Comments on the manuscript “Reconstruction of 3D precipitation measurements from FY-3G MWRI-RM imaging and sounding channels” by Yang et al.

Overview

The authors present a neural network approach to reconstruct radar reflectivity profiles from passive microwave observations. The network is trained using a month (October 23 to November 31, 2023) of spatially and temporally collocated radar and microwave radiometer data from the FengYun 3G (FY-3G) satellite, i.e., the 35 GHz Precipitation Measurement Radar (PMR) and the 10.65 to 190.31 GHz Micro-Wave Radiation Imager for the Rainfall Mission (MWRI-RM). The authors estimated the effects of temperature sounding channels at 50-53 and 118 GHz and polarization difference on the prediction by comparing three networks trained with different input channel combinations. The experiments show that the 50-53 and 118 GHz channels improve the reconstruction of radar reflectivity profiles, especially over land. The observation-based link between active and passive microwaves on global scales provides new opportunities to extract information from passive microwave observations as they do not rely on forward model assumptions and could be beneficial for global assimilation of passive microwaves.

General comments

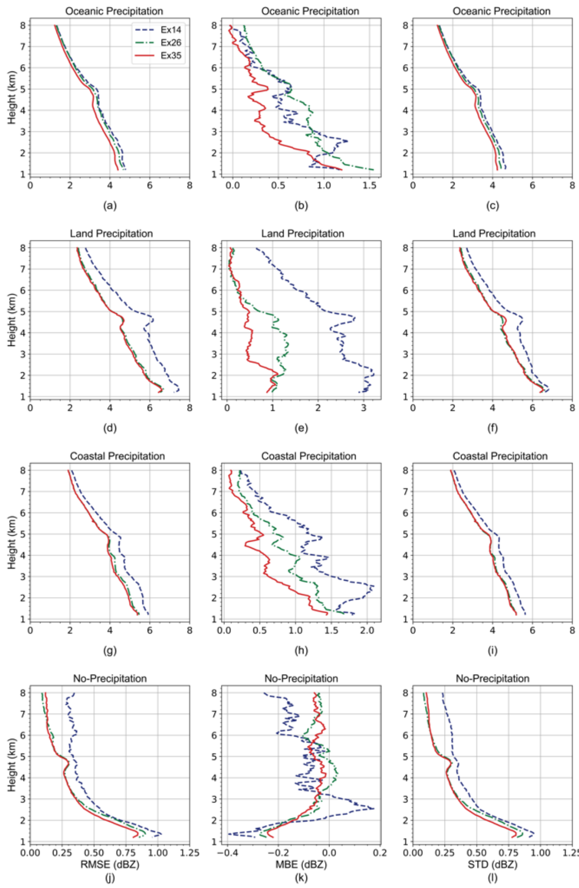
The work is well structured, and the case studies prove the model’s ability to reconstruct radar reflectivity profiles. Below are a few general comments on the neural network training and evaluation that require additional work but need to be addressed in a revised version of the manuscript.

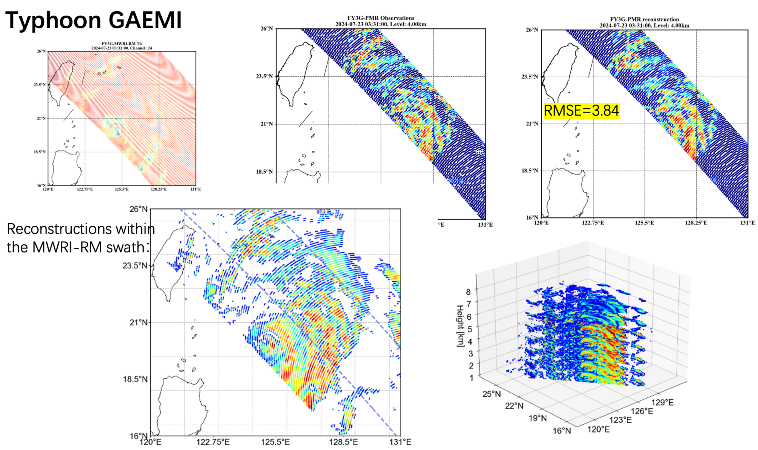
There are various problems during the data preparation, model architecture, and training procedure that likely cause overfitting and limited generalization capabilities of all three trained models. Such a lack of generalization would make it difficult to relate their prediction skill to the information content of the model input. Despite the results being relatively close to the expectation, I would highly recommend adjusting several methodological aspects.

