. (2018). Integrating camera imagery, crowdsourcing, and deep learning to improve high-frequency automated monitoring of snow at continental-to-global scales. *PLOS ONE*, *13*(12), e0209649. https://doi.org/10.1371/journal.pone.0209649

Krejcar, O., & Namazi, H. (2026). AI in remote sensing and satellite image processing-a review. *Environmental Earth Sciences*, *85*(3), 78. https://doi.org/10.1007/s12665-025-12798-w

Kumar, S., Narayan, A., Mehta, D., & Snehmani. (2022). Snow cover characterization using C-band polarimetric SAR in parts of the Himalaya. *Advances in Space Research*, *70*(12), 3959–3974. https://doi.org/10.1016/j.asr.2022.10.012

Kumawat, D., Ebtehaj, A., Kumar, S., & Colliander, A. (2025). Deep learning of seasonal peak snow water content of global boreal forest and arctic using spaceborne L-band radiometry. *Remote Sensing of Environment*, *330*, 114963. https://doi.org/10.1016/j.rse.2025.114963

Kunzi, K. F., Patil, S., & Rott, H. (1982). Snow-Cover Parameters Retrieved from Nimbus-7 Scanning Multichannel Microwave Radiometer (SMMR) Data. *IEEE Transactions on Geoscience and Remote Sensing*, *GE-20*(4), 452–467. https://doi.org/10.1109/TGRS.1982.350411

Kuter, S. (2021). Completing the machine learning saga in fractional snow cover estimation from MODIS Terra reflectance data: Random forests versus support vector regression. *Remote Sensing of Environment*, *255*, 112294. https://doi.org/10.1016/j.rse.2021.112294

Liu, Y., Chen, X., Hao, J.-S., & Li, L. (2020). Snow cover estimation from MODIS and Sentinel-1 SAR data using machine learning algorithms in the western part of the Tianshan Mountains. *Journal of Mountain Science*, *17*(4), 884–897. https://doi.org/10.1007/s11629-019-5723-1

Liu, Y., Peters-Lidard, C. D., Kumar, S., Foster, J. L., Shaw, M., Tian, Y., & Fall, G. M. (2013). Assimilating satellite-based snow depth and snow cover products for improving snow predictions in Alaska. *Advances in Water Resources*, *54*, 208–227. https://doi.org/10.1016/j.advwatres.2013.02.005

Liu, Y., Yang, J., Chen, X., Yao, J., Li, L., & Qiu, Y. (2024). Moderate-resolution snow depth product retrieval from passive microwave brightness data over Xinjiang using machine learning approach. *International Journal of Digital Earth*, *17*(1), 2299208. https://doi.org/10.1080/17538947.2023.2299208

Luo, J., Dong, C., Lin, K., Chen, X., Zhao, L., & Menzel, L. (2022a). Mapping snow cover in forests using optical remote sensing, machine learning and time-lapse photography. *Remote Sensing of Environment*, *275*, 113017. https://doi.org/10.1016/j.rse.2022.113017

Luo, J., Dong, C., Lin, K., Chen, X., Zhao, L., & Menzel, L. (2022b). Mapping snow cover in forests using optical remote sensing, machine learning and time-lapse photography. *Remote Sensing of Environment*, *275*, 113017. https://doi.org/10.1016/j.rse.2022.113017

Mahanthege, S., Kleiber, W., Rittger, K., Rajagopalan, B., Brodzik, M. J., & Bair, E. (2024). A Spatially-Distributed Machine Learning Approach for Fractional Snow Covered Area Estimation. *Water Resources Research*, *60*(11), e2023WR036162. https://doi.org/10.1029/2023WR036162

Mahoney, P. J., Liston, G. E., LaPoint, S., Gurarie, E., Mangipane, B., Wells, A. G., Brinkman, T. J., Eitel, J. U. H., Hebblewhite, M., Nolin, A. W., Boelman, N., & Prugh, L. R. (2018). Navigating snowscapes: Scale-dependent responses of mountain sheep to snowpack properties. *Ecological Applications*, *28*(7), 1715–1729. https://doi.org/10.1002/eap.1773

Malygin, E., Rets, E., Kharlamov, M., Malygin, I., & Sakirkina, M. (2024). *Operational Estimation of Snow Water Equivalent Across the Western U.S. Using Gradient Boosting Machine Ensemble*. SSRN. https://doi.org/10.2139/ssrn.4902724

https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.

