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Review article: A decadal review (2015–2025) of machine learning models applied for satellite-based snow depth retrieval

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Abstract. Ongoing climate warming is impacting the frequency and magnitude of extreme weather. The high sensitivity of snow to changes in temperature and precipitation makes it a primary indicator of climate change. Previous studies have proven that the snow cover extent has decreased with rapid warming. Nevertheless, this remains controversial, and no solid conclusion has been reached regarding snow depth changes. Numerous remote sensing-based approaches have been used to derive spatially continuous snow depth. However, challenges remain in capturing and understanding the spatial variability of snow depth because of the non-linear and so-called 'ill-posed' problems associated with inversion framework. Machine learning (ML) techniques (including deep learning) are beginning to play important roles in advancing snow depth retrieval with microwave remote sensing, owing to their strong ability to fit nonlinear, nonexplicit functional relationships between snow depth and massive amounts of geoscience data. However, a systematic review of ML applications in snow depth retrieval with remote sensing is notably absent from the literature, and the trajectory for future advancements remains ambiguous. This review comprehensively summarizes the implementation and progress of snow depth research using microwave remote sensing over the last decade (2015–2025), and analyzes current research directions and areas where further developments are needed. An analysis of the literature reveals that the number of ML-related articles has increased over the past 10 years, rising from 3 to 33. By first-author affiliation, China and the United States lead in terms of contributions, accounting for almost 70% of papers. We also found that western countries are actively engaged in high-resolution snow depth retrieval (ranging from meter to hundreds of metres) at regional or catchment scales (especially over mountains), which is attributed to their dense and comprehensive ground-based and airborne field campaigns (e.g., SnowEx, NoSREx, and ASO Lidar etc.). While China focuses on snow depth retrieval at the global scale or regional scales, typically at a coarse spatial resolution (10 or 25 km) or spatial downscaling (1 km or 500 m). Our decadal review concludes with five existing paradigms, namely, the coupling of ML and

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snow physical model (snow electromagnetic model or process model); developing snow electromagnetic models for simulating microwave signals in assimilation or iteration algorithms; optimizing snow electromagnetic models by providing key inputs or accelerating operational efficiency; improving existing gridded snow depth products by data fusion, bias correction or assembly techniques; and downscaling coarse snow depth products to a fine-scale resolution. However, some challenges and unresolved issues still exist. Our future efforts should aim to bridge the disparity in model–observation mismatch, integrate fundamental physical laws into ML structures, enhance the quality of ML training samples, and improve snow depth estimates under complex conditions (e.g., in mountainous and polar regions and during the snowmelt season). This paper provides a comprehensive review of the applications of ML techniques in snow depth remote sensing, focusing on current paradigms, existing challenges, and potential future research directions. We believe that ML techniques hold significant potential for addressing the challenges associated with the quantitative inversion of snow depth and deepening our understanding of the spatial variability of the snowpack globally.

1 Introduction

The cryosphere is the most direct and sensitive sphere in the climate system (Hock et al., 2019). Snow cover plays a critical role in the rapid change in the cryosphere because of its high reflectivity, low thermal conductivity, seasonal variation and the large geographic extent of the cryosphere components (Aguirre et al., 2018). Moreover, the snowpack is an important natural freshwater reservoir that impacts agricultural irrigation, domestic water supply, and ecological systems (Barnett et al., 2005; Sturm et al., 2017; Vano et al., 2020). Additionally, snow-related disasters are among the most serious and widespread hazards and threaten livelihoods, settlements, infrastructure, and the environment (Gao et al., 2016; Eckert et al.,2024). Therefore, monitoring spatiotemporal changes in snow cover is needed for water resource management, climate change monitoring, and disaster prevention and mitigation. In particular, snow depth and snow water equivalent (SWE) are crucial parameters for quantitatively assessing snow mass.

Microwave remote sensing is a valid tool for retrieving snow depth, as the physical properties of a snowpack modulate the emissions from the underlying substrate and the backscattering from volume scattering. This enables snow property retrievals using the brightness temperature observed by passive microwave (PM) sensors or backscattering coefficient observed by active microwave (AM) sensors. Numerous snow depth retrieval algorithms based on microwave remote sensing techniques have been developed, such as the semi-empirical operational algorithms (Kelly, 2009; Rott et al., 2012; Jiang et al., 2014; Tedesco and Jeyaratnam, 2016; Lievens et al., 2019, 2022; Yang et al., 2019, 2024), radiative transfer model (RTM)-based iterative approaches (Takala et al., 2011; Dai et al., 2012; Che et al., 2016), RTM-parameterized retrieval methods (Jiang et al., 2007, 2011; Yueh et al., 2009; Cui et al., 2016; Lemmetyinen et al., 2018; King et al., 2018; Zhu and Tan et al., 2018, 2021), and machine learning (ML)-based methods (Bair et al., 2018; Xiao et al., 2018; Yang et al., 2020, 2021; Pan et al., 2023). For conventional semi-empirical algorithms, the basic assumption is a linear relationship between snow depth and microwave signals at different frequencies (Chang et al., 1987). However, the microwave signal is typically a function of several other

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parameters, e.g., snow density, snow grain size, and soil/vegetation conditions. Thus, the relationship between snow depth and microwave signals is complex and nonlinear. Model-driven methods (RTM-iterative and RTM-parameterized retrieval approaches) can be used to describe key processes and snow-signal interactions, providing robust explanations relative to the semi-empirical methods (Jiang et al., 2007; Takala et al., 2011; Che et al., 2016; Zhu et al., 2021). However, several challenges limit their application in retrieving snow depth at a large scale.

One limitation is the computational efficiency of forward microwave models. RTM typically require a snow electromagnetic model to represent snow microstructure, calculate extinction coefficient and scattering-phase matrices, and simulate microwave signals; thus, analytical and numerical solution models are highly costly and inefficient. Moreover, a cost function is necessary to iteratively search for optimal snow depth estimates with RTM models (Takala et al., 2011; Proksch et al., 2015; Thompson and Kelly, 2021). To improve its computational efficiency, numerous researchers have attempted to solve this problem by generating lookup tables (Xu et al., 2012; Dai et al., 2012; Che et al., 2016), parameterizing the RTM equations (Shi et al., 2000; Jiang et al., 2007; Du et al., 2010; Cui et al., 2016; Zhu and Tan et al., 2018, 2021), establishing regression formulas for scattering-phase matrices versus snow parameters with ML approaches (Liu et al., 2024; de Gélis et al., 2025; Du et al., 2025; Li et al., 2026), and even substituting RTM with ML model to simulate microwave signals (Xue et al., 2015, 2018; Forman et al., 2015, 2016; Ahmad et al., 2019; Kwon et al., 2019). Another limitation of the Model-driven method is its dependence on prior information, as snow volume scattering is affected by snow depth, density, snow microstructure, and layering structure. However, snow characteristics, particularly snow grain size or exponential correlation length, are difficult to derive at a large scale. Thus, limited snow prior information increases the risk of constraining the retrieval problem.

The most challenging issue with Model-driven methods is observation–model mismatch, which is caused by ambiguous electromagnetic radiation processes and insurmountable scale effects. Typically, the microstructure parameters (e.g., the geometric grain size, the optical diameter of the grain size, and the exponential correlation length) must be scaled to effective values to better match the simulated and observed microwave signals (Royer et al., 2017; Vargel et al., 2020; Xiong et al., 2022a). For example, Royer et al. (2017) compared four commonly used microwave RTMs to simulate snow brightness temperature and reported that a model-specific scaling factor for grain size must be used to match ground-based radiometric measurements. Xiong et al. (2022a) validated active DMRT-QCA and DMRT-Bic models using ground-based radar observations and reported that a scaling factor for the geometric grain size is necessary for simulating backscattering. Previous studies have even shown that the scaling factor exhibits spatiotemporal variations because of differences in snow characteristics and sensor configurations. For example, Lemmetyinen et al. (2016) applied seasonally varying scaling factors (four seasons, 0.9~1.25) to adjust the correlation length for the MEMLS model. Vargel et al. (2020) applied frequency-varying scaling factors to match model simulations and observations. Therefore, the mismatch between RTM simulations and satellite observations limits the applications of model-driven snow depth retrieval methods at a large scale.

ML has been applied in snow communities for more than 30 years. The potential of artificial neural networks (ANN) in retrieving snow parameters was first explored on the basis of the DMRT simulations by Chang & Tang et al. (1992) and Tsang et al. (1992). An ANN-based model was subsequently developed to determine snow grain size, snow density, snow temperature

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and snow depth (Davis et al., 1993). Early satellite applications involving ANN for snow depth retrieval were explored by Chen et al. (2001) and Guo et al. (2003). They innovatively introduced a snow hydrology model and a dense media RTM to constrain ANN and iteratively computed the optimal snow depth by minimizing ANN simulations and special sensor microwave imager (SSM/I) observations. By 2003, ANN models were generally trained with simulations from snow hydrology models or snow RTMs. Tedesco et al. (2004) further compared ANN models trained with model-simulated and field-observed data and reported that an ANN trained with in-situ measurements performed better. A new ANN algorithm trained with seven-channel SSM/I brightness temperature data and geostatistics (e.g., temperatures from stations) was subsequently proposed for snow depth retrieval in Quebec, Canada (Evora et al., 2008). As AMSR-E observations have become increasingly available, scholars have compared ANN models trained with AMSR-E and SSM/I observations, finding that AMSR-E-based ANN perform much better owing to their two additional low frequencies of 6.925 and 10.65 GHz and higher native spatial resolution compared with those of SSM/I outputs (Gan., et al., 2009; Tong et al., 2010). An ANN retrieval algorithm designed for hydrological purposes (called HydroAlgo) was subsequently developed for global snow depth retrieval from AMSR-E acquisitions (Santi et al., 2012, 2014).

Since 2015, in the context of assimilation, the snow community has attempted to simulate microwave brightness temperature using ML models and has explored its sensitivity to snow depth (Xue et al., 2015; Forman et al., 2015, 2016; Kwon et al., 2019; Ahmad et al., 2019). ML models have subsequently been used as observation operators for radiance assimilation frameworks to assimilate brightness temperature observations or snow cover data into land surface models (Xue et al., 2018; Hou et al., 2021; Wang et al., 2021; Park et al., 2021; Cui et al., 2023). Moreover, ML methods have spread to various application areas, such as estimating the microscopic parameters of snow (Tedesco et al., 2016; Broxton et al., 2019; Meehan et al., 2024; Yang et al., 2024a), retrieving snow depth or SWE (Xiao et al., 2018; Bair et al., 2018; Wang et al., 2020; Yang et al., 2019, 2021, 2022; Santi et al., 2022a, 2022b; Xu et al., 2022; Li et al., 2022; Xiong et al., 2022b; Gao et al., 2023; Pan et al., 2023; Geissler et al., 2023; Ni et al., 2024; Steele et al., 2024; Ke et al., 2024; Dunmire et al., 2024), downscaling gridded snow depth products to finer scales (Zhu et al., 2021; Shrestha et al., 2021; Xing et al., 2022; Wei et al., 2022a, 2022b; 2023; Tanniru and Ramsankaran, 2023; Daudt et al., 2023; Moradizadeh et al., 2023; Gu et al., 2024; Zhao et al., 2024; Liu et al., 2025), fusing multisource snow depth data to improve snow depth estimates (Snauffer et al., 2018; Hou et al., 2019; King et al., 2020; Hu et al., 2021; Shao et al., 2022; Mantsis et al., 2022; Sun et al., 2024; Song et al., 2024), and conducting bias correction for snow depth product (King et al., 2020; Broxton et al., 2024; Yang et al., 2025; Goodarzi et al., 2025; Bai et al., 2025; Stachura et al., 2026). Undeniably, ML techniques have demonstrated tremendous success in the field of snow depth monitoring and have improved our understanding of the spatiotemporal characteristics of snow cover.

However, ML techniques still face several challenges in retrieving global snow depth. Numerous studies have proven that ML models are robust enough to predict stationary spatial elements in the Earth system, e.g., soil types, soil properties, and minerals (Reichstein et al., 2019; Shirmard et al., 2022; Zhao and Wang et al., 2024). However, the Earth system is not static but instead complex and dynamic. In particular, snow is a highly dynamic element of the Earth system. Temporally, snow begins to accumulate in autumn, continues to accumulate throughout the winter, and finally melts (ablates) in spring or summer. Spatially,

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it has different spatial patterns in various regions, such as deep snow in cold climate regions, at high latitudes or at high altitudes. Especially in mountainous regions, topographic features (e.g., elevation, slope, and aspect) are crucial for characterizing snow cover (Dozier et al., 2016; Ma et al., 2023). Moreover, snow cover is redistributed by wind, tree cover and avalanches, complicating snow heterogeneity (Quéno et al., 2024; Eckert et al., 2024). Additionally, owing to snow metamorphism, the compaction and restructuring of snow crystals lead to changes in their size, shape and bonds, greatly affecting their microwave scattering characteristics (Tsang et al., 2022). Thus, temporally and spatially dynamic snow characteristics still limit the use of ML in snow depth retrieval.