The authors perform a random split into training and test data sets with a ratio of 80/20. However, the input data is autocorrelated in space and time. In the current setup, a test scene can be as close as a few ten kilometers to the center of a training scene. This might lead to the model learning the reflectivity profile of single mesoscale precipitation systems rather than learning the generalized radiative TB feature’s relation to reflectivity profiles. I suggest that the authors split their data into, e.g., weekly chunks. Also, the oversampling of precipitation scenes before splitting the data into training and test sets might lead to the occurrence of the same precipitation scene in training and test sets. However, this should be avoided. A way to replicate but still challenge the model would be data augmentation by rotating or flipping the TB field around the central footprint. Additionally, an independent validation set is needed to compare the three models. This was done only during case studies but without any quantification. Currently, the scores are computed only on the test data, which is problematic not only for the reasons stated above but also as its loss was used to determine the optimal parameters during early stopping. Finally, the number of model parameters exceeds the number of samples by a factor of five, although it should not exceed a factor of 0.1. The first fully connected layer contains more than 5 million parameters that would be sufficient for the model to learn a range of reflectivity profiles encountered during training.

Response:

Thank you for your suggestions. We agree that there are some issues with the data splitting and model architecture design. We would have liked to retrain the models according to your recommendations, but due to time constraints, we have instead chosen to test the generalization performance of the existing models using an independent sample. Specifically, we selected 288,892 samples from the period of December 1 to December 11, 2023, and preprocessed them according to the methods section. The evaluation results are consistent with previous ones, but with some differences in the details. The specific results are presented in Table 3 and Figure 3 of the revised manuscript, along with corresponding analysis updates. Additionally, to further demonstrate the model's generalization ability, we show the reconstruction performance for Typhoon Khanun, with an overall reconstruction RMSE of approximately 3.84 dBZ.





I would like to encourage the authors to publish their prepared samples used to train, test, and evaluate the models as well as the three fully trained models to make their results reproducible.

Response:

Thank you for your suggestion to make the data and trained models publicly available for reproducibility. Unfortunately, due to the large size of the sample data, we are unable to upload the full dataset. However, we have provided the code for sample processing in the manuscript, which should allow interested researchers to replicate our data processing steps. Additionally, the Level 1 products of PMR and MWRI-RM can be downloaded from the FENGYUN Satellite Data Center website (https://satellite.nsmc.org.cn).

Regarding the trained models, we are unable to provide them due to potential copyright considerations. As such, we respectfully request your understanding in this matter. We hope that the provided sample processing code and data access will still allow others to reproduce our results to a meaningful extent.

The oversampling of precipitation scenes before splitting the data into training and test sets might lead to the occurrence of the same precipitation scene in training and test sets.

Response:

Thank you for pointing this out. Upon reviewing the manuscript, we realized that our original description was inaccurate. We did not oversample non-precipitating samples as stated; instead, we downsampled them to match the number of precipitating samples. This approach was implemented to balance the dataset and ensure equal representation of both sample types during model training.

Specific comments

Figure 1: This figure contains many errors. I suggest removing it entirely, especially since TRMM and GPM CO are not part of the manuscript. The MWRI-RM channels should be presented in a table, ideally linked to the three experiments following later. Correct the MWRI-RM channel definitions using Table 4 in

https://doi.org/10.34133/remotesensing.0097

Line 106: Provide a table that lists the footprint dimensions of the different channels.

Response:

Thank you for your suggestions. We have removed Figure 1 as recommended and added a table detailing the specifications of MWRI-RM channels. The table is also linked to the three experiments discussed later in the manuscript, ensuring better alignment and clarity.

Line 40: MWRI-RM observes only V-pol at 166 GHz, while GMI observes both polarizations at this frequency. How would the addition of polarization information at this frequency improve the reconstruction of radar reflectivity profiles, especially under higher scattering by snow?

Response:

Previous studies analyzing polarization differences from GMI have shown that at higher frequencies such as 166 GHz, the polarimetric signals are more sensitive to the scattering effects of ice particles compared to lower-frequency channels (e.g., 89 GHz). The presence of dual polarization at this high frequency can provide valuable information about the orientation, shape, and phase of frozen hydrometeors within the precipitation system. This can be especially beneficial under intense scattering conditions induced by snow and other frozen particles, allowing the model to discriminate precipitation types better, identify layered structures (including the melting layer), and refine the retrieved vertical distributions of radar reflectivity.

