Dear Editor,

We would like to thank the two Reviewers for the reviews and suggestions that helped us improve our manuscript. We kindly request that the editor grant us one more opportunity for peer review. We believe that this work will advance the application of machine learning in snow depth and snow water equivalent (SWE) monitoring with remote sensing.

We have addressed all the points highlighted by the reviewers and we modified the manuscript accordingly. In particular:

(1) Clarification of the scope and title of the review

In response to concerns that the title did not fully reflect the content, we revised the title to "A decadal review (2015–2025) of machine learning models applied to remote sensing-based snow depth/snow water equivalent retrieval: statistical analysis, existing paradigms, and future directions". We also clarified that snow depth and SWE are two key parameters characterizing snow mass, that they are highly correlated, and that both were included in the search criteria; this decision is explained in Section 2. In addition, we clarified the scope of "remote sensing," noting that ground-based, airborne, and spaceborne observations were considered.

(2) Addition of quantitative accuracy metrics

The reviewer asked for quantitative comparisons rather than qualitative statements. In response, we have added accuracy metrics throughout the manuscript, including the Abstract. For example, we now report that compared with purely data-driven machine learning, coupling machine learning with snow physical models (data-model-driven) improves snow depth/SWE retrieval accuracy by approximately 53%; that machine learning can predict microwave brightness temperature with an accuracy of approximately 2–4 K, which is comparable to that of snow radiative transfer model (RTM) models; that machine learning can accelerate RTM simulations by at least two orders of magnitude; that data fusion and bias correction improve gridded snow depth products by approximately 55%; and that multilayer RTMs reduce the bias from −13.4 cm to 2.4 cm and RMSE from 15.9 cm to 10.2 cm.

(3) Reorganization of the structure, and removal of unsupported content

We simplified the review of RTM and traditional snow depth/SWE retrieval algorithms in Introduction, removing material that was unclear or insufficiently connected to snow depth/SWE. We have also rewritten the Abstract and Introduction so that they begin directly with the importance of snow depth/SWE and the challenges in monitoring them, rather than with extreme weather or snow cover extent. In addition, we added an explicit description of the overall structure at the end of the Introduction and reorganized the paper so that Sections 2, 3, and 4 correspond directly to "statistical analysis" "existing paradigms" and "future directions". We also corrected typos and unclear expressions throughout.

(4) Clarification of the five existing paradigms and the five future challenges

We clarified the five existing paradigms in Section 3: coupling of machine learning and snow physical model (snow RTM or process model), substituting RTM with machine learning for predicting microwave signals in assimilation or iteration algorithms, optimizing RTM by providing key inputs or accelerating operational efficiency, improving existing gridded snow depth/SWE products, and downscaling coarse snow depth/SWE products to a fine-scale resolution. Our study concluded that data-model-driven machine learning retrieval algorithms outperform purely data-driven ML models, but this advantage relies on sufficiently accurate physical model simulations. Therefore, Section 4 now clearly presents five interconnected challenges from three

perspectives: physical models, machine learning, and engineering applications. Physically, we need to bridge the disparity between RTM simulations and remote sensing observations (Section 4.1). For machine learning, we need to integrate fundamental physical laws into machine learning structures to enhance interpretability (Section 4.2) and improve the quality of machine learning training samples to strengthen generalization capability (Section 4.5). Regarding water resource management, we need to focus on achieving fine-scale snow depth/SWE monitoring at large scales by integrating multi-source remote sensing data using machine learning (Section 4.3), and on enhancing snow depth/SWE estimates under complex conditions to achieve spatiotemporally continuous snowpack monitoring.

(5) Revision of the bibliometric analysis

To better understand trends and the impact of machine learning models in remote sensing-based snow depth/SWE monitoring, we conducted a statistical analysis of 127 publications. We added the research purpose in each part of Section 2 to improve the logical flow and readability. Meanwhile, we simplified the bibliometric analysis, deleted the top 10 cited articles (Section 2.4), clarified the citation source and search procedure, and explained how this analysis supports the subsequent paradigm synthesis.

In the following, we answer in detail the specific comments made by the reviewers. The author responses are reported in blue right below the reviewers' comments. Line and page numbers indicated by the reviewers are referred to the submitted paper.