Since 2021, some physics-guided ML approaches have demonstrated promise for monitoring dynamic snow cover. For example, Yang et al. (2021) first proposed a method that couples the ML technique (random forest, RF) and snow RTM to improve snow depth retrieval with PM remote sensing. In this methodology, the Helsinki University of Technology (HUT) model was used to optimize the effective snow grain size by minimizing the simulations and satellite observations, and then, together with other predictor variables, the results were applied to fit an ML retrieval algorithm. The inclusion of the effective grain size enhanced the spatial transferability and robustness of the ML models. Subsequently, Pan and Yang et al. (2023) applied a snow process model (SNTHERM) to replace RTM for simulating snow parameters (e.g., snow grain size, snow density, and first-guess snow depth) and then combined it with the PM brightness temperature to train an RF model, they reported that the proposed method significantly reduced snow depth underestimation in mountain areas. Since then, coupling snow physical models and ML techniques has become one of the dominant research areas (Gao et al., 2023; Yang et al., 2024; Wei et al., 2025; Zhao et al., 2025; Chen et al., 2025a). Moreover, some physics‑informed hybrid ML models used in hydrology have been explored and further developed (Steele et al., 2024; Crumley et al., 2024; Pomarol Moya et al., 2025; Du et al., 2025; Li and Xiong, 2026). Previous studies consistently indicated that hybrid approaches (coupling RTM or process model with ML) can yield more accurate snowpack characterizations than either physical snow models or ML alone.

Despite these developments, to date, a systematic review of ML applications involving snow depth retrieval with remote sensing is notably absent from the literature. This review aims to offer a comprehensive overview of current ML applications for snow depth retrieval from 2015 to 2025; summarize the main directions for improving snow depth research to highlight exciting developments that have been made; and most importantly, define key challenges or gaps and propose possible strategies for advancing research in this promising direction. To our knowledge, this is the first comprehensive review focusing on ML models for snow depth monitoring with microwave remote sensing.

2 Overview of published articles from 2015–2025

The selection of the analysed publications is based on Science Citation Index (SCI) papers in the Web of Science (WoS) database. The search criteria are TS = ((machine learning OR deep learning OR AI OR data-driven) AND (snow depth OR snow water equivalent OR SWE OR snow thickness OR snow mass))) AND DOP = (2015-01-01/2025-12-31) AND English (Languages))). Based on the above search criteria, 295 publications were identified. To ensure that only publications focusing

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on either SWE or snow depth with remote sensing techniques were included in the review, we then manually filtered the search results. After manual filtering, 127 publications remained in the review pool for quantitative analysis of publication metrics

2.1 Timeline of ML for snow depth retrieval from 2015–2025

The number of SCI articles published yearly from 2015 to 2025 are shown in Fig.1. Obviously, the number of related articles has gradually increased over the past decade. Essentially, the 'time-node' year is 2020, when more than 5 papers were first published. Since 2020, artificial intelligence (AI), especially the emergence of modularized ML techniques (e.g., Transformer in 2017) and the development of large models (e.g., GPT-2 from OpenAI in 2019 and GPT-3 in 2020), has entered a phase of rapid development, inspiring more snow-focused remote sensing communities to attempt to retrieve snow depth or SWE using ML techniques.

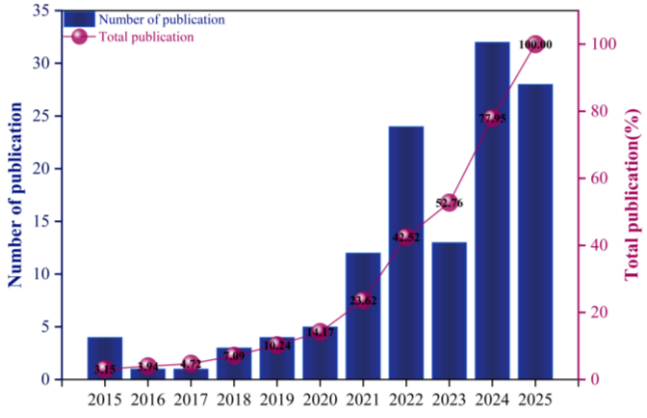

Figure 1: Yearly publications during the period of 2015–2025.

The key milestones of snow depth retrieval with ML techniques during the past decade are shown in Fig.2. Initially, the ML approaches (e.g., ANN and SVM) were applied to simulate microwave brightness temperature coupled with land surface model outputs (Fig.2), after which the sensitivity of brightness temperature simulations to snow depth was explored (Xue, et al., 2015; Forman, et al., 2015, 2017). Their studies revealed that the ML-simulated brightness temperature is sensitive to snow depth and could potentially serve as a more efficient and effective model operator within the data assimilation frameworks (Xue et al., 2018; Kwon et al., 2019). Subsequently, more communities have focused on developing snow depth retrieval algorithms based on ML techniques, by combining the PM remote sensing data and other auxiliary data (Fig.2), e.g., the SVR (Xiao et al., 2018) and the RF (Bair et al., 2018).

Owing to the influence of snow metamorphism on microwave volume scattering, snow depth retrieval with microwave remote sensing is challenging. A recent trend is the combination of ML with physical models. Yang et al. (2021) first proposed a paradigm that couples a snow RTM with the ML approach to improve snow depth estimation (Fig.2). Santi et al. (2022a) applied the DMRT simulations (microwave backscattering information from at the X/Ku-band and snow parameters) to train an ANN model and then retrieved snow depth (Fig.2). The results revealed that the DMRT-trained ML model performed well

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in terms of snow depth overprediction across a field experimental site. Pan et al. (2023) tested the combination of a snow process model and an ML technique, in which a snow process model (SNTHERM) was applied to simulate snow grain size and snow density, and to first assess snow depth as prior information for the RF model; the authors reported that the proposed method significantly reduced the snow depth underestimation in mountain areas (Fig.2).

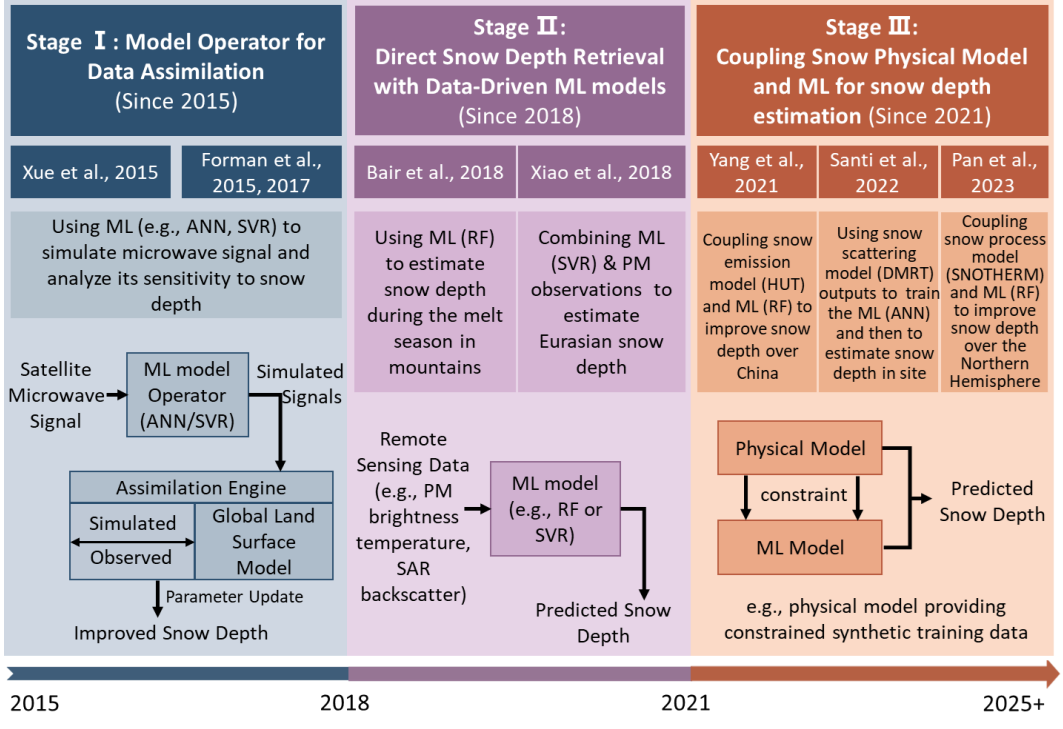

Figure 2: Key milestones in snow depth retrieval with ML techniques during the past decade.

2.2 Main countries and journals of published articles from 2015–2025

A summary of the geographic distribution (according to first author affiliation) of published articles is shown in Fig.3a. China and the United States are the dominant contributors, together accounting for almost 70% of the papers, followed by Iran, Canada, Italy and Germany, Morocco, India, Switzerland, Norway, and Belgium. The publication distribution from 2015 to 2025 is shown in Fig.3b. The top six journals are *RS*, *WRR*, *TC*, *JH*, *RSE* and *IEEE TGRS*. Publications in the *RS* journal involve snow depth retrieval (Kwon et al., 2019; Mei and Maksym, 2020; Yang et al., 2022; Xing et al., 2022; Dong et al., 2022), spatial downscaling (Zhu et al., 2021; Wei et al., 2022; Wang et al., 2023; Zhao et al., 2024) and data fusion (Hou et al., 2019; Hu et al., 2021; Xiao et al., 2021). Publications in *WRR* mainly focus on improving the predictions of hydrological models by enhancing the snow depth distribution at a fine resolution in mountain basins, such as in the mountains over the western US (Oroza et al., 2016; Broxton et al., 2019; Xue et al., 2018; Crumley et al., 2024; Breen et al., 2024; Duan et al., 2024; He et al., 2024), the Altai Mountains over China (Hou et al., 2021), and the Alptal valley over Switzerland (Geissler et al., 2023). Publications in *JH* mainly focus on improving snow depth by merging multisource snow depth datasets, such as

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those from GlobSnow, ERA-Interim, ERA5-Land, and GLDAS at 25 km (Sun et al., 2024); reconstructing SNODAS reanalysis data at 1 km (Cui et al., 2023); extrapolating point-based snow depth for spatiotemporally continuous mapping (Buckingham et al., 2015; Guidicelli et al., 2024); enhancing snowfall forecasts at 4 km by integrating the ML techniques with the Weather Research and Forecasting (WRF) model (Khaira et al., 2024); and retrieving snow depth by using Lidar data at 1 m (Cho et al., 2021), GNSS-R measurements at 25 km (Wang et al., 2020), Sentinel-1 SAR observations at 500 m (Ni et al., 2024), and FY-3 observations at 12.5 km (Ke et al., 2024). Publications in *TC* include snow depth retrieval (Bair et al., 2018; Yang et al., 2020; Meehan et al., 2024), data checks for the quality of network measurements (Blandini et al., 2023), and the determination of representative sampling sites in remote mountainous areas (Bachand et al., 2025). Publications in *RSE* focus on the methodology for retrieving snow depth using satellite passive (Xue et al., 2015; Xiao et al., 2018; Yang et al., 2021; Gao et al., 2023) and active (Dunmire et al., 2024) remote sensing. Publications in *IEEE TGRS* are mainly from Italy and China. Italian scholars tend to develop snow depth retrieval methods using active SAR observations (tens of meters) at the X- and Ku-band in alpine areas (Santi et al., 2022a, 2022b), an approach aligning with their dense field campaigns and the launch of the COSMO-SkyMed satellite. Chinese scholars prefer to use satellite passive radiometer (tens of kilometers) to map global snow depth (Xu et al., 2022; Pan et al., 2023; Yang et al., 2024; Wang et al., 2025).

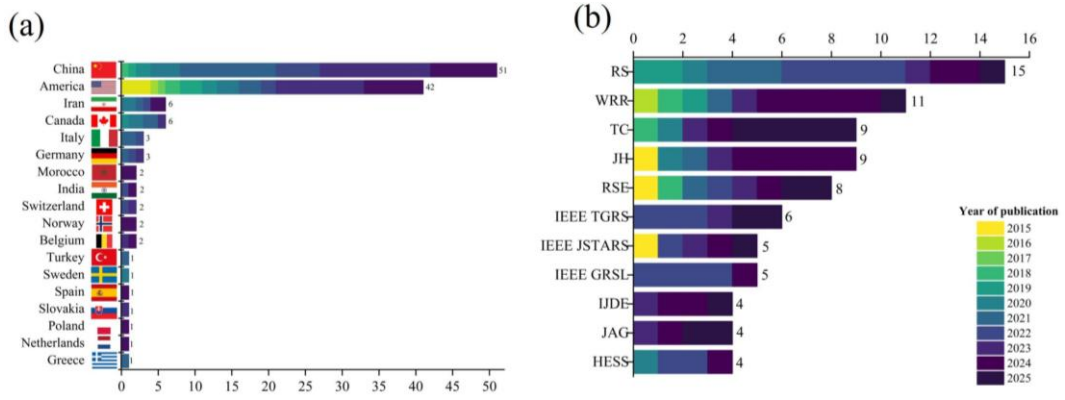

Figure 3: Main (a) countries and (b) journals of published articles from 2015–2025. RS: *Remote Sensing*; WRR: *Water Resources Research*; TC: *The Cryosphere*; JH: *Journal of Hydrology*; RSE: *Remote Sensing of Environment*; IEEE TGRS: *IEEE Transactions on Geoscience and Remote Sensing*; IEEE JSTARS: *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*; IEEE GRSL: *IEEE Geoscience and Remote Sensing Letters*; IJDE: *International Journal of Digital Earth*; JAG: *International Journal of Applied Earth Observation and Geoinformation*; HESS: *Hydrology and Earth System Sciences*.