However, in the current study, we do not specifically analyze the influence of polarization at the 166 GHz channel on the reconstruction of radar reflectivity profiles. While we recognize that incorporating polarization differences at this frequency could potentially enhance the accuracy and vertical structure representation—particularly in cases of heavy snow scattering—this aspect remains an avenue for future investigation.

Line 45: How many independent height levels of liquid water content can be retrieved from dual oxygen absorption sounding channels? This information would be helpful to understand the physical limitations of reconstructing radar profiles with >100 vertical degrees of freedom.

Response:

Thank you for your comment. As indicated by Han et al. (2015), each dual oxygen absorption sounding channel pair provides roughly one independent piece of vertical information in terms of liquid water content retrieval. Given that our MWRI-RM configuration includes four sets of such dual-channel pairs, we can obtain on the order of four independent vertical layers of liquid water content. This is a fundamental limitation due to the physical nature of passive microwave measurements. Unlike radar observations, which can resolve over a hundred vertical layers due to their much finer vertical resolution, microwave radiometers are inherently constrained by their weighting functions' limited vertical information content. We have added the relevant discussion in section 4 of the revised manuscript.

Line 52: Provide a table with the accuracy for each channel. How does the channel accuracy affect the reconstructed radar profiles? Would it be helpful to inform the model on channel accuracy?

Response:

Thank you for your insightful suggestion. He et al. (2024). provides a cross-comparison between MWRI-RM and GMI instruments, with the reported differences serving primarily as a reference for understanding the potential accuracy of MWRI-RM. As with any satellite-based observation, there are inherent measurement errors in both instruments, which may affect the accuracy of individual channels. However, a detailed analysis of how channel accuracy impacts the reconstructed radar profiles was beyond the scope of the current study. We agree that investigating the influence of channel accuracy is both important and necessary. For example, assessing the model's sensitivity to input uncertainties by perturbing the brightness temperatures in specific channels could help identify how robust the reconstructed radar reflectivity profiles are to observational errors. Such experiments could provide valuable insights into channel contributions and model stability. Additionally, informing the model explicitly about the accuracy or uncertainty of each channel might improve its ability to weigh the channels appropriately during training.

We acknowledge the significance of this topic and plan to address it in future work. This will include systematic experiments to quantify the impact of channel errors on the reconstruction performance and explore methods to enhance the model's robustness under input uncertainties. Thank you for raising this point, which will help guide our future investigations.

Line 65: This sentence is unclear to me. Which direct relationships between active and passive microwave observations need to be identified? Explain why a direct relationship between TB and radar reflectivity is needed. In general, forward models can simulate both the active and passive signal. Is it due to assumptions in the forward model or due to differences in weather models and reality? This is a key question of this work that needs to be explained.

Response:

Thank you for pointing out the confusion in our original wording. We have removed the problematic sentence in the revised manuscript. Our intention was not to overstate the direct correlation between active and passive microwave observations but rather to emphasize that meaningful relationships exist and can be explored using deep learning techniques. By doing so, we aim to better understand how two fundamentally different types of observations—active radar data and passive microwave radiances—can be mapped onto each other to retrieve more detailed three-dimensional precipitation structures.

Line 73: It would be helpful to have a table of previous work and the respective methods. How does the method used in this work differ from the Res-UNet in Brüning et al. (2024), and how are the differences motivated? What is the accuracy of other work that replicates radar reflectivity profiles?

Response:

Thank you for the suggestion. In the revised manuscript, we have reorganized the literature review to focus on a selection of representative studies that are most relevant to our work. Due to time constraints, we have not provided a comprehensive table listing all related studies. Instead, we have highlighted some key works that illustrate the range of methodologies, data sources, and achieved accuracies in **Lines 69-77**. This approach allows us to give a more detailed and meaningful comparison without overwhelming the reader.

Our study primarily builds upon the work of Yang et al. (2024), which pioneered the use of passive microwave (PMW) radiances from GMI to reconstruct DPR reflectivities. While their study achieved an RMSE below 4 dBZ across all altitudes by incorporating polarization differences and temperature profiles, it was limited to oceanic precipitation scenarios. In contrast, we extend their approach by leveraging the newly launched FY-3G satellite's MWRI-RM and PMR instruments. The addition of dual oxygen absorption channels (50 and 118 GHz) addresses the challenges of reconstructing reflectivity over land and provides more detailed information about the melting layer. We also explicitly analyze the impact of polarization differences, a factor not thoroughly examined in Yang et al. (2024), to further refine our retrievals and capture precipitation structures with greater fidelity.