Reviewer 2 (anonymous)

Thank you for the invitation to review this manuscript. The paper is a review of machine learning (ML) applications in satellite-based snow depth retrieval. This topic is highly relevant to the journal and represents an important area of development for the community. The authors have compiled a large number of papers that contribute to this field.

We would like to thank the two anonymous reviewers for their affirmation of the originality of the paper. Our main motivation for this study was to summarize the progress and existing challenges of machine learning in snow depth/SWE retrieval over the past decade and to better understand how machine learning techniques can serve snow remote sensing.

My primary concern is that the manuscript frequently mischaracterizes the methodology and findings of the cited literature, and provides more of a superficial review of the source material. In numerous examples, the claims made in the text are entirely unrelated to, or unsupported by, the cited papers. Furthermore, the manuscript lacks logical flow and synthesis; rather than providing deep insights into the evolution of ML-based snow-depth retrieval algorithms, it reads like an uncritical compilation of information lacking careful findings about the main knowledge gaps, contributions of the paper, and future directions.

We sincerely appreciate the reviewer's constructive suggestions and comments, which have helped us substantially to improve the manuscript. We have checked and revised the manuscript point by point in response to all the comments. In addition, following the suggestions of both reviewers, we have restructured the manuscript and improved its content, producing better flow in the logic and making the paper more readable. Detailed responses are given in the "Major Concerns" and "Specific Comments" sections.

Below, I have detailed my major concerns and specific line-by-line corrections.

Major Concerns:

Mischaracterization of cited literature:

Throughout the manuscript, papers are cited incorrectly. A major flaw is the cross-use and conflation of snow cover, snow properties, snow depth, and SWE. These are distinct parameters. The papers included in this review cover all of these types but are not well separated. The manuscript needs to explicitly focus on snow depth (as the title suggests) and properly distinguish it from SWE and snow cover.

We sincerely apologize for the poor readability caused by the unclear logic. We have adjusted the structure of the paper in the following aspects:

(1) We clarified that snow depth and snow water equivalent (SWE) are highly correlated and that both were included in the search criteria; we explained this decision in Section 2. In addition, we clarified the scope of "remote sensing," noting that ground-based, airborne, and spaceborne observations were considered.

(2) Therefore, we modified the title of the paper to make its content immediately clear to readers: "A decadal review (2015–2025) of machine learning models applied to remote sensing-based snow depth/snow water equivalent retrieval: statistical analysis, existing paradigms, and future directions".

(3) We rewrote the abstract, removing the content on snow cover and extreme weather, and moving directly to the topic of snow depth and SWE:

"Understanding snow depth and snow water equivalent (SWE) distribution is crucial for studying water processes, weather, and climate. Numerous remote sensing-based approaches have been used to derive spatially continuous snow depth/SWE. However, challenges remain in capturing their changes because of the nonlinear and so-called 'ill-posed' problems in retrieval algorithms. Machine learning (ML) techniques (including deep learning) are beginning to play important roles in advancing snow depth/SWE retrieval, particularly with microwave remote sensing, owing to their strong ability to fit nonlinear, nonexplicit functional relationships between snow depth/SWE and massive amounts of geoscience data. However, a systematic review of ML applications in snow depth/SWE retrieval with remote sensing is notably absent from the literature, and the trajectory for future advancements remains ambiguous. This review comprehensively summarizes the implementation (with an overview of the literature) and current paradigms of snow depth/SWE retrieval using ML techniques and remote sensing observations over the past decade (2015–2025) and proposes future research directions in response to the existing challenges. A statistical analysis of 127 studies revealed that the number of ML-related articles has increased over the past 10 years, from 3 to 33 per year. By first author affiliation, China and the United States lead in terms of contributions, accounting for almost 70% of the papers. We also report that nearly 50% of the studies focus on high-resolution snow depth/SWE retrieval (from a few metres to hundreds of metres) at regional or catchment scales, especially over mountains, which can be attributed to comprehensive ground-based and airborne field campaigns (e.g., SnowEx, NoSREx, and Airborne Snow Observatory (ASO) Lidar) and spaceborne SAR observations (e.g.,