Mankin, J. S., Viviroli, D., Singh, D., Hoekstra, A. Y., & Diffenbaugh, N. S. (2015). The potential for snow to supply human water demand in the present and future. *Environmental Research Letters*, *10*(11), 114016. https://doi.org/10.1088/1748-9326/10/11/114016

Marsocci, V., Jia, Y., Bellier, G. L., Kerekes, D., Zeng, L., Hafner, S., Gerard, S., Brune, E., Yadav, R., Shibli, A., Fang, H., Ban, Y., Vergauwen, M., Audebert, N., & Nascetti, A. (2025). *PANGAEA: A Global and Inclusive Benchmark for Geospatial Foundation Models* (arXiv:2412.04204). arXiv. https://doi.org/10.48550/arXiv.2412.04204

Meloche, J., Leroux, N. R., Montpetit, B., Vionnet, V., & Derksen, C. (2025). Radar-equivalent snowpack: Reducing the number of snow layers while retaining their microwave properties and bulk snow mass. *The Cryosphere*, *19*(8), 2949–2962. https://doi.org/10.5194/tc-19-2949-2025

Miller, Z. S., Peitzsch, E. H., Sproles, E. A., Birkeland, K. W., & Palomaki, R. T. (2022). Assessing the seasonal evolution of snow depth spatial variability and scaling in complex mountain terrain. *The Cryosphere*, *16*(12), 4907–4930. https://doi.org/10.5194/tc-16-4907-2022

Mjolsness, E., & DeCoste, D. (2001). Machine Learning for Science: State of the Art and Future Prospects. *Science*, *293*(5537), 2051–2055. https://doi.org/10.1126/science.293.5537.2051

Moosavi, V., Malekinezhad, H., & Shirmohammadi, B. (2014). Fractional snow cover mapping from MODIS data using wavelet-artificial intelligence hybrid models. *Journal of Hydrology*, *511*, 160–170. https://doi.org/10.1016/j.jhydrol.2014.01.015

Ni, Z., Yang, Q., Yue, L., Peng, Y., & Yuan, Q. (2024). Estimating high-resolution snow depth over the North Hemisphere mountains utilizing active microwave backscatter and machine learning. *Journal of Hydrology*, *645*, 132203. https://doi.org/10.1016/j.jhydrol.2024.132203

Nijhawan, R., Das, J., & Raman, B. (2019). A hybrid of deep learning and hand-crafted features based approach for snow cover mapping. *International Journal of Remote Sensing*, *40*(2), 759–773. https://doi.org/10.1080/01431161.2018.1519277

Oroza, C. A., Zheng, Z., Glaser, S. D., Tuia, D., & Bales, R. C. (2016). Optimizing embedded sensor network design for catchment-scale snow-depth estimation using LiDAR and machine learning: OPTIMIZING SNOW SENSOR PLACEMENTS. *Water Resources Research*, *52*(10), 8174–8189. https://doi.org/10.1002/2016WR018896

Painter, T. H., Berisford, D. F., Boardman, J. W., Bormann, K. J., Deems, J. S., Gehrke, F., Hedrick, A., Joyce, M., Laidlaw, R., Marks, D., Mattmann, C., McGurk, B., Ramirez, P., Richardson, M., Skiles, S. M., Seidel, F. C., & Winstral, A. (2016). The Airborne Snow Observatory: Fusion of scanning lidar, imaging spectrometer, and physically-based modeling for mapping snow water equivalent and snow albedo. *Remote Sensing of Environment*, *184*, 139–152. https://doi.org/10.1016/j.rse.2016.06.018

Palermo, G., Raparelli, E., Tuccella, P., Orlandi, M., & Marzano, F. S. (2023). Using Artificial Neural Networks to Couple Satellite C-Band Synthetic Aperture Radar Interferometry and Alpine3D Numerical Model for the Estimation of Snow Cover Extent, Height, and Density. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *16*, 2868–2888. https://doi.org/10.1109/JSTARS.2023.3253804