2.3 Spatial resolution and source of target predictors in snow depth retrieval

The spatial resolution levels applied in snow depth retrieval, ranging from coarse (tens of kilometers) to fine (metres and even points) scales, are shown in Fig.4a. Almost 24% of studies focused on snow depth retrieval at the tens of kilometers level, benefitting from the rich and long-term satellite PM remote sensing data, e.g., SSM/I and SSMIS (Forman et al., 2016; Xiao et al., 2018; Wang et al., 2020; Adib et al., 2021b; Xu et al., 2022), AMSR-E and AMSR2 (Xue et al., 2018; Ahmad et al., 2019; Kwon et al., 2019; Yang et al., 2021; 2022; Xiong et al., 2022b; Li et al., 2022; Dong et al., 2022; Pan et al., 2023; Gao et al., 2023; Hou et al., 2024; Wang et al., 2025), and FY-3/MWRI (Yan et al., 2024; Ke et al., 2024; Yang et al., 2024) data.

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At the kilometre level, the related publications include spatial downscaling based on PMW data (Bair et al., 2018; Tanniru and Ramsankaran, 2023; Moradizadeh et al., 2023), snow depth retrieval based on high-resolution SAR (Yu et al., 2022) or MEaSUREs enhanced-resolution PM data (Wei et al., 2022a, 2023, 2025; Liu et al., 2024) and data fusion with SNODAS (King et al., 2020), Sentinel-1 product (Mantsis et al., 2022), and reanalysis data (Cui et al., 2023). At the hundreds of meters level, it mainly involves spatial downscaling based on PM data (Zhang et al., 2021; Zhu et al., 2021; Xing et al., 2022; Wei et al., 2022b; Gu et al., 2024; Bai et al., 2024; Tanniru et al., 2025) and snow cover products (Hou et al., 2021; Zhu et al., 2021; Xiong et al., 2022b; Wang et al., 2023; Elyoussfi et al., 2025) and snow depth retrieval using SAR data (Dunmire et al., 2024; Zhao et al., 2024) have been the main research trends. Almost 10% of researchers have applied airborne (Santi et al., 2022a, 2022b) or spaceborne (Zhu et al., 2022; Daudt et al., 2023; Yu et al., 2024) SAR data to derive snow depth at a resolution of tens of meters. Terrestrial and airborne applications involving Lidar (Broxton et al., 2019; Mei and Maksym, 2020; Douglas et al., 2021; Cho et al., 2021; Cartwright et al., 2021; Geissler et al., 2023; Betato et al., 2025), ground-penetrating radar (GPR) (Meehan et al., 2024), InSAR (Alabi et al., 2025), and photogrammetry (Daudt et al., 2023) have been explored to estimate snow depth at the metre level at catchment scales. The data in Fig.4a also show that 16% of studies involved ground- and airborne-based GPR radar (Holt et al., 2015) and Lidar (Oroza et al., 2016; Broxton et al., 2019; Cho et al., 2021; Geissler et al., 2023; Meehan et al., 2024) observations, which were used to retrieve snow depth at the submeter level.

The source of the target predictor for ML methods is shown in Fig.4b. The most commonly used target samples mainly rely on in situ snow depth measurements (e.g., Xiao et al., 2018; Yang et al., 2020, 2021; Xu et al., 2022; Hu et al., 2022; Pan et al., 2023; Gao et al., 2023; Blandini et al., 2023; Crumley et al., 2024; Gu et al., 2024; Hou et al., 2024; Sun et al., 2024; Umirbekov et al., 2024; Duan et al., 2024; Bai et al., 2025; Wang et al., 2025). To improve the representativeness of target samples, many novel observation techniques have been used to provide reliable snow depth data, such as GNSS-R (Wang et al., 2020), airborne Lidar/GPR/photogrammetry (Oroza et al., 2016; Mei and Maksym, 2020; Cho et al., 2021; Cartwright et al., 2021; Daudt et al., 2023; Hojatimalekshah et al., 2023; Dunmire et al., 2024; Liljestrand et al., 2024; Meehan et al., 2024; Alabi et al., 2025; Betato et al., 2025; Chen et al., 2025b; Feng et al., 2025), radar (Varshney et al., 2021), and GPS (Altuntas et al., 2022). Many model-based simulations also involve ML training, e.g., the land surface model (Shrestha et al., 2021; Santi et al., 2022a; Yao et al., 2022; Singh et al., 2024), snow emission model (Santi et al., 2022b), and snow process model (Pan et al., 2023; Li et al., 2024; Singh et al., 2024). Recently, many snow depth products have also been used to provide reliable target samples for ML model in specific areas, such as GlobSnow (Kraft et al., 2022), monthly mean AMSR2 (Moradizadeh et al., 2023), Sentinel-1 C-snow (Xiong et al., 2022b; Yang et al., 2024), AMSR2-ML (Li et al., 2024), and reanalysis data (Ma et al., 2023; Cui et al., 2023; Khaira et al., 2024). Recent trends include the combination of multisource training samples for ML training, such as combining the station and RTM simulations (Santi et al., 2022a), station and airborne Lidar/GNSS/photogrammetry data (Broxton et al., 2019; Wang et al., 2020; Dunmire et al., 2024; Liljestrand et al., 2024, 2025), and satellite and airborne photogrammetry data (Daudt et al., 2023).

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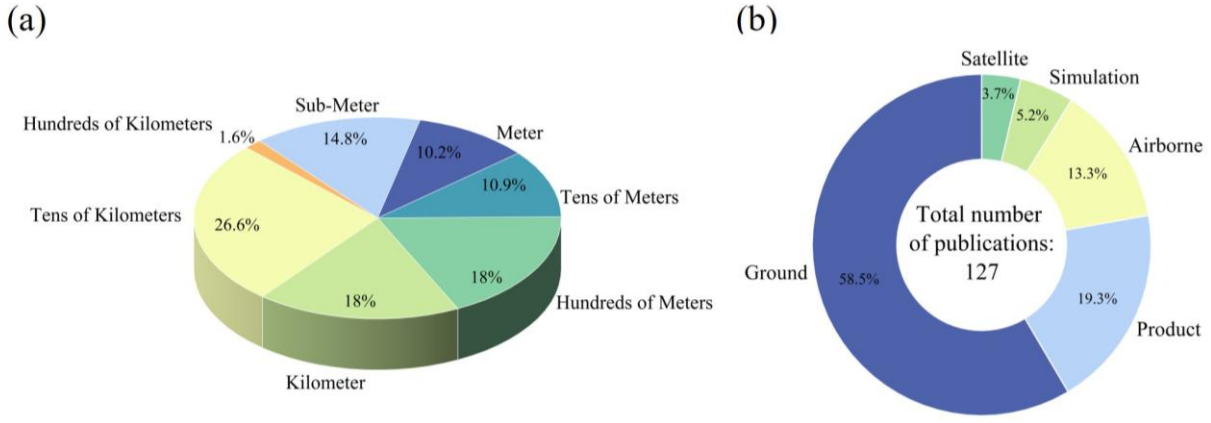

Figure 4: (a) Spatial scale for snow depth retrieval and (b) the source of the target snow depth for training ML model.

The relationships among the countries (according to first author affiliation), studied regions, and spatial resolution of publications are shown in Fig.5. Most studies from China have been conducted at regional (Northeast China, Northern Xinjiang, and Tibetan Plateau, Arctic and Antarctic), country (China), and Northern Hemisphere scales with low spatial resolutions (6.25km, 12.5km and 25km). Researchers in the United States have focused mainly on regional and catchment scales, e.g., the mountains of North America, high-mountain Asia, and frozen soil and glacier areas (Alaska, Arctic and Antarctic). In the United States, snow depth tends to be estimated at fine spatial resolutions (mostly below 1 km) by combining land surface model, satellite observations and densely sampled field data (especially the data obtained with airborne instruments, e.g., Lidar, SAR, and GPR). Researchers in Canada, Iran and Germany have focused on improving the snow depth estimates in mountain basins, for example, by conducting bias correctio for reanalysis products or ground-based data using ML techniques (King et al., 2020; Umirbekov et al., 2024; Stachura et al., 2026), extending the spatial-temporal continuity of ground-based measurements (Cartwright et al., 2021; Geissler et al., 2023) and developing the hydrological forecasting model (Adib et al., 2021a; Kraft et al., 2022; Shrestha et al., 2022; Vafakhah et al., 2022; Arnal et al., 2024). Publications from Italy focus on developing snow depth retrieval algorithms based on active SAR remote sensing (typically at the X- and Ku-band) in alpine areas (Santi et al., 2022a, 2022b). ML methods have commonly been applied in India to retrieve high-resolution snow depth, such as those in Alaska (Tanniru et al., 2023) and the Himalayas (Tanniru et al., 2025) using PM (AMSR2) and optical (MODIS) remote sensing observations. Since Lievens et al. (2019) demonstrated the sensitivity of C-band backscattering information at cross-polarization to mountainous snow depth, some countries , e.g. Switzerland (Daudt et al., 2023), Belgium (Dunmire et al., 2024; Boeykens et al., 2025), the USA (Broxton et al., 2024), India (Prabhat et al., 2026) and China (Yu et al., 2024; Ni et al., 2024; Cui et al., 2025), have raised concerns about the use of the C-band in the estimation of snow depth using ML methods.

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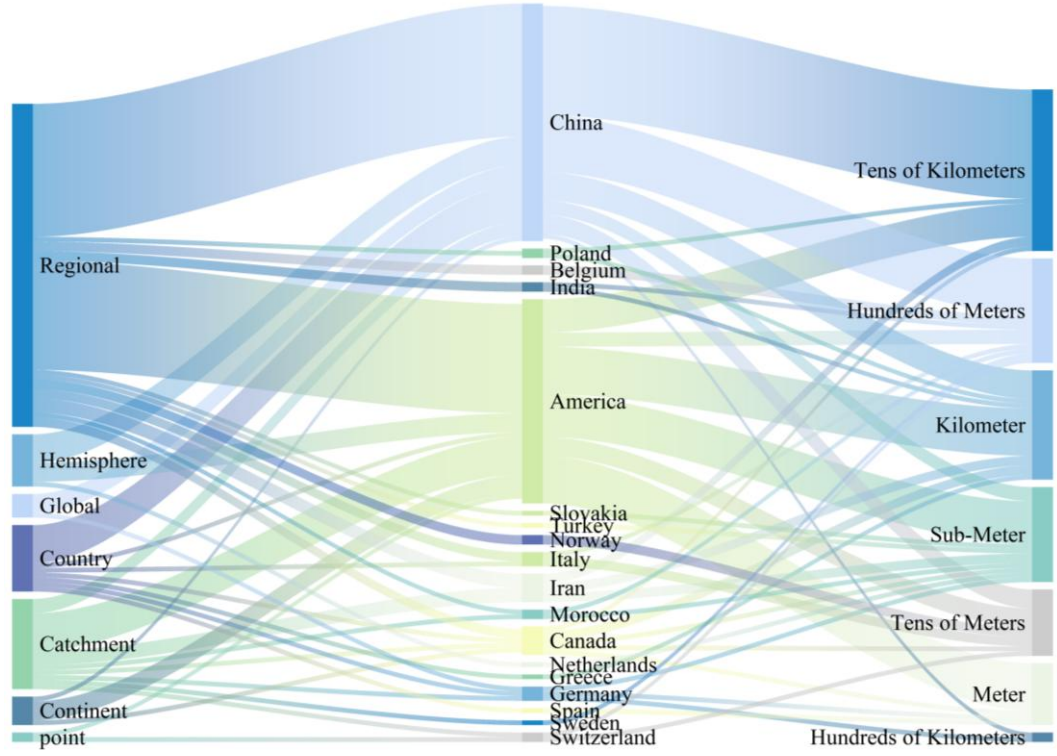

290 **Figure 5: Sankey diagram of countries, study areas and spatial resolutions.**

2.4 Top 10 most cited articles in the past 10 years

The top 10 most cited articles according to the Web of Science (until March 16, 2026) are displayed in Fig.6. Since 2015, Xiao et al. (2018) first developed a snow depth retrieval algorithm based on the SVR technique using PM remote sensing data and other auxiliary data. To predict snow depth during melt seasons, Bair et al. (2018) attempted to combine a snowmelt process
295 model (ParBal) with an RF for real-time estimates in the watersheds in Afghanistan. Kraft et al. (2022) innovatively proposed a hybrid hydrological model that exploits a DNN for representing uncertain processes on the basis of physical principles to simulate the dynamics of snow globally at a spatial resolution of 100 km. To improve SWE estimates in a semiarid interior region, Broxton et al. (2019) used an ANN to estimate snow density by combining snow surveys and Lidar measurements. Yang et al. (2020) first explored the potential of a RF approach in snow depth retrieval and demonstrated that its spatial
300 transferability is poor due to the dynamic snow characteristics. A paradigm that couples the snow RTM with the ML approach was subsequently proposed to improve snow depth estimation (Yang et al., 2021). Wang and Yuan et al. (2020) first applied a DNN to estimate snow depth in Alaska by combining satellite observations, in-situ data, and GNSS-R estimates. To monitor snow depth at a fine scale, Zhu et al. (2021) proposed a downscaling method based on the DNN approach and achieved high-spatial-resolution snow depth mapping in Northern Xinjiang, China. To incorporate the individual advantages of existing snow
305 depth products, Hu and Che et al. (2021) applied the RF approach to fuse five gridded snow depth datasets over the Northern

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Hemisphere. The abovementioned 9 papers focused on snow parameter retrieval, whereas Forman and Reichle (2015) first demonstrated the feasibility of simulating brightness temperature using an ANN, which demonstrates the potential of ML to serve as a model operator within the data assimilation frameworks (see Section 2.1).