Sentinel-1). Our decadal review concludes with five existing paradigms: (1) coupling ML with snow physical models (data-model-driven ML), which improves snow depth/SWE retrieval accuracy by 53% compared with purely data-driven ML methods; (2) substituting snow RTM with ML for simulating microwave signals, where ML can simulate signals with an accuracy of 2–4 K; (3) optimizing snow electromagnetic models by improving their operational efficiency, with ML accelerating RTM simulations by at least two orders of magnitude; (4) improving existing gridded snow depth/SWE products, which enhances their accuracy by approximately 55% through data fusion; and (5) downscaling coarse snow depth/SWE products from the conventional tens of kilometres to the hundred-metre level. However, some challenges and unresolved issues still exist. Future efforts in snow remote sensing research should aim to bridge the disparity between forward model simulations and remote sensing observations to facilitate data-model-driven ML; integrate fundamental physical laws into ML structures to enhance the interpretability of ML; achieve fine-scale snow depth/SWE monitoring at large scales through the integration of multisource remote sensing data (PM, SAR, Lidar, etc.); enhance ML-based snow depth/SWE estimates under complex conditions to achieve spatiotemporally continuous snowpack monitoring; and improve the quality of ML training samples to strengthen its generalizability. Overall, this paper provides a comprehensive review of the applications of ML techniques in snow depth/SWE remote sensing, focusing on statistical analysis, current paradigms, 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/SWE and deepening our understanding of the spatial variability of snowpack globally."

(4) We revised the Introduction, e.g., by removing the content on cryosphere, snowpack, and global climate change, and instead directly emphasising the importance of snow depth/SWE for water resource management, weather and climate forecasting, and global change research (Page 2, Lines 49-55 in the revised manuscript): "The amount of snowfall (snow mass) is typically measured by two different parameters, snow depth and snow water equivalent (SWE). Since the SWE is the product of snow depth and snow density, snow depth and SWE are highly correlated. The successful estimation of snow depth/SWE can improve the accuracy of snowmelt-runoff prediction and the management of water supply (Tanasienko et al., 2011; Barnett et al., 2005; Sturm et al., 2017; Vano et al., 2020), contribute to predicting potential snow-related disasters, e.g., flooding in spring, snowstorms, and snow avalanches (Gao et al., 2016; Eckert et al.,2024), and enhance the understanding of the global water cycle in the climate system (Hock et al., 2019). Remote sensing techniques are the only means to monitor spatiotemporally continuous snow depth/SWE at large scales." The logical flow is added to make the paper readable (Page 6, Lines 166-173 in the revised manuscript): "The remainder of this article is organized as follows. Section 2 provides statistics on the literature published over the past decade, including the number of publications, research scales, key milestones, and citation counts. Section 3 summarizes five existing paradigms for improving snow depth/SWE with ML approaches, namely, the coupling of ML and snow physical models, the substitution of RTM for simulating microwave signals, the optimization of snow physical models, the improvement of gridded snow depth/SWE products, and the downscaling of coarse snow depth/SWE datasets. Section 4 details the challenges faced and proposes solution directions, involving the simulation accuracy of RTM, the interpretability of ML, the enhancement of spatial resolution, spatiotemporally continuous monitoring in complex

scenarios, and the quality of training samples. Finally, Section 5 concludes this study."
(5) We simplified the review of microwave radiative transfer models (RTMs) and traditional snow depth/SWE retrieval algorithms. Here, we did not directly delete them for three main reasons. First, microwave remote sensing is a valid tool for retrieving snow depth/SWE because of the ability of microwave signals to penetrate snowpack. Second, our review revealed that almost 80% of the studies indeed used microwave observations or microwave-derived products as predictor variables of the ML model. Third, three of the existing paradigms we summarized are closely related to RTM, namely, coupling with RTM to improve snow depth/SWE (Section 3.1), substituting RTM for simulating microwave signals (Section 3.2), and optimizing the RTM by providing key parameters or improving the run speed (Section 3.3). Two of the future research directions we proposed are related to the RTM: reducing the discrepancy between forward model simulations and remote sensing observations (Section 4.1) and integrating ML with a physical model to improve its interpretability (Section 4.2). Therefore, we provide a brief review of RTM and snow depth/SWE retrieval algorithms in the introduction section (Pages 3-4).