Pestana, S., Arendt, A. A., Boudreau, E., Burgess, A., Denolle, M., Haley, C., Henderson, S. T., Kaczmarczyk, L., Sun, Z., & Cristea, N. C. (2024). *Insights from Applying a Novel Collaborative Project Design Model for GeoSMART Hackweeks*. *2024*, ED11D-2384. https://ui.adsabs.harvard.edu/abs/2024AGUFMED11D2384P

Pflug, J. M., Kumar, S., Hall, D. K., Riggs, G. A., Konapala, G., Whitney, K., Wrzesien, M. L., Nie, W., Sun, Z., & Arsenault, K. R. (2025). *Lightweight and Regionally Transferrable Snow Water Equivalent Estimation Using a Long Short-Term Memory Network*. Wiley. https://doi.org/10.22541/essoar.173687304.49130953/v1

Pflug, J. M., Margulis, S. A., & Lundquist, J. D. (2022). Inferring watershed-scale mean snowfall magnitude and distribution using multidecadal snow reanalysis patterns and snow pillow observations. *Hydrological Processes*, *36*(6), e14581. https://doi.org/10.1002/hyp.14581

Pflug, J. M., Yang, K., Cristea, N., Boudreau, E. T., Vuyovich, C. M., & Kumar, S. V. (2024). Using Commercial Satellite Imagery to Reconstruct 3 m and Daily Spring Snow Water Equivalent. *Water Resources Research*, *60*(11). https://doi.org/10.1029/2024wr037983

Pulliainen, J., Luojus, K., Derksen, C., Mudryk, L., Lemmetyinen, J., Salminen, M., Ikonen, J., Takala, M., Cohen, J., Smolander, T., & Norberg, J. (2020). Patterns and trends of Northern Hemisphere snow mass from 1980 to 2018. *Nature*, *581*(7808), 294–298. https://doi.org/10.1038/s41586-020-2258-0

Raleigh, M. S., & Small, E. E. (2017). Snowpack density modeling is the primary source of uncertainty when mapping basin-wide SWE with lidar. *Geophysical Research Letters*, *44*(8), 3700–3709. https://doi.org/10.1002/2016GL071999

Raleigh, M. S., Small, E. E., Bair, E. H., Wobus, C., & Rittger, K. (2025). Snow monitoring at strategic locations improves water supply forecasting more than basin-wide mapping. *Communications Earth & Environment*, *6*(1), 665. https://doi.org/10.1038/s43247-025-02660-z

https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.

Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., & Prabhat. (2019a). Deep learning and process understanding for data-driven Earth system science. *Nature*, *566*(7743), 195–204. https://doi.org/10.1038/s41586-019-0912-1

Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., & Prabhat. (2019b). Deep learning and process understanding for data-driven Earth system science. *Nature*, *566*(7743), 195–204. https://doi.org/10.1038/s41586-019-0912-1

Reinking, A. K., Højlund Pedersen, S., Elder, K., Boelman, N. T., Glass, T. W., Oates, B. A., Bergen, S., Roberts, S., Prugh, L. R., Brinkman, T. J., Coughenour, M. B., Feltner, J. A., Barker, K. J., Bentzen, T. W., Pedersen, Å. Ø., Schmidt, N. M., & Liston, G. E. (2022). Collaborative wildlife–snow science: Integrating wildlife and snow expertise to improve research and management. *Ecosphere*, *13*(6). https://doi.org/10.1002/ecs2.4094

Rittger, K., Krock, M., Kleiber, W., Bair, E. H., Brodzik, M. J., Stephenson, T. R., Rajagopalan, B., Bormann, K. J., & Painter, T. H. (2021). Multi-sensor fusion using random forests for daily fractional snow cover at 30 m. *Remote Sensing of Environment*, *264*, 112608. https://doi.org/10.1016/j.rse.2021.112608

Saberi, N., Kelly, R., Flemming, M., & Li, Q. (2020). Review of snow water equivalent retrieval methods using spaceborne passive microwave radiometry. *International Journal of Remote Sensing*, *41*(3), 996–1018. https://doi.org/10.1080/01431161.2019.1654144