Line 76: What is meant by "limited to specific precipitation scenarios due to limited spectral channels of GMI"? Are only specific scenarios used to train the model in that work?

Response:

Thank you for your comment. The statement refers to the fact that the previous work focused on reconstructing radar reflectivity specifically for oceanic precipitation scenarios. This limitation arises because the GMI sensor has fewer spectral channels, which restricts its ability to capture the diverse atmospheric and surface conditions necessary for reconstructing reflectivity over land. We have clarified this point in the revised manuscript in **Lines 82-83**.

Line 85: It might be confusing to mention 3D structures when the output of your model is 1D. The network does not know about the 3D nature of radar reflectivity fields and is not forced to be spatially consistent in the radar reflectivity space. Only the consecutive application of the model along and across track dimensions leads to a 3D field. Would an improved model performance be expected if the output is a 3D field? Why was this approach not chosen for this work?

Response:

Thank you for your insightful comment. We agree that the vertical information provided by passive microwave observations has certain limitations, making it challenging to fully achieve realistic 3D radar reflectivity reconstruction. In this work, we focused on using 2D multi-channel brightness temperature data to reconstruct multi-layer reflectivity profiles. This approach was chosen to leverage spatial information in the brightness temperature data to

compensate for the limited vertical information.
In future work, we aim to address this challenge by incorporating more diverse input data sources and adopting more powerful deep learning architectures. These enhancements could enable more complete 3D radar reflectivity reconstructions, improving spatial consistency and capturing the 3D nature of radar reflectivity fields.

Line 86: Why are the non-precipitating scenes not split into land and ocean as well?

Response:
Thank you for your comment. We have now split the non-precipitating scenes into land and ocean categories, and the corresponding evaluation results are presented in Table 3.

Figure 2b: Mention how the footprints are scaled in size and number instead of adding "not to scale." What does "*Npoints" mean? Indicate the footprints used for training here and combine them with Fig. 3.
Figure 3: This should be added to Fig. 2 for better understanding. Indicate the size of a 15x15 patch in kilometers.

Response：
Thank you for your helpful suggestions. "Npoints" refers to the number of scanning points along each scan line, and we have added an explanation of this in the revised manuscript in the caption of Figure 1. Figure 2b is a schematic illustration of the observation geometry of PMR and MWRI-RM, and it is not intended to represent an exact scale based on real observations. The precise instantaneous field of view for each channel is provided in Table 1. The footprints used for training are shown in Figure 3, which correspond to 15x15 footprints around each matching point. We have merged Figures 2 and 3 for better clarity and understanding, as suggested.

Line 115: Are the Level 1 products of PMR corrected for two-way attenuation by liquid water and water vapor? If not, how does this affect the reconstruction and comparison with PMR observations under varying incidence angles? How does multiple scattering affect the reconstruction in the presence of high-density ice particles typical for extreme precipitation events?

Response:
Thank you for your comment. The PMR Level 1 product we used has not been corrected for two-way attenuation by liquid water and water vapor. We acknowledge that varying incidence angles result in different path lengths, leading to varying degrees of attenuation. However, in this study, we only used reflectivity profiles with an incidence angle less than 2° for training, where the differences in path length are negligible. For consistency, our model evaluations also focused primarily on reconstructing reflectivity profiles with an incidence angle below 2°. As the model directly learns relationships from the data, it is possible that it has implicitly accounted for some attenuation effects caused by precipitation particles. This remains an interesting topic for further investigation. The PMR Level 2 product provides reflectivity

corrected for attenuation, and we plan to use this product in future work to refine our reconstructions and analyze the differences between using corrected and uncorrected reflectivity data. This will help better understand the effects of attenuation and multiple scattering under extreme precipitation conditions.

Line 116: Why are case studies using data from July 2023 if the data is released after October 23, 2023? Clarify this. I assume the model was trained on the October/November data. If that is true, do you expect the same performance for other months of the year? What is meant by "used here for the preliminary research"?
Line 259: The month of July is not mentioned in the data section.