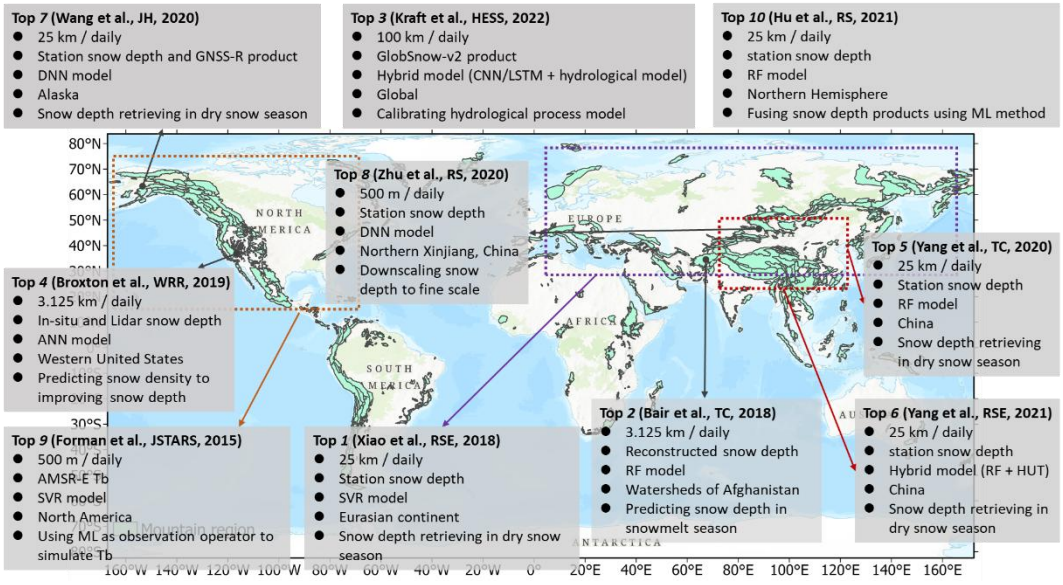

Figure 6: Summary of the top 10 most cited articles, displaying the spatial and temporal resolution, source of target predictor, ML model, study areas, and their research topics.

3 Current directions for improving snow depth with ML approaches

ML contributes to accurate snow depth retrieval with remote sensing techniques. Here, we summarize five main directions for improving snow depth estimation.

3.1 Coupling ML technique with snow physical model

Previous studies have proven that ML model, coupled with physics-based snow models, can be used to predict snow patterns with lower errors than physical or ML model alone. The specific objective is to add snow-related prior knowledge (e.g., snow grain size or density) into the ML model. Here, for examples, we focus on a snow electromagnetic model and a snow process model.

3.1.1 Coupled with snow electromagnetic model

Both model simulations and field experiments indicate that snow microstructure strongly impacts the volume scattering of the snowpack. Thus, the quantitative monitoring of snow microstructure parameters can contribute to snow depth retrieval. Yang et al. (2021) first proposed a strategy that integrates the prior knowledge, and effective grain size optimization by minimizing the HUT model simulations and spaceborne AMSR2 observations, in an ML approach to predict snow depth. The results

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325 demonstrated that the inclusion of grain size in the ML model greatly enhanced the snow depth retrieval, e.g., decreasing the ubRMSE from 7.52 to 3.50 cm across China (Fig.7b and 7c). This study demonstrated the potential utility of combining a snow electromagnetic model with an ML approach to improve snow depth retrieval.

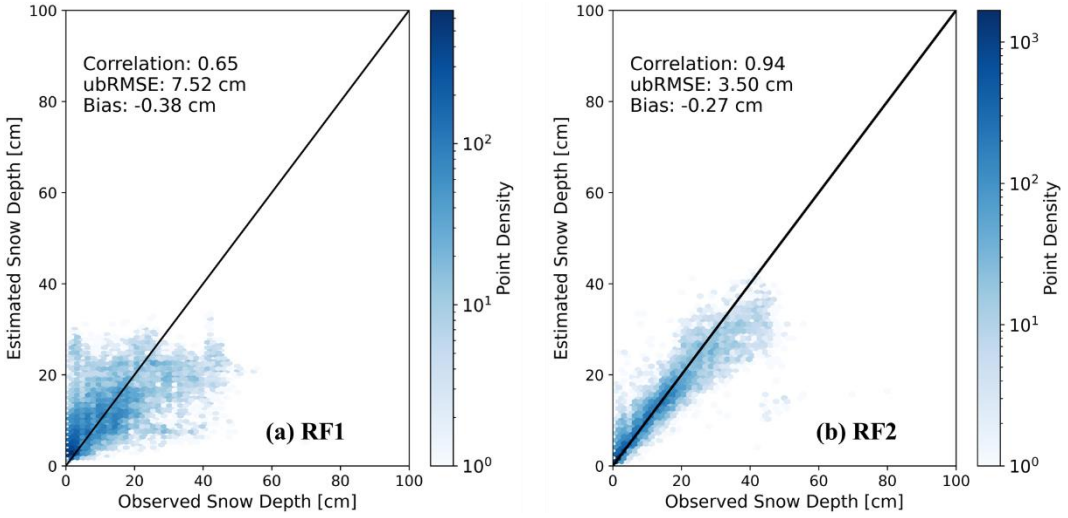

Figure 7: Evaluation of snow depth estimates retrieved with the well-trained (a) RF1 and (b) RF2 models across China. The predictor 330 **variables for RF1 include brightness temperature (AMSR2), longitude, and elevation, whereas RF2 additionally incorporates the effective grain size. The figures are adapted from Yang et al. (2021).**

3.1.2 Coupled with snow process model

The RTM-optimized grain size in Section 3.1.1 is typically dependent on ground-based observations. Thus, snow depth retrieval is characterised by significant uncertainty in areas where stations are sparse, especially in mountain regions. A snow 335 process model is an effective tool for simulating snow parameters (e.g., snow depth, grain size, and density), providing massive amounts of prior information. Pan and Yang et al. (2023) proposed a method that uses simulated snow parameters from snow process models to construct a ML retrieval algorithm, achieving an RMSE of 12.4 cm at the global scale (Fig.8). Supported by the first-guess snow depth from the snow process model, the underestimation of deep snowpack was also greatly reduced. These findings demonstrated that the use of prior information from a snow process model provides another group of valuable 340 independent information related to meteorological forcing for PM retrieval; this approach can greatly improve the accuracy of snow depth products.

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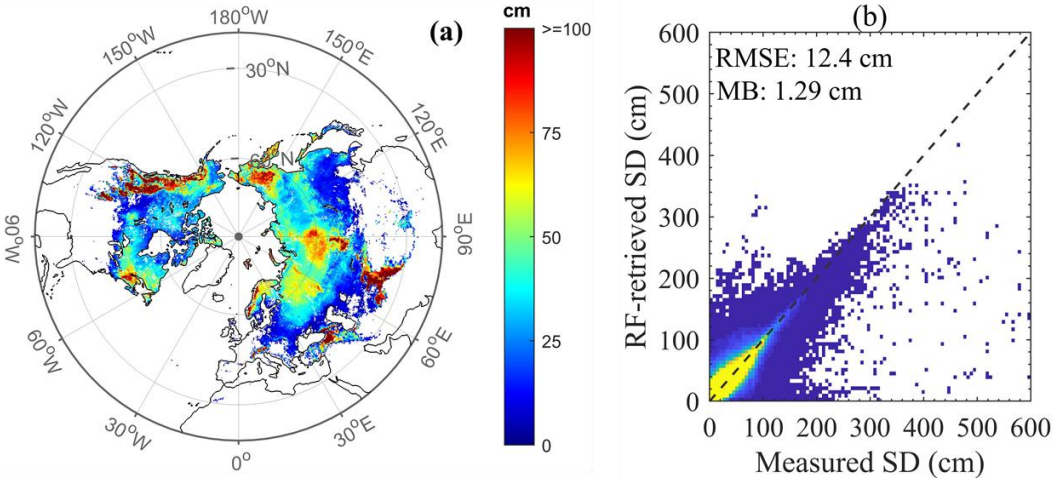

Figure 8: Snow depth estimates retrieved with a ML model trained with snow process model outputs: (a) example of estimated snow depth on Feb 15, 2017; (b) validation against in-situ measurements from 2012–2020 (N=1,722,200). The data in Figure 4(b) are adapted from Pan et al. (2023).

3.2 Applying RTM for simulating microwave signals

Accurately and efficiently simulating brightness temperature and backscattering information with RTM can improve our ability to retrieve snowpack characteristics from spaceborne observations. Here, we use the DMRT-Bic model to generate a database (20000 samples). Then, 80% of the samples are used to train an ANN model, and the remaining 20% of the samples are used to test its performance. The predictor variables for the ML model are the same as those for the DMRT-Bic inputs, and include soil (e.g., bulk density, moisture, roughness, texture, and temperature) and snow (e.g., snow depth, grain size, density, and temperature) parameters. The target variable is brightness temperature simulated by DMRT-Bic. To demonstrate the predictive power of the ANN model, the NoSREx field measurements from 2009–2013 are used (Lemmetyinen et al., 2016). The fitted ANN models (top panel) and validation results compared to NoSREx measurements (bottom panel) at 10.6, 18.7 and 36.5 GHz are shown in Fig.9. The simulated brightness temperatures have RMSE values of 2.06, 3.59 and 4.67 K at 10.6, 18.7 and 36.5 GHz, respectively. This analysis verifies the effectiveness of using ML models to replace numerical electromagnetic models for simulating brightness temperature.

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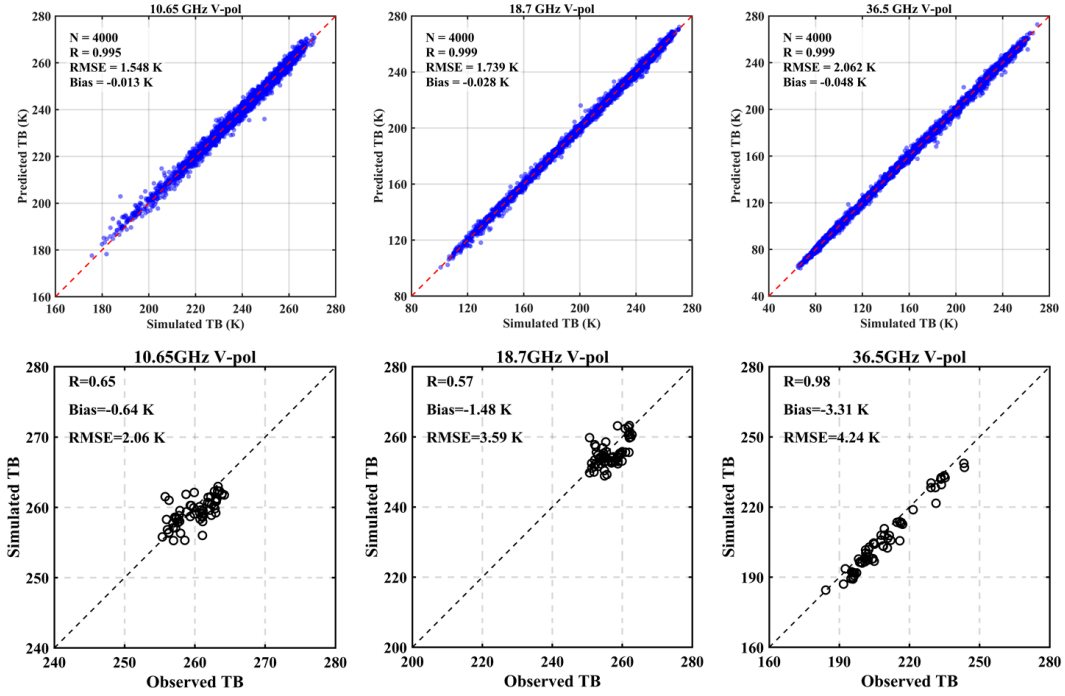

Figure 9: Scatter plots of the DMRT-Bic-simulated and ML-predicted brightness temperature data (bottom panel) and validation results against field measurements from Finland (bottom panel).