Santi, E., Brogioni, M., Leduc-Leballeur, M., Macelloni, G., Montomoli, F., Pampaloni, P., Lemmetyinen, J., Cohen, J., Rott, H., Nagler, T., Derksen, C., King, J., Rutter, N., Essery, R., Menard, C., Sandells, M., & Kern, M. (2022). Exploiting the ANN Potential in Estimating Snow Depth and Snow Water Equivalent From the Airborne SnowSAR Data at X- and Ku-Bands. *IEEE Transactions on Geoscience and Remote Sensing*, *60*, 1–16. https://doi.org/10.1109/TGRS.2021.3086893

Schilling, S., Dietz, A., & Kuenzer, C. (2024). Snow Water Equivalent Monitoring—A Review of Large-Scale Remote Sensing Applications. *Remote Sensing*, *16*(6), 1085. https://doi.org/10.3390/rs16061085

Schneider, R., Bonavita, M., Geer, A., Arcucci, R., Dueben, P., Vitolo, C., Le Saux, B., Demir, B., & Mathieu, P.-P. (2022). ESA-ECMWF Report on recent progress and research directions in machine learning for Earth System observation and prediction. *Npj Climate and Atmospheric Science*, *5*(1), 51. https://doi.org/10.1038/s41612-022-00269-z

Shaw, T. E., Gascoin, S., Mendoza, P. A., Pellicciotti, F., & McPhee, J. (2020). Snow Depth Patterns in a High Mountain Andean Catchment from Satellite Optical Tristereoscopic Remote Sensing. *Water Resources Research*, *56*(2), e2019WR024880. https://doi.org/10.1029/2019WR024880

Shen, C., Appling, A. P., Gentine, P., Bandai, T., Gupta, H., Tartakovsky, A., Baity-Jesi, M., Fenicia, F., Kifer, D., Li, L., Liu, X., Ren, W., Zheng, Y., Harman, C. J., Clark, M., Farthing, M., Feng, D., Kumar, P., Aboelyazeed, D., … Lawson, K. (2023). Differentiable modelling to unify machine learning and physical models for geosciences. *Nature Reviews Earth & Environment*, *4*(8), 552–567. https://doi.org/10.1038/s43017-023-00450-9

Smith, G. R., Bello, C., Bialic-Murphy, L., Clark, E., Delavaux, C. S., Fournier De Lauriere, C., Van Den Hoogen, J., Lauber, T., Ma, H., Maynard, D. S., Mirman, M., Mo, L., Rebindaine, D., Reek, J. E., Werden, L. K., Wu, Z., Yang, G., Zhao, Q., Zohner, C. M., & Crowther, T. W. (2024). Ten simple rules for using large language models in science, version 1.0. *PLOS Computational Biology*, *20*(1), e1011767. https://doi.org/10.1371/journal.pcbi.1011767

Sthapit, E., Abel, M. R., Currier, W. R., Cifelli, R., & Fickenscher, P. (2026). Evaluating data-driven models to estimate snow water equivalent in the Sierra Nevada. *Journal of Hydrology: Regional Studies*, *65*, 103481. https://doi.org/10.1016/j.ejrh.2026.103481

Stigter, E. E., Wanders, N., Saloranta, T. M., Shea, J. M., Bierkens, M. F. P., & Immerzeel, W. W. (2017). Assimilation of snow cover and snow depth into a snow model to estimate snow water equivalent and snowmelt runoff in a Himalayan catchment. *The Cryosphere*, *11*(4), 1647–1664. https://doi.org/10.5194/tc-11-1647-2017

Sturm, M., Goldstein, M. A., & Parr, C. (2017). Water and life from snow: A trillion dollar science question. *Water Resources Research*, *53*(5), 3534–3544. https://doi.org/10.1002/2017WR020840

Sturm, M., & Liston, G. E. (2021). Revisiting the Global Seasonal Snow Classification: An Updated Dataset for Earth System Applications. *Journal of Hydrometeorology*. https://doi.org/10.1175/JHM-D-21-0070.1