Lack of proper synthesis and organization:
The papers are not organized or grouped to reflect the evolution of ML techniques or retrieval algorithms. Strangely, the authors summarize findings based on the country of publication (Lines 270-285) rather than treating the topic as a unified community effort or organizing by methodological advancements.
We fully agree that the content in the manuscript should be linked to methodological advances. We have adjusted the structure of the paper in the following aspects:
(1) We referred to published review articles (Vivone et al., 2025, GRSM; Demil et al., 2025, JH; Sabut et al., 2025, WRR; Hong et al., 2026) and conducted a statistical analysis of 127 studies to better understand their trends and impact. In our view, an overview of the articles is necessary. On the one hand, it supports the subsequent paradigm synthesis and corresponding strategies; on the other hand, it demonstrates the reliability and authenticity of our reference database. If necessary, we would be happy to share the reference database.
(2) To improve the logical flow and readability, we added the research purpose in each part of Section 2:
***A** (Page 6, Lines 163-164 in the revised manuscript): "To better understand the trends and research impact of ML in snow depth/SWE retrieval, we conducted a bibliometric analysis of the literature."*
***B** (Page 6, Lines 182-184 in the revised manuscript) subsection 2.1: "To summarize the contributions that ML has made to snow depth/SWE monitoring and the paradigms that have emerged, we reviewed the key milestones during the past decade."*
***C** (Page 8, Lines 209-210 in the revised manuscript) subsection 2.2: "To better understand country contributions, a summary of the geographic distribution (according to first author affiliation) of published articles is shown in Fig. 3a."*
***D** (Page 8, Lines 212-213 in the revised manuscript) subsection 2.2: "To highlight the contributions of the journals and to help readers understand the topics of interest for each journal, the publication distribution from 2015 to 2025 is shown in Fig. 3b."*
***E** (Page 9, Lines 243-246 in the revised manuscript) subsection 2.3: "Coarse snow depth/SWE products are typically sufficient for climate analysis, seasonal forecasting and environmental*

prediction, but they are not suitable for applications such as hydrological forecasting and water management. To present the current status and trends of spatial resolution in existing studies, we conducted a statistical analysis of the spatial resolution levels (Fig. 4a)."

***F** (Page 10, Lines 267-268 in the revised manuscript) subsection 2.3: "The quality of the training samples, particularly the target variable (snow depth/SWE), is a key factor influencing ML models. The source of the target variable for ML models is shown in Fig. 4b."*

Misunderstanding of scientific and technical challenges:

The authors' assessment of the challenges facing ML in snow depth retrieval (e.g., Line 130) fundamentally misrepresents the state of the science. Stating that ML struggles because snow is not a "stationary spatial element" and that it "accumulates and melts" is scientifically inaccurate. This is basic seasonality. The actual, well-documented challenges in the PMW/ML community like domain transferability (models failing outside their training geography), a severe lack of high-quality spatial training data in complex terrain, deep-snow signal saturation, and the physical transition to wet snow, which drastically alters microwave emissivity. This section must be entirely rewritten to discuss true technical bottlenecks.

We respectfully disagree with the reviewer's statement regarding "Misunderstanding of scientific and technical challenges… fundamentally misrepresents the state of the science". We would like to clarify it here.

We fully agree with the reviewer that snow cover is a seasonal variable. We further note that snow cover is a rapidly varying variable characterized by strong spatiotemporal heterogeneity owing to snow accumulation and ablation, snow metamorphism and compaction (grain size, density, etc.), and redistribution by terrain and wind (Page 4, Lines 125-135 in the revised manuscript). For this reason, purely data-driven ML models often suffer from poor robustness, namely, the poor domain transferability raised by the reviewer. Our intention here is to highlight the challenges faced by ML, rather than by microwave remote sensing, and to lead into the next paragraph on the data-model-driven ML model.

We agree that the challenges (…lack of high-quality spatial training data in complex terrain, deep snow signal saturation, and the physical transition to wet snow…) indeed limit the potential of microwave remote sensing for snow depth/SWE retrieval. To address these challenges, we further propose future research directions in Section 4.

To improve the readability of the paper, we have revised and rewritten this paragraph (Page 4, Lines 120-134 in the revised manuscript): "However, purely data-driven ML models still face several challenges in retrieving global snow depth/SWE. Beyond the traditional challenges of microwave remote sensing (e.g., signal saturation in deep snowpack, snow metamorphism, and wet snow), data-driven ML itself suffers from poor spatial extrapolation. This is particularly problematic because snow cover is a seasonal and highly dynamic component of the Earth system. It is typically characterized by strong spatiotemporal heterogeneity arising from seasonal accumulation and ablation, snow metamorphism and compaction, and topographic redistribution. Seasonally, snow begins to accumulate in autumn, continues to accumulate through winter, and finally melts (ablates) in spring or summer. Spatially, especially in mountainous regions, topographic features (e.g., elevation, slope, and aspect) are crucial for characterizing snow depth/SWE (Dozier et al., 2016; Ma et al., 2023). Additionally, snow compaction and metamorphism can cause variations in snow grain size, density, shape, and bonds, which in turn

affect microwave scattering signals. Thus, the seasonally and spatially dynamic characteristics of snow limit the use of standalone data-driven ML for snow depth/SWE retrieval."