3.3 Optimizing snow RTM model

3.3.1 Providing key parameters for snow electromagnetic model

Snow volume scattering is affected by snow depth, snow grain size, snow density, and layering structure. Thus, priors are necessary for driving snow electromagnetic model. For example, in the GlobSnow retrieval methodology, a parameter, effective grain size, was optimized by RTM simulations and satellite observations in advance, and then was used to drive a snow electromagnetic model (e.g., HUT) for SWE retrieval. To map the snow microstructure at a large scale, Yang et al. (2024) proposed a ML-based method to simulate the effective grain size, substituting this approach for the iterative RTM iteration in GlobSnow. The RF model was trained with target (GlobSnow-v3.0 effective grain size) and predictor variables (AMSR2 brightness temperature, DEM, land cover fraction, etc.). The validation results demonstrated the feasibility of retrieving effective grain size without sacrificing accuracy or improving computational efficiency (Fig.10). Therefore, ML model is a promising tool for providing input parameters for snow electromagnetic models, and even process models in the future.

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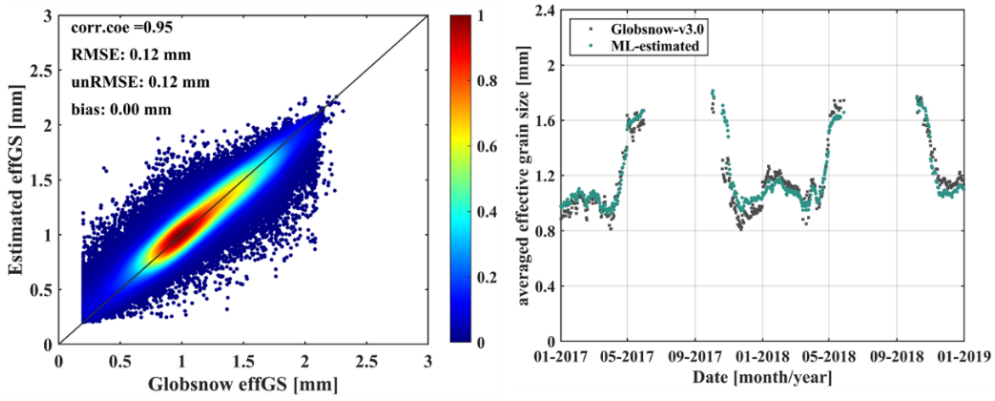

Figure 10: Comparison of the ML-estimated and HUT-optimized effective grain sizes in the Northern Hemisphere. The figures are adapted from Yang et al. (2024b).

3.3.2 Improving the run speed of snow electromagnetic model

Snow electromagnetic models, e.g., the DMRT-Bic, typically employ the discrete dipole approximation (DDA) to solve the volume integral equation (VIE), yielding a phase matrix, an extinction coefficient, a scattering coefficient, etc. However, a significant challenge arises because of the time-consuming scattering calculations. Therefore, the exploration of ML method to accelerate the electromagnetic model is crucial. Here, we focus on the simulation of scattering characteristics and the solution of the VIE.

(1) Simulating snow scattering characteristics using ML

Using ML to simulate the scattering phase matrices, and the extinction and scattering coefficients of snow can be used as inputs to accelerate snow electromagnetic models. For example, a neural-network-accelerated DMRT-Bic model (DMRT-Bic-NN) was developed by training an ANN with simulations from the DMRT-Bic model (Li and Xiong, 2026). It accurately reproduced snow scattering parameters at multiple microwave frequencies and enabled rapid brightness temperature simulations. The validation results against in situ data over China and Finland demonstrated that it achieves excellent performance, with RMSE values of 3–5 K (Fig.11). Sensitivity analyses further showed that the DMRT-Bic-NN model captures realistic responses to variations in snow grain size and density, and exhibits a frequency dependence similar to that of experimental observations. DMRT-Bic-NN preserves the high physical fidelity of the original bicontinuous representations while reducing the computational cost by several orders of magnitude. This work exemplifies how ML can be effectively integrated with physically based electromagnetic models to achieve both high accuracy and high operational efficiency in snow radiative transfer simulations.

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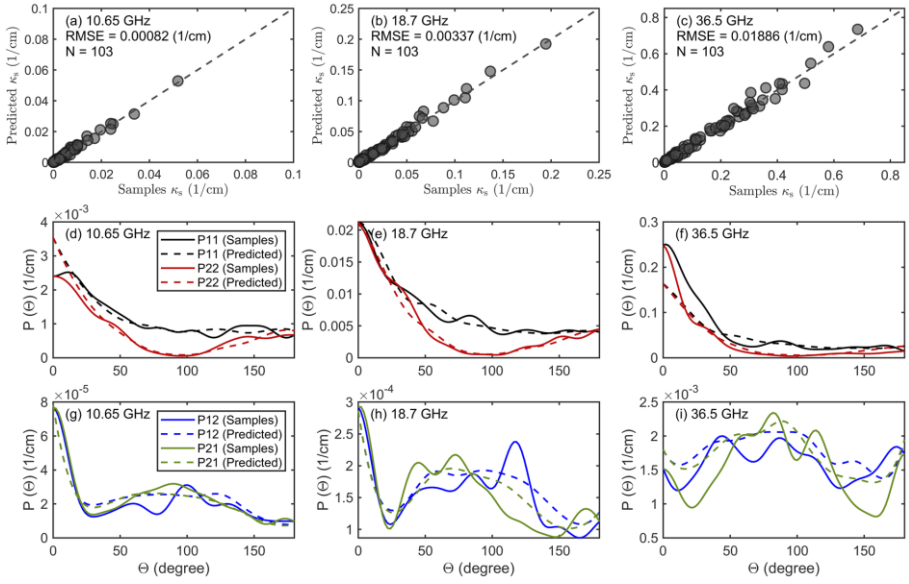
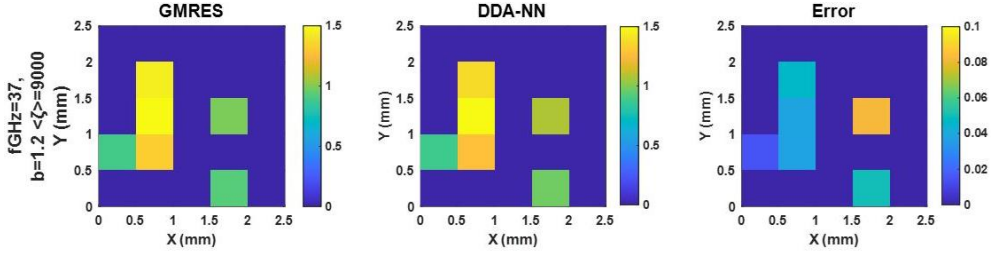


Figure 11: Comparison of the DMRT-Bic- and ML-simulated scattering coefficients, and phase matrices. The figures are adapted from Li and Xiong (2026).

(2) Solving the electric field VIE through ML

In parallel with the path of directly simulating the snow scattering characteristics based on statistical geometric parameters, as performed by Li and Xiong (2026), another independent approach is to solve the VIE through an ML technique, rather than the DDA, which involves a computationally demanding iterative method. For example, Du et al. (2025) introduced a physics-informed neural network framework (DDA-NN), establishing a direct mapping from the discretized bicontinuous snow microstructure to the induced dipole moments of the snowpack volume (Fig.12). Crucially, the VIE residual is embedded as a physical constraint in the loss function of the network. The results demonstrated that the predicted dipole moments strongly agree with the benchmark solutions from the generalized minimal residual (GMRES) algorithm. Moreover, the coherent scattering amplitude and the resulting phase matrix derived from the DDA-NN closely match the benchmark results in co-polarization mode. At the expense of a one-time training cost, the DDA-NN achieves inference speeds approximately two orders of magnitude faster than the GMRES does. This physics-embedded learning paradigm enables efficient large-ensemble computations and thus supports scalable modelling workflows essential for advancing snow remote sensing.



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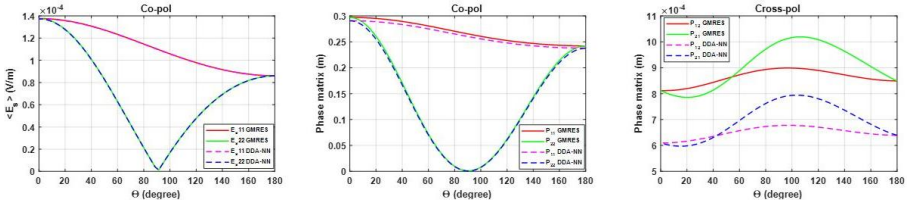

Figure 12: Comparison of dipole moments predicted with the DDA-NN against the benchmark solutions from GMRES. The figures are adapted from Du et al. (2025).

3.4 Improving existing gridded snow depth products

The use of ML has led to tremendous success in improving the existing gridded snow depth products. The specific methods include multisource dataset fusion, bias correction and model stacking.

3.4.1 Multisource fusion of snow depth products

In this methodology, ML is typically used to establish the relationship between reference snow depth (e.g., station measurements) and multisource gridded products, to achieve complementary advantages. For example, Hu et al. (2021) proposed a data fusion framework based on a RF model, in which various snow depth products from AMSR2, GlobSnow-v2.0, NHSD, ERA-Interim, and MERRA-2, incorporating geolocation (latitude and longitude), and topographic data (elevation), were used to train the relationship with station snow depth references. This fusion framework resulted in a long time series of continuous daily snow depth products over the Northern Hemisphere with a spatial resolution of 25 km from 1980 to 2019 (Hu et al., 2024). The evaluation results indicated that the fused snow depth product presented the best performance among all the datasets, with the highest R^2 (0.81), and the lowest RMSE (7.69 cm) and MAE (2.74 cm) (Fig.13).

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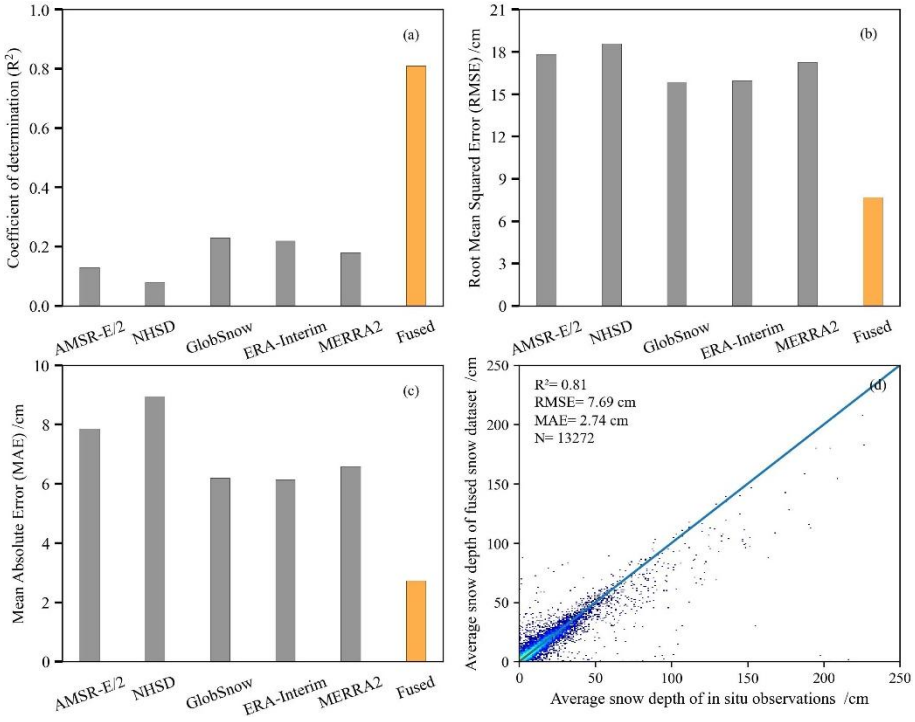

425 **Figure 13: Validation and comparison of the fused snow depth dataset with five gridded products for the Northern Hemisphere. The raw products are displayed in grey, while the fused dataset is shown in orange. The figures are adapted from Hu et al. (2021).**

3.4.2 Bias correction for snow depth products

To reduce the uncertainties of snow depth estimation due to complex terrain, snow–vegetation interactions, and other challenging factors, bias correction is necessary and prevalent, e.g., by means of ground-based measurements (King et al., 430 2020; Luojus et al., 2021; Stachura et al., 2026), wireless-sensor network observations (Zheng et al., 2018), and the airborne Lidar data (Yang et al., 2025). Here, for example, the four widely used gridded snow depth products over China are selected as examples, and scatterplots of the RF-predicted and station-observed residuals for the GlobSnow-v3.0, AMSR2, FY-3D/MWRI and ERA5-land products are shown in Fig.14. The residuals are calculated from the station observations and gridded snow depth estimates from 2017–2021. The RF model was trained using the target variable (residual) and predictor variables, 435 e.g., the AMSR2 brightness temperature, DEM, and land cover fraction. The results indicate that the ML model can accurately and continuously predict the bias spatiotemporally (Fig.14). Then, bias correction, such as spatiotemporally dynamic residual subtraction, can be used to improve snow depth estimates. Of course, the quality of the reference residuals, including the accuracy, representativeness, and balance (see Section 4.5), is crucial to the robustness of the ML model.