Sun, L., Zhang, X., Wang, H., Xiao, P., & Wang, Y. (2024). Estimating Daily Snow Density Through a Spatiotemporal Random Forest Model. *Water Resources Research*, *60*(7), e2023WR036942. https://doi.org/10.1029/2023WR036942

Sun, Z., Ten Brink, T., Carande, W., Koren, G., Cristea, N., Jorgenson, C., Janga, B., Asamani, G. P., Achan, S., Mahoney, M., Huang, Q., Mehrabian, A., Munasinghe, T., Liu, Z., Margolis, A., Webley, P., Gong, B., Rao, Y., Burgess, A., … Duzgun, S. (2024). Towards practical artificial intelligence in Earth sciences. *Computational Geosciences*, *28*(6), 1305–1329. https://doi.org/10.1007/s10596-024-10317-7

https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.

Szwarcman, D., Roy, S., Fraccaro, P., Gíslason, Þ. E., Blumenstiel, B., Ghosal, R., Oliveira, P. H. de, Almeida, J. L. de S., Sedona, R., Kang, Y., Chakraborty, S., Wang, S., Gomes, C., Kumar, A., Truong, M., Godwin, D., Lee, H., Hsu, C.-Y., Asanjan, A. A., … Moreno, J. B. (2025). *Prithvi-EO-2.0: A Versatile Multi-Temporal Foundation Model for Earth Observation Applications* (arXiv:2412.02732). arXiv. https://doi.org/10.48550/arXiv.2412.02732

Tabari, H., Marofi, S., Abyaneh, H. Z., & Sharifi, M. R. (2010). Comparison of artificial neural network and combined models in estimating spatial distribution of snow depth and snow water equivalent in Samsami basin of Iran. *Neural Computing and Applications*, *19*(4), 625–635. https://doi.org/10.1007/s00521-009-0320-9

Tang, G., Wood, A. W., & Swenson, S. (2025). On Using AI-Based Large-Sample Emulators for Land/Hydrology Model Calibration and Regionalization. *Water Resources Research*, *61*(7), e2024WR039525. https://doi.org/10.1029/2024WR039525

Tanniru, S., & Ramsankaran, R. (2023a). Machine Learning-Based Estimation of High-Resolution Snow Depth in Alaska Using Passive Microwave Remote Sensing Data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *16*, 6007–6025. https://doi.org/10.1109/JSTARS.2023.3287410

Tanniru, S., & Ramsankaran, R. (2023b). Machine Learning-Based Estimation of High-Resolution Snow Depth in Alaska Using Passive Microwave Remote Sensing Data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *16*, 6007–6025. https://doi.org/10.1109/JSTARS.2023.3287410

Tanniru, S., Singh, D. K., Singh, K. K., & Ramsankaran, R. (2025). Exploring Machine Learning's Potential for Estimating High Resolution Daily Snow Depth in Western Himalaya Using Passive Microwave Remote Sensing Data Sets. *Earth and Space Science*, *12*(2), e2024EA003849. https://doi.org/10.1029/2024EA003849

Tarricone, J., Palomaki, R. T., Bonnell, R., Hoppinen, Z., Oveisgharan, S., Ruiz, J. J., Marshall, H., Deeb, E. J., Vuyovich, C., Margulis, S. A., Yueh, S., Forster, R. R., Webb, R. W., McGrath, D., Lemmetyinen, J., Elder, K., Shah, R., & Xu, X. (2026). Interferometric Synthetic Aperture Radar (InSAR) for Monitoring Seasonal Snow. *Water Resources Research*, *62*(9), e2025WR042866. https://doi.org/10.1029/2025WR042866

Tarricone, J., Webb, R. W., Marshall, H.-P., Nolin, A. W., & Meyer, F. J. (2023). Estimating snow accumulation and ablation with L-band interferometric synthetic aperture radar (InSAR). *The Cryosphere*, *17*(5), 1997–2019. https://doi.org/10.5194/tc-17-1997-2023

Taylor, L. S., Quincey, D. J., Smith, M. W., Baumhoer, C. A., McMillan, M., & Mansell, D. T. (2021). Remote sensing of the mountain cryosphere: Current capabilities and future opportunities for research. *Progress in Physical Geography: Earth and Environment*, *45*(6), 931–964. https://doi.org/10.1177/03091333211023690