Lots of unrelated material:

The introduction is poorly structured and fails to provide a clear view of the evolution of ML models in snow depth retrieval. Instead, it contains extensive unrelated material about snow cover, SWE, general Large Language Models (which have not been used in snow remote sensing).

On the basis of the two reviewers' comments, we adjusted the manuscript structure and deleted unrelated material. Please refer to the responses to "Major concerns" and to the editor above.

Other information like how to use ML to solve the VIE, ML applications in RTMs, generational challenging in snow remote sensing (i.e. the whole 4.4 session), which all show little connection to satellite-based snow depth.

We appreciate the comment. On this point, we would like to offer an alternative interpretation. In our view, this is exactly the key role that ML can play in improving the operational efficiency of RTMs. Combining RTMs with ML is a classic paradigm for snow depth/SWE retrieval (Section 3.1). On the one hand, it improves the accuracy of snow depth/SWE retrieval; on the other hand, the RTM enhances the interpretability of ML. However, RTMs rely heavily on prior information and are computationally inefficient, restricting their application in remote sensing. We therefore summarize the paradigm (Section 3.3), namely, improving the run speed of the snow electromagnetic model. In this section, we present two parallel cases: using ML to simulate the scattering phase matrices and the extinction and scattering coefficients, and using ML to solve the electric field of the volume integral equation (VIE).

To improve the readability of the manuscript, we have rewritten this section as follows:

A (Page 16, Lines 389-399 in the revised manuscript):

"Combining RTM with ML indeed improves snow depth/SWE retrieval (Section 3.1). The snow electromagnetic model is among the most critical components of RTMs. In the snow electromagnetic model, the discrete dipole approximation (DDA) is typically employed to represent the electric field volume integral equation (VIE) for characterizing electromagnetic scattering interactions with snow volume. An iterative method, such as the generalized minimal residual (GMRES) algorithm, is then used to solve the DDA to obtain the phase matrix, extinction coefficients, and scattering coefficients. However, the process of scattering calculations is computationally expensive. Therefore, exploring the use of the ML method to accelerate snow electromagnetic models is crucial. Here, we present two parallel cases. In the first case, the ML is trained to learn the relationship between the scattering characteristics simulated from the snow electromagnetic model and the input snow parameters and then to predict the phase matrix, extinction coefficients, and scattering coefficients. In the second case, ML is used to replace the GMRES in the snow electromagnetic model to solve the DDA for obtaining the phase matrix, extinction coefficients, and scattering coefficients."

B (Page 17, Lines 400-415 in the revised manuscript):

"(1) Predicting snow scattering characteristics using ML

In this paradigm, the database (scattering field and snow parameters) generated by the snow electromagnetic model is typically used to train the relationship between the scattering characteristics and the input snow parameters. The trained-ML model is subsequently used to

predict the scattering phase matrices and the extinction and scattering coefficients. For example, a neural network-accelerated DMRT-Bic model (DMRT-Bic-NN) was developed (Li and Xiong, 2026). In this methodology, the DMRT-Bic model simulates the scattering characteristics, and an ANN model is then trained on the resulting database. It accurately reproduced snow scattering parameters at multiple microwave wavenumbers, with RMSE values of 0.00082–0.01886 cm-1 (Fig. 11). Moreover, the predicted and reference phase matrices for copolarization are in good agreement, whereas the cross-polarized phase matrices exhibit some mismatch (Fig. 11). The validation results against ground-based brightness temperature observations over China and Finland demonstrated that the DMRT-Bic-NN achieves excellent performance, with RMSE values of 3–5 K (Li and Xiong, 2026). The sensitivity analyses further revealed 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 the experimental observations. Most importantly, the DMRT-Bic-NN preserves the high physical fidelity of the original bicontinuous representations while reducing the computational cost by several orders of magnitude (from approximately 20.1 h with the original DMRT-Bic model to approximately 0.54 s). This work exemplifies how ML can be effectively integrated with snow electromagnetic models to achieve both high accuracy and high operational efficiency in RTM simulations."