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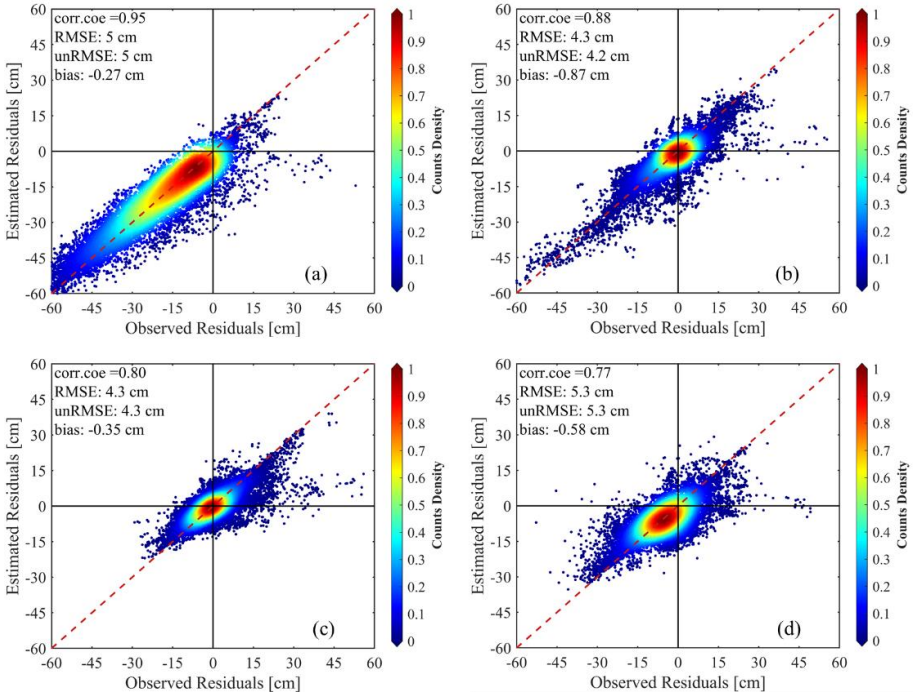

Figure 14: Scatter plots of observed and estimated residuals for (a) AMSR2, (b) ERA5-Land, (c) FY-3D/MWRI, and (d) GlobSnow-v3.0 products across China.

3.4.3 Assembling multiple ML models via the stacking technique

The basic idea of the stacking technique is to use the estimates of multiple base models as inputs to a meta-model and generate the final estimation. Current studies tend to treat station measurements as the target variables of the ML model. However, most meteorological stations are distributed in flat areas, and the percentage of deep snow samples is usually less than 5% (e.g., over China), resulting in an underestimation in deep snow-covered areas. To address the imbalance of training samples, Bai et al. (2025) proposed a stacking method that combines the advantages of multiple ML models for retrieving snow at various depths. In this work, a base model 1 (LightGBM) and a base model 2 (ANN) were constructed, and the weights of the deep and shallow snow samples were adjusted respectively. The estimates of the two base models were used as features and input into the constructed meta-model (RF) to generate the final snow depth. The results indicated that the stacked model reduces the errors in deep snow (>30 cm) by more than 12% compared with a single model (Fig.15).

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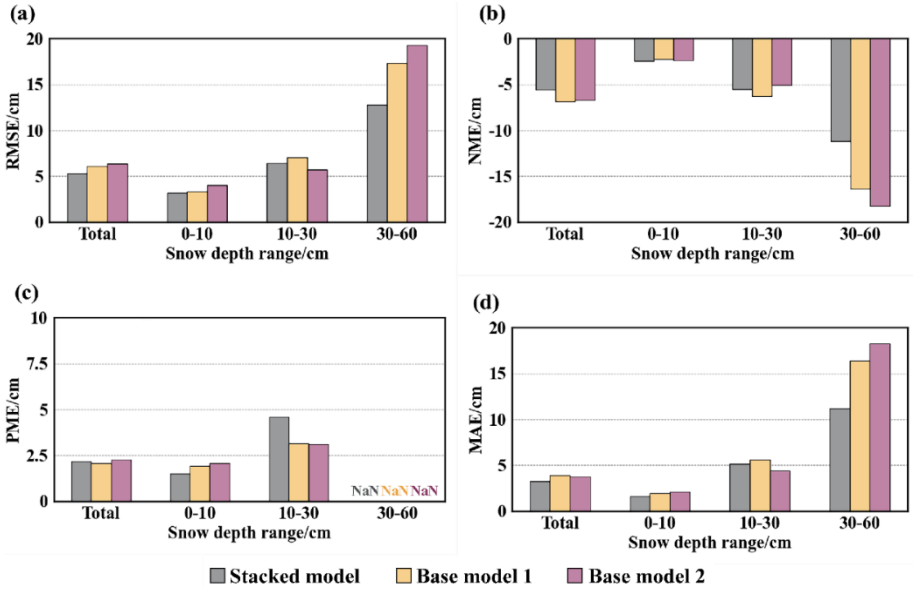

Figure 15: Comparison of snow depth retrieval results with only one ML model and with multiple ML models. The figures are adapted from Bai et al. (2025).

3.5 Downscaling snow depth products to a fine resolution

There is an increasing interest in using ML models to predict snow depth at high resolutions. To improve the spatial resolution of PM snow depth products, for example, Wei et al. (2025) proposed a ML-based downscaling method by using multisource auxiliary data, producing a new 500 m resolution snow depth dataset from the original 6.25 km PM data across Northeast China. The results indicated that the downscaled snow depth can significantly reveal important spatial details compared to the original coarse spatial resolution product (Fig.16). Owing to the significant uncertainties of coarse-resolution snow depth products, the accuracy of the downscaled snow depth may not be significantly improved.

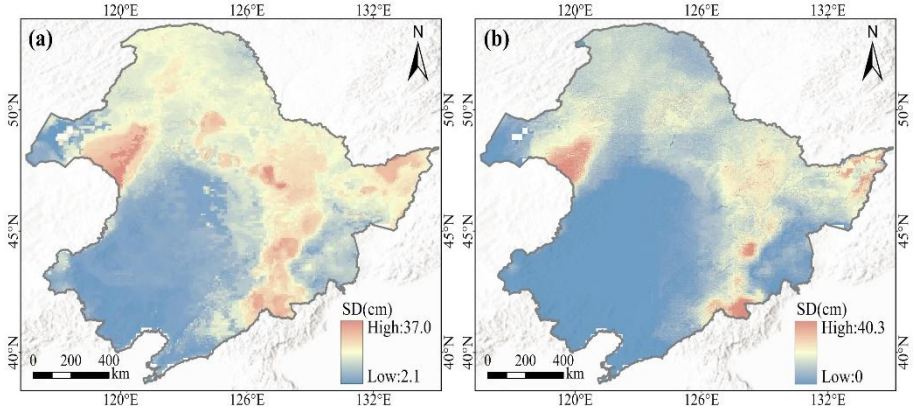

Figure 16: Downscaled snow depth from (a) 6.25 km to (b) 500 m across China. The figures are adapted from Wei et al. (2025).

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Typically, a ML model trained at a coarse resolution (e.g., 10 km) is directly used to retrieve fine-scale snow depth, neglecting the scale effects. Zhang and Jiang et al. (2025) still applied a ML model trained at coarse resolution to retrieve snow depth at a 10 km resolution, and then further proposed a Self-Adaptive Geographically Weighted Regression (SGWR) framework to downscale the coarse ML-based snow depth to the 1 km scale (Fig.17). This method outperforms the traditional full-domain ML regression in capturing local heterogeneity within complex terrain in terms of both accuracy and spatial details, offering a robust local statistical learning paradigm (combining the ML technique and a geostatistics method) for downscaling snow depth.

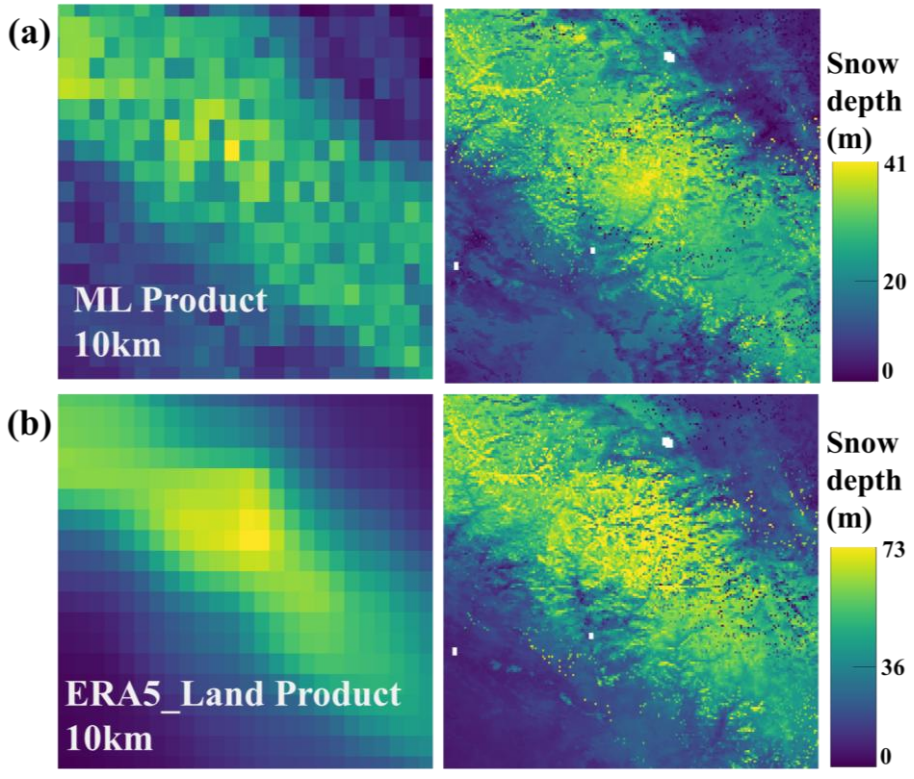

Figure 17: Comparison of the original coarse-resolution (left panels) and downscaled 1 km (right panels) snow depths for (a) ML, and (b) ERA5-Land. The figures are adapted from Zhang et al. (2025).

4 Challenges and future prospects

Ongoing climate warming has added further complexity to changes in the snowpack, such as reductions in snow cover, increasingly wet and patchy snowpack areas, and frequent snow avalanches and droughts, making accurate snow depth retrieval more challenging. There is a growing consensus that solutions to complex science and engineering problems require the integration of traditional physics-based modeling approaches with state-of-the-art ML techniques. Here, we primarily focus on the challenges of ML-based snow depth retrieval from a remote sensing perspective, rather than the architectures of ML models.

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4.1 Bridging the disparity of model–observation mismatch

To date, coupling the physical models and ML techniques has been has been explored as a paradigm to improve snow depth retrievals. However, a significant gap remains between physical-model simulations and satellite observations. Previous studies have demonstrated that RTMs have been adapted to work with field-derived measurements through a scaling factor applied to grain size. Thus, a ML model trained with RTM simulations is only applied at the point/station scale (Santi et al., 2022a); however, researchers have not yet applied the model-driven ML algorithms at a large scale.

To address the mismatch between model simulations and satellite observations, many scholars have focused on electromagnetic theory, such as snow microstructure and physical snow modelling (Zhu and Tan et al., 2018; Sandells et al., 2021; Tsang et al., 2022). However, some challenges still remain, such as cross-pol modeling at low frequencies (e.g., the C-band). Dense ice aggregates and anisotropic crystals typically result in stronger scattering in cross-polarization. However, previous RTM did not consider the effects of dense aggregates. Zhu and Tan et al. (2021) recently modified the spectral density of a bicontinuous model to characterize the dense ice aggregates, and the simulations of a DMRT for snow with dense ice aggregates indicated that C-band volumetric scattering at cross-polarization can be stronger than surface scattering, indicating the sensitivity of backscatterers at cross-polarization mode to snow depth. In addition to electromagnetic theory, the snow layering structure significantly affects the microwave scattering. Previous studies have demonstrated that a multi-layer RTM is superior to a one-layer model (Zhu and Tan et al., 2018; King et al., 2018, 2020; Rutter et al., 2019; Pan et al., 2024). However, snow layering priors are difficult to acquire via remote sensing at a large scale. The snow process model is an effective tool for determining snow layering parameters. For example, coupling ML and land surface models could potentially aid in simulating microwave brightness temperatures (Xue et al., 2015; Forman et al., 2016) and improve snow depth retrievals (Pan et al., 2023) at large scales. In the future, integrating RTM, process models, and ML techniques is a promising research direction (Fig.18), in which the process model provides snow layering priors; the RTM simulates microwave signals; and the ML technique can be used to optimize the RTM and process models and establish the nonlinear relationship between snow depth and multiple variables.