Tedesco, M., & Narvekar, P. S. (2010). Assessment of the NASA AMSR-E SWE Product. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *3*(1), 141–159. https://doi.org/10.1109/JSTARS.2010.2040462

Tedesco, M., Pulliainen, J., Takala, M., Hallikainen, M., & Pampaloni, P. (2004). Artificial neural network-based techniques for the retrieval of SWE and snow depth from SSM/I data. *Remote Sensing of Environment*, *90*(1), 76–85. https://doi.org/10.1016/j.rse.2003.12.002

Thaler, E. A., Crumley, R. L., & Bennett, K. E. (2023). Estimating snow cover from high-resolution satellite imagery by thresholding blue wavelengths. *Remote Sensing of Environment*, *285*, 113403. https://doi.org/10.1016/j.rse.2022.113403

Tong, J. (2010). Testing snow water equivalent retrieval algorithms for passive microwave remote sensing in an alpine watershed of western Canada. *Canadian Journal of Remote Sensing*, *36*.

Tsang, L., Chen, Z., Oh, S., Marks, R. J., & Chang, A. T. C. (1992). Inversion of snow parameters from passive microwave remote sensing measurements by a neural network trained with a multiple scattering model. *IEEE Transactions on Geoscience and Remote Sensing*, *30*(5), 1015–1024. https://doi.org/10.1109/36.175336

Tsang, L., Durand, M., Derksen, C., Barros, A. P., Kang, D.-H., Lievens, H., Marshall, H.-P., Zhu, J., Johnson, J., King, J., Lemmetyinen, J., Sandells, M., Rutter, N., Siqueira, P., Nolin, A., Osmanoglu, B., Vuyovich, C., Kim, E., Taylor, D., … Xu, X. (2022). Review article: Global monitoring of snow water equivalent using high-frequency radar remote sensing. *The Cryosphere*, *16*(9), 3531–3573. https://doi.org/10.5194/tc-16-3531-2022

Varshney, D., Gupta, P. K., Persello, C., & Nikam, B. R. (2018). SNOW AND CLOUD DISCRIMINATION USING CONVOLUTIONAL NEURAL NETWORKS. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *IV–5*, 59–63. https://doi.org/10.5194/isprs-annals-IV-5-59-2018

Wang, G., Niu, S., Hao, X., Chu, X., Sun, X., Feng, T., Zhao, Q., Liang, S., & Li, H. (2025). Snow Depth Downscaling Retrieval Based on Spatial-Environment XGBoost Model: A Case Study of the Arid Region of Northwest China. *IEEE Transactions on Geoscience and Remote Sensing*, *63*, 1–15. https://doi.org/10.1109/TGRS.2025.3597950

https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.

Wang, J., Yuan, Q., Shen, H., Liu, T., Li, T., Yue, L., Shi, X., & Zhang, L. (2020). Estimating snow depth by combining satellite data and ground-based observations over Alaska: A deep learning approach. *Journal of Hydrology*, *585*, 124828. https://doi.org/10.1016/j.jhydrol.2020.124828

Wei, Y., Li, X., Gu, L., Zheng, X., & Jiang, T. (2023). A novel fine-resolution snow depth retrieval model to reveal detailed spatiotemporal patterns of snow cover in Northeast China. *International Journal of Digital Earth*, *16*(1), 1164–1185. https://doi.org/10.1080/17538947.2023.2196446

Wei, Y., Li, X., Gu, L., Zheng, X., Jiang, T., & Zheng, Z. (2022). A Fine-Resolution Snow Depth Retrieval Algorithm From Enhanced-Resolution Passive Microwave Brightness Temperature Using Machine Learning in Northeast China. *IEEE Geoscience and Remote Sensing Letters*, *19*, 1–5. https://doi.org/10.1109/LGRS.2022.3196135