C (Page 17, Lines 420-433 in the revised manuscript):

"(2) Replacing the GMRES with ML for solving the DDA

In parallel with the path of directly predicting snow scattering characteristics through ML based on snow parameters, as performed by Li and Xiong (2026), another independent approach is to solve the DDA by ML to obtain dipole moments rather than the time-consuming GMRES method. Once the dipole moments are predicted, all the quantities related to scattering can be readily derived from Maxwell's equations. Du et al. (2025) introduced a physics-informed neural network framework (PINN) to solve the DDA (hereafter termed DDA-NN), establishing a direct mapping from the discretized bicontinuous snow microstructure to the induced dipole moments of the snowpack volume. Crucially, the VIE residue is embedded as a physical constraint in the loss function of the network, eliminating the need for precomputed training labels. The results demonstrated that the predicted dipole moments strongly agree with the benchmark solutions from the traditional GMRES algorithm (Fig. 12). Moreover, the coherent scattering amplitude and the resulting phase matrix derived from the DDA-NN closely match the benchmark results in co-polarization, whereas the cross-polarization performance remains more sensitive. 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 depth/SWE remote sensing."

Excessive reproduction of figures:

The manuscript includes far too many figures adopted directly from original papers (Figures 7 through 17). A review paper should synthesize concepts and data into original summary figures, rather than simply adopting a dozen figures from existing literature.

We appreciate this important comment. We agree that a review paper should present original synthesized figures rather than simply reproducing figures from existing studies. Although Figures 7–17 were provided by our co-authors and properly cited, we are now working with them to

redraw these figures into original summary figures using newly compiled data. In the revised manuscript, these figures will be substantially revised or replaced accordingly.

Inconsistent terminology:
Please use consistent language throughout the manuscript. For example, choose one standard term among "Physics-informed," "Physics-based," "Physics-guided," or "physics-embedded," and apply it consistently.
Revised.

Specific Comments:
(Note: because the original line numbers appear incorrect in places, these comments refer to the corresponding line sessions).
We thank the reviewer for this reminder.

Line 50: Please rewrite these two sentences to clearly define the differences between snow cover, snow depth, and SWE, and explicitly state the main focus of this review paper.
We rewrote the Abstract and Introduction, removed the snow cover and extreme weather content, and moved directly to snow depth and SWE. We also clarified that snow depth and SWE are highly correlated and that both were included in the search criteria; we explained this decision in Section 2. Please refer to the responses to "Major concerns" and to the editor above.

Lines 60-65: Please double-check the papers cited here. Several of these focus on SWE retrieval from Passive Microwave data, not snow depth.
We thank the reviewer for this reminder. We clarified that snow depth and SWE are included in the search criteria. Please refer to the responses to "Major concerns" and to the editor above.

Line 70: Consider reducing the historical content regarding radiative transfer models, as this is not the core focus of the paper.
In accordance with the two reviewers' comments, we simplified the review of microwave radiative transfer models (RTMs) and traditional snow depth/SWE retrieval algorithms. Please refer to the responses to "Major concerns 1" above.

Line 95: Spell out "DMRT".
Added.

Line 105: Evora et al., 2008 is about SWE retrieval, not snow depth.
Corrected.

Line 110: Please verify this statement. Both Gao et al., 2009 and Tong et al., 2010 focused on SWE retrievals. Furthermore, only Tong et al., 2010 compared ANN models trained with AMSR-E and SSM/I.
Corrected.

Line 115: Do you mean "data assimilation"? It is unclear what is meant by "observation operators

for radiance assimilation framework" and how ML models are used in this circumstance. Please clarify.

Revised: "Subsequently, data-driven ML models have been used as surrogates for RTMs, serving as the observation operator in data assimilation to simulate microwave signals, thereby enabling the assimilation of remote-sensing brightness temperature observations or snow cover data into land surface models".

Lines 115-125: A large number of ML-related papers are listed here, but very few relate to the actual focus of this paper (snow depth retrieval). Please remove unrelated papers to keep the context concise.

We checked and revised the text accordingly. We also clarified that snow depth and SWE are included in the search criteria. Please refer to the responses to "Major concerns" and to the editor above.