Innovative observational technologies (e.g., snow radar, TomoSAR, GPR, and Lidar) have shown promise as tools for monitoring and imaging the internal snowpack structure (Holt et al., 2015; Picard et al., 2019; Qiao et al., 2023; Dupuy et al., 2026). However, tracing each of these layers manually for large-scale images is laborious and time consuming. ML can contribute to accurate and efficient quantitative characterization of snowpack stratification (Fig.18). For example, Varshney et al. (2021) attempted to apply ML to trace the vertical snow layers by using snow radar echograms across the Greenland Ice Sheet. Meehan et al. (2024) estimated bulk snow density using a ML approach by combining GPR and Lidar observations. Akbar et al. (2026) proposed a ML-based method to estimate two key snow parameters (permittivity and conductivity) using GPR data.

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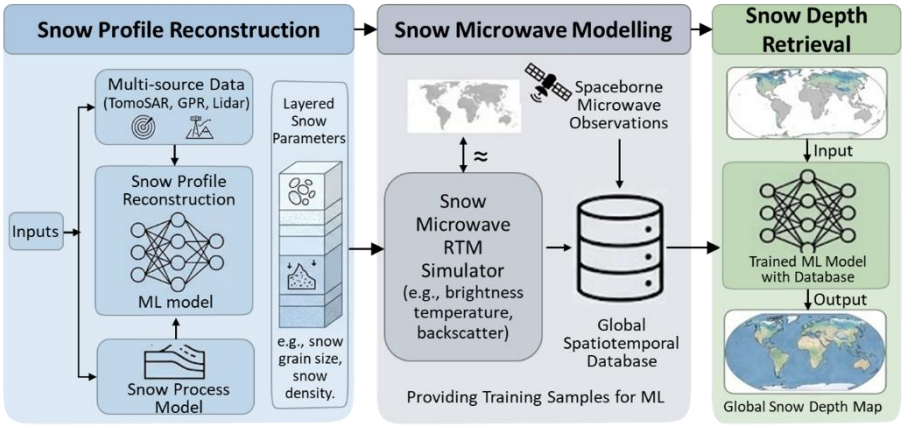

Figure 18: Bridging the disparity of model–observation mismatch by integrating the RTM, snow process model and ML technique.

4.2 Integrating fundamental physical laws into ML structures

With the rapid development of AI, ML methods have achieved high predictive power and strong fitting ability for nonlinear, nonexplicit functional relationships. However, the interpretability, generalizability, and extrapolation of purely data-driven ML models remain limited. Many ML practitioners and users have recently begun to focus on the interpretability problem by embedding physical equations and laws into ML model, such as physics-informed neural networks (PINNs) (Raissi et al., 2019; Li et al., 2025) and differentiable modelling (DM) frameworks (Li et al., 2024; Shen et al., 2023).

A comparison of purely data-driven ML models and physics-based ML models is shown in Fig.19. Purely data-driven retrieval models have been controversial because of their lack of physical interpretability. In the RTM-ML paradigm, the output (e.g., snow grain size) from the RTM or process model serves as the initial input for the ML model, mitigating errors associated with snow volume scattering (see Section 3.1 for details). Typically, an RTM-ML model produces snow depth estimates via a limited backward explanation of the snow depth estimation process, because only a key variable is included, rather than a physical equation. Recently, two innovative paradigms have prevailed in the scientific community: the Loss Function Embedding ML (LFC-ML) model (Raissi et al., 2019) and Differentiable Modeling based RTM-ML (DM-RTM-ML) model (Shen et al., 2023; Li et al., 2024; Zheng et al., 2025). In the LFC-ML configuration, physical laws are incorporated as subcomponents of the loss function in ML training, leading to a physically constrained ML approach for target prediction (Kraft et al., 2022; Wang et al., 2023; Du et al., 2025). LFC-ML predictions not only align closely with the actual snow depth measurements, but also obey the fundamental physical laws governing the dynamics of snowpacks, thus providing a backward explanation basis for obtaining the predictions (Fig.19). In the snow community, for example, Du et al. (2025) proposed a physics-informed loss function (DDA-NN) to efficiently compute the electromagnetic scattering of snow structures, in which a loss function combining a physical scattering model, discrete dipole approximation (DDA), with neural networks (NN) was defined. This approach was verified as a novel strategy for merging physical equations with ML techniques (see Section 3.3.2). DM encompasses accurately and efficiently calculating gradients with respect to model variables or parameters. It offers a

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transformative approach to simultaneously improve process representations, parameter estimation, knowledge discovery, and predictive accuracy. Currently, DM offers interpretability and physical consistency in many geoscience domains, e.g., hydrological modelling and parameter retrieval. For example, several innovative soil moisture retrieval algorithms that integrate physical water cloud model (Li et al., 2024), or hydrological model (Xie et al., 2024) or tau-omega model (Zheng et al., 2025) and ML have been proposed. Therefore, this approach provides new ideas for the combination of ML and physical knowledge in snow depth retrieval studies. With respect to the DM-RTM-ML model, a semiempirical RTM (e.g., the tau-omega model, or a water cloud model) is typically used as the skeleton to simulate the microwave signals (e.g., backscatter), and the ML model can provide inputs for the RTM, e.g., the vegetation index in the WCM model. Then, corrected microwave signals of the target (e.g., snow or soil) to vegetation can be simulated. Finally, the ML model is used to establish the nonlinear relationship between corrected microwave signals and target predictors. Because the formulas of these semiempirical models are explicit or straightforward, contributing to capturing the intermediate variable in DM, the DM-RTM-ML model presents a strong backward explanation for the predictions. In the future, we can apply a soil–snow–vegetation–atmosphere RTM as a skeleton to conduct differentiable modelling.

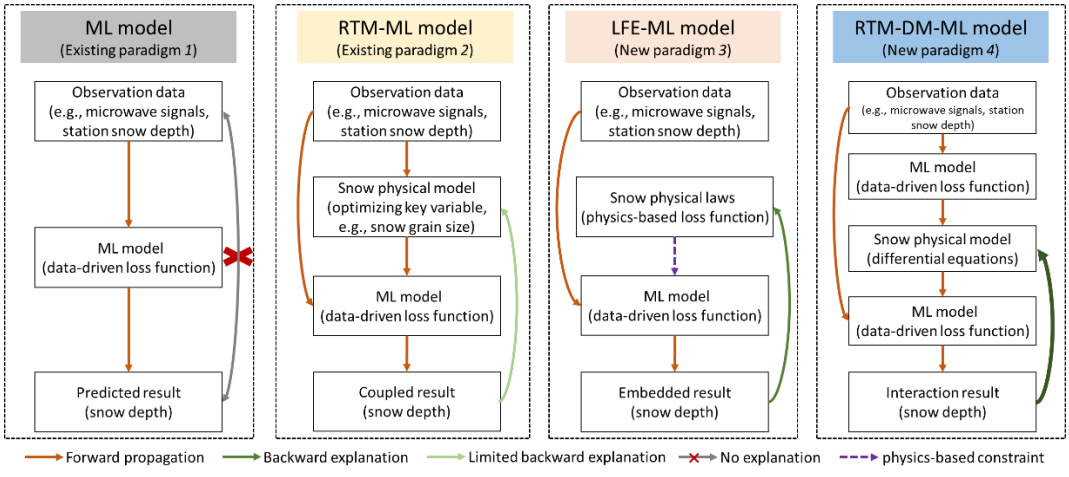

Figure 19: Schematic diagrams of purely data-driven ML, series RTM and ML (RTM-ML), physics-based loss function embedding ML (LFC-ML) and differentiable modelling-based RTM of ML (RTM-DM-ML) models for snow depth retrieval.

4.3 Developing high-spatial-resolution snow depth products

Our review revealed that most previous studies focused on coarse scales, ranging from kilometer to dozens of kilometers (see Section 2.4). Coarse-scale snow depth products are sufficient for climate analysis (Varga et al., 2024; Lin et al., 2025), seasonal forecasting (Terzago et al., 2023), environmental prediction (Cho et al., 2023; Kim et al., 2021) and climate model evaluation (Zhang et al., 2022). However, these datasets are not suitable for applications such as hydrological forecasting and water management, especially during anomalous years (Swain et al., 2025). Several studies have attempted to apply airborne Lidar or satellite SAR data to derive fine-scale snow depth using ML model at the catchment scale (see Section 2.4). The most mainstream approach in the snow community is to downscale coarse-resolution products through high-resolution auxiliary

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data (e.g., SCF) by using ML methods (see Section 3.5). However, the existing coarse-resolution snow depth products still exhibit significant uncertainties; for example, GlobSnow has RMSE values of 38–85 mm (Luojus et al., 2021).

With the increasing availability of multimodal data (ground measurements, modeling data, and remote sensing data), ML has emerged as a powerful alternative, leveraging in-situ snow surveys, altimeter-based observations, and model predictors to map snow depth at high resolutions (Meloche et al., 2022; Revuelto et al., 2020; Pan et al., 2025). In particular, altimeter satellites have emerged as effective tools for measuring snow depth across watersheds, and they include ICESat/ICESat-2 (Treichler and Kääb, 2016; Enderlin et al., 2022; Besso et al., 2024; Deschamps-Berger et al., 2023; Fair et al., 2025; Chen et al., 2025b; Feng et al., 2025), GEDI (Shean et al., 2021), CryoSat/CryoSat-2 (Zhou and Zhang et al., 2025) and dual-altimeter combinations of CryoSat-2/ICESat-2 (Kwok et al., 2020; Carret et al., 2025; Saha et al., 2025) or CryoSat-2/SARAL (Guerreiro et al., 2016; Garnier et al., 2021). Additionally, some planned spaceborne missions (which rely on two-dimensional imagery) are also expected to provide high-resolution snow depth data. For example, Environment and Climate Change Canada (ECCC) is developing the first dual Ku-band SAR (13.5 and 17.3 GHz) satellite mission (the Terrestrial Snow Mass Mission, TSMM) , with the goal of imaging the Northern Hemisphere at a resolution of 500 m on a weekly basis (Derksen et al., 2021). The European Space Agency (ESA) is promoting the development of Copernicus missions, e.g., the Radar Observation System for Europe at the L-band (ROSE-L), which is dedicated to meter-resolution observations (Davidson et al. 2023); the Copernicus Imaging Microwave Radiometer (CIMR) which aims to obtain daily kilometer-level resolution observations; and the Copernicus Polar Ice and Snow Topography Altimeter mission (CRISTAL) which is designed for polar regions (Landy et al., 2026).

Spaceborne altimeter platforms could theoretically be used for routine measurements of snow depth with centimeter-level accuracy (Painter et al., 2016; Adam et al., 2020; Brunt et al., 2021), but they are also limited in their revisit frequency (e.g., 91d for ICESat-2) and their global coverage (beam sampling mode). Spaceborne SAR instruments, especially the future satellite missions (TSMM and ROSE-L), can provide spatially distributed high-resolution snow depth data in mountainous basins, but at a low temporal frequency (weekly). Spaceborne microwave radiometers present their advantages in retrieving daily snow depth globally over other remote sensing techniques. Although their spatial resolutions are coarse, from the perspective of spatial extrapolation, their estimates can serve as a snow depth background. In particular, the CIMR mission is expected to provide daily snow depth at kilometer-level resolution, which could improve the reliability of background values. To achieve spatiotemporally continuous mapping at a large scale, the use of ML techniques to extrapolate altimeter-based snow depth estimates in time and space might offer a potential solution (Fig.20). In this methodology, the PM-based snow depth product (even the reanalysis datasets) can be used to provide background values of snow depth; altimeter-based sampling snow depth measurements serve as reference values; whereas SAR-based estimates effectively serve as a bridge for spatial scaling because of their balanced moderate spatial resolution (Fig.20). For example, the most recent studies have attempted to incorporate altimeter-based snow depth measurements with the climate reanalysis ERA5 (Liu et al., 2025; Pan et al., 2025) or into hydrological models via data assimilation methods (Mazzolini et al., 2025) to produce gridded snow depth maps at a resolution of up to 10 m.