Wei, Y., Li, X., Gu, L., Zheng, Z., Shi, Y., Li, Y., Zheng, X., & Jiang, T. (2026). Enhancing snow depth estimation in forested regions of the northern hemisphere: A physically-constrained machine learning approach with spatiotemporal dynamics. *ISPRS Journal of Photogrammetry and Remote Sensing*, *231*, 576–594. https://doi.org/10.1016/j.isprsjprs.2025.11.006

Wei, Y., Li, X., Gu, L., Zheng, Z., Zheng, X., & Jiang, T. (2025). Snow depth inversion and mapping at 500 m resolution from 1980 to 2020 in Northeast China using radiative transfer model and machine learning. *International Journal of Applied Earth Observation and Geoinformation*, *139*, 104533. https://doi.org/10.1016/j.jag.2025.104533

Wulder, M. A., White, J. C., Goward, S. N., Masek, J. G., Irons, J. R., Herold, M., Cohen, W. B., Loveland, T. R., & Woodcock, C. E. (2008). Landsat continuity: Issues and opportunities for land cover monitoring. *Remote Sensing of Environment*, *112*(3), 955–969. https://doi.org/10.1016/j.rse.2007.07.004

Xiao, X., Liang, S., He, T., Wu, D., Pei, C., & Gong, J. (2021). Estimating fractional snow cover from passive microwave brightness temperature data using MODIS snow cover product over North America. *The Cryosphere*, *15*(2), 835–861. https://doi.org/10.5194/tc-15-835-2021

Xiao, X., Zhang, T., Zhong, X., Shao, W., & Li, X. (2018). Support vector regression snow-depth retrieval algorithm using passive microwave remote sensing data. *Remote Sensing of Environment*, *210*, 48–64. https://doi.org/10.1016/j.rse.2018.03.008

Xu, J., Feng, M., Sui, Y., Su, Y., Zhang, X., Wu, Q., Hu, Z., & Wang, R. (2026). Enhancing lake identification in Alpine periglacial environments by leveraging the global context of transformers. *The Cryosphere*, *20*(5), 2851–2870. https://doi.org/10.5194/tc-20-2851-2026

Xue, Y., & Forman, B. A. (2015). Comparison of passive microwave brightness temperature prediction sensitivities over snow-covered land in North America using machine learning algorithms and the Advanced Microwave Scanning Radiometer. *Remote Sensing of Environment*, *170*, 153–165. https://doi.org/10.1016/j.rse.2015.09.009

Yan, Y., Qin, Y., Liu, Y., Qiu, Y., & Liu, Y. (2025). Estimation of Moderate-Resolution Snow Depth in Xinjiang With Enhanced-Resolution Passive Microwave and Reanalysis Data by Machine Learning Methods. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *18*, 11250–11262. https://doi.org/10.1109/JSTARS.2025.3562216

Yang, J., Jiang, L., Luojus, K., Pan, J., Lemmetyinen, J., Takala, M., & Wu, S. (2020). Snow depth estimation and historical data reconstruction over China based on a random forest machine learning approach. *The Cryosphere*, *14*(6), 1763–1778. https://doi.org/10.5194/tc-14-1763-2020

Yang, K., John, A., Shean, D., Lundquist, J. D., Sun, Z., Yao, F., Todoran, S., & Cristea, N. (2023). High-resolution mapping of snow cover in montane meadows and forests using Planet imagery and machine learning. *Frontiers in Water*, *5*, 1128758. https://doi.org/10.3389/frwa.2023.1128758

Yang, K., Musselman, K. N., Rittger, K., Margulis, S. A., Painter, T. H., & Molotch, N. P. (2022). Combining ground-based and remotely sensed snow data in a linear regression model for real-time estimation of snow water equivalent. *Advances in Water Resources*, *160*, 104075. https://doi.org/10.1016/j.advwatres.2021.104075

Yang, K., Painter, T. H., Deems, J. S., & Molotch, N. P. (2025). Bias correction for near-real-time estimation of snow water equivalent using machine learning algorithms: A case study in the Tuolumne River basin, California. *Remote Sensing of Environment*, *323*, 114693. https://doi.org/10.1016/j.rse.2025.114693