Line 130 - 135: As noted in my major concerns, comparing the seasonal changes of a snowpack to "stationary spatial elements" (like soil types) as a limitation of ML is scientifically inaccurate. The challenges section must reflect actual ML limitations. Furthermore, Line 135 shifts to snow cover, which is off-topic.

Corrected. Please refer to the responses to "Major concerns" above.

Line 170: While LLMs are a recent advancement, they have not yet been meaningfully applied to snow remote sensing. This information is irrelevant to the paper's scope.

Deleted.

Line 255: The authors need to review all papers cited here, as many are unrelated to ML snow depth retrieval. Consequently, the accuracy of the main Figure 4, which is based on this text, is highly questionable.

Revised accordingly. We would like to clarify that snow depth and SWE are included in the search criteria. Please refer to the responses to "Major concerns" and to the editor above.

Line 295 (Bair et al., 2018): The information provided regarding Bair et al., 2018 is incorrect. This paper is about using ML for SWE estimation, not attempting "to combine a snowmelt process model (ParBal) with an RF for real-time estimates in the watersheds in Afghanistan." Furthermore, ParBal is an energy balance model, not strictly a snowmelt process model.

In Bair et al. (2018), the snowmelt process model (ParBal) was used to reconstruct the SWE, which was then combined with AMSR-E brightness temperatures to train a random forest (RF) model for SWE prediction, achieving a real-time estimate during the snow season in remote mountains.

We revised the text to "To predict the SWE during melt seasons, Bair et al. (2018) used a snowmelt process model (ParBal) to reconstruct spatially distributed SWE, which was then combined with AMSR-E brightness temperatures to train an RF model for real-time SWE prediction in the remote mountains of Afghanistan."

Line 295 (Broxton et al., 2019): This paper is about SWE estimation using ML, not "using an ANN to estimate snow density."

SWE is the product of snow depth and snow density. To reduce the uncertainty in SWE caused by density, Broxton et al. (2019) proposed an ANN model to improve snow density. We revised this sentence to "To reduce the uncertainty in SWE caused by density, Broxton et al. (2019) used an ANN to estimate snow density by combining snow surveys and Lidar measurements."

Line 330: This sentence is logically flawed. Please reword for clarity.
Revised.

Lines 375-405: This entire section focuses on using ML to solve the VIE, which has little practical connection to the core topic of satellite-based snow depth retrieval.
Combining RTMs with ML is a classic paradigm for snow depth/SWE retrieval (Section 3.1). However, RTMs are computationally inefficient, restricting their application in remote sensing. We therefore summarize the paradigm (Section 3.3), namely, improving the run speed of the snow electromagnetic model. In this section, we present two parallel cases, using ML to simulate the scattering phase matrices and the extinction and scattering coefficients and using ML to solve the discrete dipole approximation (DDA).
To improve the readability of the manuscript, we have revised this section. Please refer to the responses to "Major concerns" above and the revised manuscript (Page 16, Lines 389-401; Page 17, Lines 420-431).

Lines 484-510: The challenges and future prospects section lacks deep scientific insight and reads as a disconnected compilation of recent ML developments that do not link back to the specific limitations of snow depth retrieval.
Combining RTMs with ML indeed improves snow depth/SWE and enhances the interpretability of ML. However, this advantage is related to the accuracy of RTM simulations, which is particularly uncertain for microwave signals influenced by snow metamorphism and compaction. We therefore propose the use of ML to reconstruct snow laying to better support ML-based snow depth/SWE retrieval. To improve the readability of the manuscript, we have rewritten this section as follows:
"Our review revealed that data-model-driven ML has been explored as a paradigm to improve snow depth/SWE retrievals (see Section 3.1). However, a significant gap remains between physical-model simulations and remote sensing observations (model–observation), constraining the generalization ability of the ML in terms of snow depth/SWE retrieval. To address the mismatch between physical model simulations and remote sensing 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). In addition to electromagnetic theory, the snow layering structure due to snow metamorphism and compaction significantly affects the microwave scattering of snowpack. Previous studies have shown that multilayer RTMs outperform single-layer models in snow depth/SWE retrieval (Zhu and Tan et al., 2018; King et al., 2018, 2020; Rutter et al., 2019). For example, Pan et al. (2024) reported that a dual-layer model reduced the bias from −13.4 to 2.4 cm and the RMSE from 15.9 to 10.2 cm, significantly reducing the underestimation and uncertainty of snow depth. 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 aid in simulating microwave brightness temperatures (Xue et al., 2015; Forman et al., 2016) and improve snow depth/SWE retrievals (Pan et al., 2023) at large scales. Therefore, integrating RTM, process models (e.g., SNOTHERM and SNOWPACK), and ML techniques is a promising research direction for reducing the differences in model–observation (Fig. 16), in which the snow 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 a nonlinear relationship between snow depth/SWE and multiple variables.
Additionally, some novel remote sensing-based 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. 16). For example, Varshney et al. (2021) attempted to apply ML to trace vertical snow layers by using snow radar echograms across the Greenland Ice Sheet. Meehan et al. (2024) estimated bulk snow density using an ML approach by combining GPR and Lidar observations. Akbar et al. (2026) proposed an ML-based method to estimate two key snow parameters (permittivity and conductivity) using GPR data. Therefore, using ML to track and quantify snowpack layering parameters from these remote sensing observations is crucial for improving physical-model simulations."