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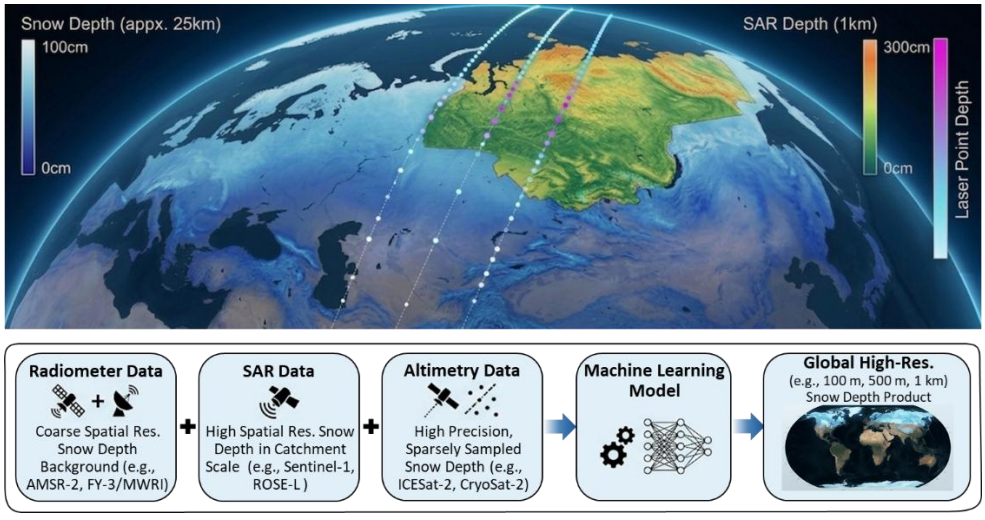

595 **Figure 20: Workflow of spatiotemporally extrapolating snow depth using ML techniques by combining spaceborne radiometer, SAR and altimeter data.**

4.4 Improving the ability to estimate snow depth under complex conditions

The seasonal snowpack in the mountains acts as a vital natural reservoir that regulates runoff downstream in snowfed basins. Estimating snow depth in mountainous terrain is currently the most important unsolved problem (Dizoer et al., 2016; Fayad et
600 al., 2017). These challenges include the sparse in situ measurements, the high spatiotemporal heterogeneity of snowpack due to inclement weather and rugged topographical conditions, and complex snow layering structures (Fig.21). Additionally, deep snowpacks are typically obscured in mountain regions, resulting in signal saturation in the microwave domain, especially at the X- and Ku-bands (Tsang et al., 2022).Although recent works have demonstrated the possibility of snow depth estimation for deep snow using C-band radar (Lievens et al., 2019, 2022), it presents high uncertainty because of the complex topography,
605 various landcover types, wet snow and long revisit periods of Sentinel-1 (Hoppinen et al. 2024; Lemos et al., 2025; Ying et al., 2025, 2026).

Snow depth monitoring over polar regions (e.g., Arctic and Antarctic sea ice) is another unsolved research task. The greatest limiting factor is the lack of in situ snow depth measurements since 2022 (Fig.21). In particular, some observation missions have ceased the collection and updating of their datasets, e.g., airborne campaigns such as the Operation IceBridge (OIB) and
610 IceBird programs and those based on snow buoys which provide ice mass balance (IMB) data. Moreover, the scattering characteristics of snow-covered sea ice are significantly complex because the brine and air inclusions within the snow dominate volume scattering (Nandan et al., 2016; Soriot et al., 2022), snow-ice interface roughness increases surface scattering (Liu et al., 2025; Wang et al., 2025), and multiyear sea ice has similar microwave behaviours as the snowpack (Brucker et al., 2013; Rostosky et al., 2018; He et al., 2024; Zhou et al., 2025). Additionally, sea ice types (e.g., FYI and MYI), the sea ice
615 concentration (SIC) and the sea ice thickness (SIT) increase the complexity of the scattering mechanism (Gill et al., 2015; Huang et al., 2025). In this context, accurate snow depth retrieval over polar sea ice regions remains challenging. Snowmelt is

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a major component of streamflow in cold regions and serves as an important supply of freshwater resources. However, we have still not resolved the challenge of snow depth monitoring during the snowmelt season with remote sensing technique. Theoretically, monitoring snow depth under wet snow conditions with microwave remote sensing is difficult because of the high liquid water content of the snowpack. Reconstruction via backward calculation of the daily snowmelt depth is currently the mainstream approach (Premier et al., 2023). However, the reconstructed snow depth data are available only retrospectively and do not support forecasts (Bair et al., 2018).

Figure 21: Challenges associated with monitoring spatiotemporally continuous snow depth under complex conditions.

The lack of in situ snow depth data under the complex conditions mentioned above is the greatest challenge in the field. Spaceborne altimetry sensors (e.g., ICESat/ICESat-2, CryoSat/CryoSat-2, and SARAL) and two-dimensional imagery sensors (e.g., C-band Sentinel-1 and planning dual Ku-band TSMM and L-band ROSE-L) are particularly well suited for snow depth retrieval in mountainous and polar regions (see Section 4.3). During the snowmelt season, accurately determining four snow parameters (maximum snow depth, snowmelt onset date, snow disappearance date and snowmelt rate) is critical for monitoring and understanding the snowpack depletion process. Microwave remote sensing is effective at determining the maximum snow depth during the snow season. Moreover, the microwave backscattering signal (e.g., in the C-band) is sensitive to wet snow and can be used to determine the snowmelt onset date. Additionally, combining optical and microwave remote sensing methods can reduce the effects of cloud cover, making calculating the snow disappearance date possible. A snow process model or hydrological model can be used to simulate the snowpack depletion process, and a ML method can be used to spatiotemporally predict the snowmelt rate at a large scale. Thus, combining snow physical models (RTM and process model), remote sensing observations and ML techniques is expected to improve snow depth retrieval across a complete hydrological year in the future.

4.5 Enhancing data quality for ML model training in three dimensions

The performance of data-driven ML models heavily relies on the quality of the training samples. Previous studies generally used in-situ snow depth data as target predictors (see Section 2.3). To improve the accuracy of training samples, bias correction

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methods, e.g., linear fitting (Venäläinen et al., 2025) and data fusion (Qiao et al., 2025), were used to calibrate the airborne- and satellite-based snow depth estimates (Fig.22). However, their representativeness at the satellite pixel-scale is an enduring question, especially in complex mountain areas. Moreover, their imbalance (e.g., fewer deep snowpack samples) also directly affects the generalization capability of ML model.

To assess the spatial representativeness of the point-scale measurements, some metrics were utilized to characterize the spatial heterogeneity, such as the clustering indicators (Galeati et al., 1986), the mean relative difference based on dense sampling data (Herbert et al., 2024, 2025) or data from neighboring sites (Meromy et al., 2013; Chen et al., 2017), a snow cover day-based score (Pan et al., 2023), and the triple collocation-derived error (Wang and Zheng, 2020; Yang et al., 2025) or correlation coefficient (Peng et al., 2025). Recently, ML technique has been used to study the representativeness of field sampling locations. For example, Liljestrand et al. (2025) applied an unsupervised Gaussian mixture model to identify sampling locations within the Franklin Basin on the basis of topographic features, and reported that information from 10 sampling sites can be used to determine snow depth across the basin with high accuracy. Xie et al. (2024) proposed a physics-constrained ML scheme to identify optimal sensor placement in a field, thereby enhancing soil moisture prediction for the entire study area. On flat terrain, snow depth is well represented by a Gaussian distribution. However, owing to the heterogeneity of the snowpack and sparsely distributed stations, training samples typically follow a skewed-normal distribution, resulting in imbalanced learning samples (Liljestrand et al., 2025). In the field of ML, it is typically assumed that the number of samples in each class (e.g., shallow and thick snowpack) is approximately equal. However, the lack of measurements in mountains and for deep snow conditions typically results in an imbalance of training samples. Some scholars have attempted to increase the deep snow samples using airborne (Daudt et al., 2023; Dunmire et al., 2024; Feng et al., 2025) and spaceborne (Xiong et al., 2022b; Yang et al., 2024) measurements. Moreover, a simulation database from a snow RTM and a process model can contribute to balancing training samples (Santi et al., 2022a, 2022b). Additionally, data resampling (Carvalho et al., 2025) and category weight adjustment (Zhang and Yu et al., 2022) are commonly used to solve sample imbalance issues. Overall, leveraging in-situ snow surveys, altimeter-based observations and two-dimensional imagery datasets (see Section 4.3) can contribute to improving training sample quality, including accuracy, representativeness, and balance.

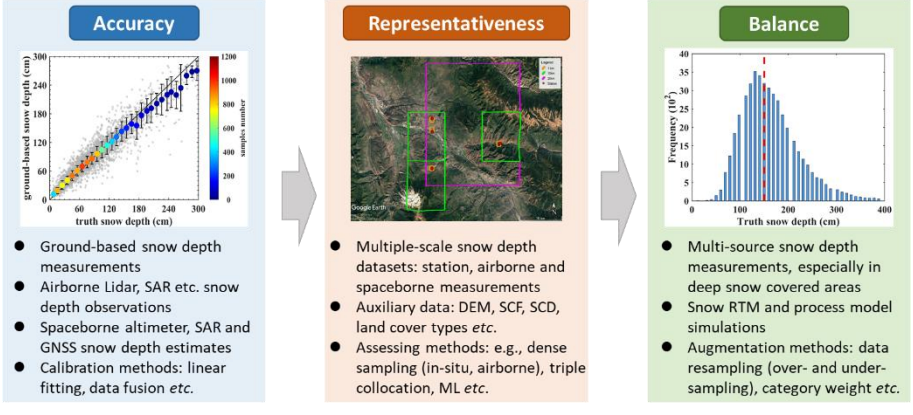

Figure 22: Three dimensions of improving ML training samples.

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5 Conclusions

Ongoing climate warming makes accurate snow depth retrieval with remote sensing more challenging because of rapidly changing snow characteristics, increasingly wet and patchy snowpack features, and frequent extreme weather events (e.g., snow avalanches and droughts). Emerging advances in ML are creating new opportunities to accelerate scientific and engineering progress in the snow community through the synergistic integration of state-of-the-art ML techniques with traditional physics-based modelling. For the first time, this study comprehensively reviews the current status, existing paradigms and challenges associated with ML techniques in the snow depth remote sensing domain. A decadal review (2015–2025) of the literature reveals the following:

- From 2015 to 2025, the number of ML-related articles in the snow depth remote sensing domain has increased from 3 to 33, with a notable surge in deep learning methods emerging from 2020 onward. According to the first authors' affiliation, China and the United States are the top two contributors to the literature, together accounting for almost 70% of the papers.
- In spatial mapping, western countries (America and Europe) tend to focus on fine-scale (from meter to hundreds of meters) snow depth retrieval in mountainous regions or catchment basins, because of their intensive ground-based observation networks and synchronous airborne experiments (e.g., ASO Lidar). Chinese scholars have focused more on the spatial distribution of snow depth across large regions (Northern Hemisphere or China's three snow cover areas), typically using coarse-resolution (10 or 25 km) or downscaled products. In terms of methodology, western countries excel in integrating process-based or hydrological models with ML, while China tends to focus more on the direct application of ML or its combination with RTMs.
- ML has achieved tremendous success in retrieving snow depth. Five common paradigms are being pursued for applications in snow depth retrieval, including coupling ML approaches and snow physical models to improve snow depth estimates, applying ML models for RTMs for simulating microwave signals in assimilation or iteration algorithms, optimizing snow physical models by providing key inputs or accelerating operational efficiency, improving existing gridded snow depth products via data fusion, bias correction or assembly techniques, and downscaling coarse snow depth products to fine resolutions.
- Although various paradigms coupling ML techniques and snow physical models have been proposed since 2021, their interpretability is limited by their backwards process. Embedding physical principles into ML techniques, such as the recently proposed differentiable modelling (DM) algorithm, will play an invaluable role in improving snow depth estimates and enhancing the physical interpretability and generalizability of models, providing new ideas for the combination of ML and physical knowledge.
- Future focus should be on bridging the disparity of model–observation mismatch, integrating fundamental physical laws into ML structures, enhancing the data quality of ML training samples, and improving snow depth estimates in mountainous and polar regions, and during the snowmelt season.

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- Skilfully utilizing recent technical improvements (e.g., Sentinel-1, ICESat-2, and CryoSat-2) and next-generation satellite missions (e.g., TSMM, ROSE-L, and CIMR), particularly in combination with the power of ML, is expected to benefit data-needy ML architectures, and improve the data quality of ML training samples, thus significantly enhancing the capability of ML methods in practical applications.

This study presents some of the current approaches and diverse applications of ML for snow depth retrieval with remote sensing, describes the limitations of physics-forward models and ML training samples, summarizes the challenges of achieving spatiotemporally continuous snow depth monitoring at both spatial (mountainous and polar regions) and temporal (snowmelt season) scales, and provides suggestions for future studies. Our hope is that this review will accelerate the cross-pollination of ideas among these diverse research communities.

Author contributions

JWY and LMJ designed the research, wrote the manuscript and edited the manuscript. MQC, JWY, JJY carried out the analyses, created the figures. JMP, CX, SRT, YQC wrote the subsections and helped edited the manuscript. JYD, XDL, YNB, YXH, GJL, CZ, YLW wrote the subsections.

Competing interests

The contact author has declared that none of the authors have any competing interests.

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