Response:
Thank you for your comments. Before the official data release, we were granted access to PMR observations from July 2023, including data from Typhoon Khanun and the Beijing extreme rainfall event. These two cases represent extreme precipitation events, making them valuable for further evaluating the model's generalization ability. We have clarified this in the revised manuscript in **Lines 281-283.**
Our model was trained using one month of officially released data from October 23 to November 31, 2023. Due to the limited amount of officially released data available at the time of our research, we used only one month of data for training. We acknowledge that this may affect the model's generalization ability. However, the trained model still demonstrated reasonably good reconstruction performance when applied to independent test samples, including these July case studies.
In future work, we plan to use more data to fine-tune the current model and further enhance its generalization ability. We have clarified this information in the revised manuscript, including the mention of July in the data section. Thank you for highlighting these points.

Line 126: Mention the PMR scan interval of 0.7° and provide the number of cross-track scans that match the 2° incidence angle criterion.

Response:
Thank you for your comment. We have included the PMR scan interval of 0.7° in the revised manuscript in **Line 104.** Based on the 2° incidence angle criterion, five cross-track scan points per scan line meet this requirement. This information has been included in the revised manuscript in **Line 136.**

Line 130: A threshold of 8 km cuts off the reflectivity profiles during the case studies. Also, the additional 183.31+/-2 GHz channel of MWRI-RM compared to GMI peaks around this height, depending on humidity levels. By how much does the threshold of 8 km change the ratio of clear-sky and cloudy pixels compared to a 9 or 10 km threshold?

Response:
Thank you for your comment. Based on our analysis of reflectivity profile samples under

precipitation conditions, the ratio of clear-sky to cloudy pixels is approximately 0.4 when using an 8 km threshold. When the threshold is increased to 10 km, this ratio decreases to approximately 0.3.

Line 133: How do 136 range bins from 1.1 to 8 km match with the range resolution of 250 m of PMR? Also, note that in Table 1, the output is 138. Why are both different? How was the noise, sidelobe clutter, and ground clutter filtered, and is the filter considered surface type?

Response:

Thank you for your comment. The mention of 136 range bins in Line 133 is incorrect and has been revised to 138. The PMR samples in the range direction at 50 m intervals, resulting in 138 bins from 1.1 to 8 km.

The noise, sidelobe clutter, and ground clutter were filtered based on the quality flag data (flagEcho) provided in the PMR's HDF file. This ensures the filtering process considers the surface type and other relevant quality indicators.

We appreciate your feedback and have corrected this in the revised manuscript.

Line 138: What does NaN mean in the context of the loss function? How is terrain treated, i.e., subsurface PMR pixels? It would be important information for the reconstruction to know the lowest boundary of the precipitation field. In Fig. 7, it seems that mountains extend up to 2 km, and the models add precipitation below the surface (see. Fig. 7i right above the letter A)

Line 236: How much of the uncertainty over land can be attributed to the lack of topography information?

Response:

In the context of the loss function, NaN indicates bins that are marked as invalid due to the influence of sidelobes or ground clutter, which can negatively affect the reconstruction. These bins are excluded during loss calculation to ensure that they do not introduce bias or degrade the model's performance. By skipping these NaN values, the loss function focuses only on valid data points, leading to a more robust and accurate reconstruction.

Thank you for your insightful comments. We have indeed noticed the issue of reflectivity appearing below the surface when reconstructing reflectivity profiles over land. In our future work, we will address this problem by developing a targeted model specifically for reconstructing land-based precipitation reflectivity.

We plan to incorporate the strategies, such as adding terrain height information as an input feature, applying post-processing techniques to mask invalid reflectivity values below the surface, and designing the loss function to account for surface constraints. These improvements aim to enhance the model's accuracy and ensure physically consistent outputs. The discussion on this issue is provided in the revised manuscript in **Lines 348-354**.

Line 143: Could it happen that two PMR columns are assigned to the same MWRI-RM footprint due to their different spatial resolution? Are those duplicates filtered out?

Response:

Thank you for your comment. In our matching process, the MWRI-RM observation point is used as the target, and each MWRI-RM point is matched to the nearest PMR observation point. This ensures that each MWRI-RM footprint corresponds to a single PMR column, avoiding any duplication issues.

We have clarified this process in the revised manuscript in **Lines 148-150** to address your concern. Thank you for bringing this up.

Line 152: How is a precipitation event defined? Provide information on the filter method or threshold.

Line 215: See comment on line 152.

Response:

Thank you for your comment. In our analysis, precipitation events were defined based on the precipitation flag (flagPrecip) provided in the PMR data. This flag distinguishes between precipitating and non-precipitating samples.