Comments on Figures:
Figure 1: Change the right y-axis label to 'Percent of total publications (%)'.
Revised.

Figure 2: The authors list Bair et al., 2018 as the milestone for stage two. As noted above, this paper is about SWE retrieval, not specifically snow depth during the melt season in mountains.
We thank the reviewer for this reminder. We clarified that snow depth and SWE are included in the search criteria. Please refer to the responses to "Major concerns" and to the editor above.

Reproduced Figures: For all figures adopted from original papers (e.g., Fig 9), it is strictly necessary to include the figure number of the original paper and properly cite the source in the caption.
Added and checked accordingly.

Figure 18: The proposed future direction is highly speculative and merely compiles current research workflows. It is unconvincing without an explicit, physically grounded explanation of why and how this workflow would succeed.
To reduce the effects of snow metamorphism and compaction on microwave signals, we propose a framework that reconstructs snow layering using ML and thereby improves RTM simulations. This idea is not unfounded. A review of the literature reveals that ML has already been integrated with snow radar, TomoSAR, GPR, and LiDAR observations to reconstruct snow stratigraphic parameters, including snow density, permittivity, and conductivity.
In accordance with the reviewer's comments and our in-depth understanding, we rewrote this part as follows:

"Our review revealed that data-model-driven ML has been explored as a paradigm to improve snow depth/SWE retrievals (see Section 3.1). However, a significant gap remains between physical-model simulations and remote sensing observations (model–observation), constraining the ML's generalizability in retrieving snow depth/SWE . To address the mismatch between physical model simulations and remote sensing 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). In addition to electromagnetic theory, the snow layering structure due to snow metamorphism and compaction significantly affects the microwave scattering of snowpack. Previous studies have shown that multilayer RTMs outperform single-layer models in snow depth/SWE retrieval (Zhu and Tan et al., 2018; King et al., 2018, 2020; Rutter et al., 2019). For example, Pan et al. (2024) reported that a dual-layer model reduced the bias from −13.4 to 2.4 cm and the RMSE from 15.9 to 10.2 cm, significantly reducing the underestimation and uncertainty of snow depth. 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 aid in simulating microwave brightness temperatures (Xue et al., 2015; Forman et al., 2016) and improve snow depth/SWE retrievals (Pan et al., 2023) at large scales. Therefore, integrating RTM, process models (e.g., SNOTHERM and SNOWPACK), and ML techniques is a promising research direction for reducing the differences in model–observation (Fig. 16), in which the snow 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 a nonlinear relationship between snow depth/SWE and multiple variables.

Additionally, some novel remote sensing-based 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. 16). For example, Varshney et al. (2021) attempted to apply ML to trace vertical snow layers by using snow radar echograms across the Greenland Ice Sheet. Meehan et al. (2024) estimated bulk snow density using an ML approach by combining GPR and Lidar observations. Akbar et al. (2026) proposed an ML-based method to estimate two key snow parameters (permittivity and conductivity) using GPR data. Therefore, using ML to track and quantify snowpack layering parameters from these remote sensing observations is crucial for improving physical-model simulations."

Figure 19: Should this be "Loss Function Embedding (LFE)"? Please correct the caption and the main text where this is mentioned (e.g., Line 525).

This has been corrected accordingly.