Yatheendradas, S., & Kumar, S. (2022). A Novel Machine Learning–Based Gap-Filling of Fine-Resolution Remotely Sensed Snow Cover Fraction Data by Combining Downscaling and Regression. *Journal of Hydrometeorology*, *23*(5), 637–658. https://doi.org/10.1175/jhm-d-20-0111.1

Yin, M., Wang, P., Ni, C., & Hao, W. (2022). Cloud and snow detection of remote sensing images based on improved Unet3+. *Scientific Reports*, *12*(1), 14415. https://doi.org/10.1038/s41598-022-18812-6

Ying, J. J., Yang, J. W., Jiang, L. M., Pan, J. M., Zhang, C., Xiong, C., & Shi, J. C. (2025). Evaluation of the Sentinel-1 SAR-based snow depth product over the Northern Hemisphere. *Journal of Hydrology*, *661*, 133593. https://doi.org/10.1016/j.jhydrol.2025.133593

https://doi.org/10.5194/egusphere-2026-5868
Preprint. Discussion started: 6 November 2026
© Author(s) 2026. CC BY 4.0 License.



Yu, G., Gu, L., Li, X., & Fan, X. (2024). Forest Snow Depth Estimation Based on Optimized Features and DNN Network Using C-Band SAR Data. *IEEE Geoscience and Remote Sensing Letters*, *21*, 1–5. https://doi.org/10.1109/LGRS.2024.3379202

Yu, X., Hu, X., Wang, G., Wang, K., & Chen, X. (2022). Machine-Learning Estimation of Snow Depth in 2021 Texas Statewide Winter Storm Using SAR Imagery. *Geophysical Research Letters*, *49*(17), e2022GL099119. https://doi.org/10.1029/2022GL099119

Zaerpour, A., Adib, A., & Motamedi, A. (2020). Snow depth retrieval from passive microwave imagery using different artificial neural networks. *Arabian Journal of Geosciences*, *13*(15), 696. https://doi.org/10.1007/s12517-020-05642-x

Zhang, C., Jiang, L., Pan, J., Yang, J., Wang, J., & Jin, Z. (2026). Daily seamless 30-m fractional snow cover mapping via an adaptive Time-Series approach. *International Journal of Applied Earth Observation and Geoinformation*, *146*, 105068. https://doi.org/10.1016/j.jag.2025.105068

Zhang, J., Pohjola, V. A., Pettersson, R., Norell, B., Marchand, W.-D., Clemenzi, I., & Gustafsson, D. (2021). Improving the snowpack monitoring in the mountainous areas of Sweden from space: A machine learning approach. *Environmental Research Letters*, *16*(8), 084007. https://doi.org/10.1088/1748-9326/abfe8d

Zhao, T., Wang, S., Ouyang, C., Chen, M., Liu, C., Zhang, J., Yu, L., Wang, F., Xie, Y., Li, J., Wang, F., Grunwald, S., Wong, B. M., Zhang, F., Qian, Z., Xu, Y., Yu, C., Han, W., Sun, T., … Wang, L. (2024). Artificial intelligence for geoscience: Progress, challenges, and perspectives. *The Innovation*, *5*(5), 100691. https://doi.org/10.1016/j.xinn.2024.100691

Zhao, Y., Yang, X., & Vatsavai, R. R. (2021). A Scalable System for Searching Large-scale Multi-sensor Remote Sensing Image Collections. *2021 IEEE International Conference on Big Data (Big Data)*, 3780–3783. https://doi.org/10.1109/BigData52589.2021.9671679

Zheng, K., Li, J., Ding, L., Yang, J., Zhang, X., & Zhang, X. (2021). Cloud and Snow Segmentation in Satellite Images Using an Encoder–Decoder Deep Convolutional Neural Networks. *ISPRS International Journal of Geo-Information*, *10*(7), 462. https://doi.org/10.3390/ijgi10070462

Zhu, X. X., Tuia, D., Mou, L., Xia, G.-S., Zhang, L., Xu, F., & Fraundorfer, F. (2017). Deep Learning in Remote Sensing: A Comprehensive Review and List of Resources. *IEEE Geoscience and Remote Sensing Magazine*, *5*(4), 8–36. https://doi.org/10.1109/MGRS.2017.2762307