We have clarified this definition and the use of flagPrecip in the revised manuscript in **Lines 164-165** to ensure transparency and address your concern. Thank you for pointing this out.

Line 155: How many samples were available prior to the oversampling? Based on this description and the diagram in Fig. 4, it seems that oversampling was performed prior to the data splitting. Clarify this. See also the general comment regarding random data splitting.

Response:

Thank you for pointing this out. Upon reviewing the manuscript, we realized that our original description was inaccurate. We did not oversample non-precipitating samples as stated; instead, we undersampled them to match the number of precipitating samples. This approach was implemented to balance the dataset and ensure equal representation of both sample types during model training.

Regarding the number of samples prior to undersampling, while we did not explicitly record the exact number of non-precipitating samples, it is clear that this number was significantly larger than the undersampled total, as non-precipitating samples far outnumbered precipitating ones in the original dataset. We will clarify this in the revised manuscript in **Lines 162-164**.

Line 157: Describe the standardization method.

Respons:

Thank you for your comment. The standardization method used in our study follows the approach shown in Equation (1):

$$x' = \frac{x - \mu}{\sigma}$$

where x is the original value, μ is the arithmetic mean, and σ is the standard deviation. This normalization is applied independently to each channel using the mean and standard deviation.

This information has been included in the revised manuscript in **Lines 172-175**.

Line 157: Does logarithmic transformation mean Ze was transformed to dBZ? Clarify this.

Response:

The reflectivity data provided in PMR Level 1 is already in **dBZ**. In our preprocessing, we applied a logarithmic transformation to these dBZ values using np.log(). This transformation was not a unit conversion, but rather a preprocessing step aimed at enhancing the model's learning process. The logarithmic transformation was used to normalize the data distribution and reduce the range of values, which helps the model better handle variations in the reflectivity data

Figure 4: Explain the meaning of "values adjustment" in the PMR branch.

Response:

Thank you for pointing out the ambiguity in the term "values adjustment" in the PMR branch. We agree that the original description was unclear, and we have updated it in the revised manuscript for better clarity.

Specifically, "values adjustment" refers to **noise marking** in the PMR branch. Radar bins affected by noise were assigned a baseline value of 10 dBZ. This baseline value helps to differentiate non-precipitating and precipitating conditions while minimizing the influence of radar noise on the reconstruction process. Importantly, this adjustment does not significantly alter the overall distribution of reflectivity values, ensuring the integrity of the reconstructed profiles.

Table 1: The number of parameters is very large and exceeds the number of samples. The first dense layer contains 28800 * 200 + 200 (5.76 M parameters). This is much more than the number of samples (about 1 M) and will likely lead to poor generalization of all three trained models. Pooling layers could help to reduce dimensionality before passing to dense layers. Also, note that the number of parameters is not correctly shown in the table because the bias terms are missing for Conv (32, 64, 128) and FC (200, 138). It might be more meaningful to show the activation shape, activation size, and total number of parameters for each layer. Mention the kernel size in the text. Also, see the comment on line 133 regarding the confusion about the vertical resolution of the Ze profile (136 or 138 bins).

Response:

Thank you for your detailed feedback and suggestions. We acknowledge the concerns regarding the large number of parameters, particularly in the fully connected layers, and the potential for overfitting due to the current architecture. While we agree that introducing pooling layers could help reduce dimensionality and improve generalization, due to time constraints, we are unable to modify the model architecture and retrain the models for this version of the manuscript.

To address your comments, we have revised Table 2 to provide accurate information, including the bias terms for the convolutional and fully connected layers. Additionally, we now include the activation shapes, activation sizes, and the total number of parameters for each layer to ensure clarity. The kernel size for convolutional layers (3×3) has been explicitly stated, and the table reflects the current model architecture used in our experiments.

We acknowledge that the parameter count in the dense layers is large relative to the sample size, which may limit the model's generalization ability. This is an important observation, and we will explore architectural refinements such as the addition of pooling layers or regularization techniques in future work to optimize model performance and efficiency.

Thank you for raising these valuable points, which will guide our future improvements. For now, the updated table ensures transparency regarding the model's current configuration.

Line 170: Use shorter names for the experiments (e.g., Ex14, Ex26, etc.).

Response:

Thank you for your suggestion. We have simplified the experiment names to shorter forms, such as Ex14, Ex26, etc., throughout the manuscript to improve clarity and readability. We appreciate your feedback, which has helped enhance the presentation of our work.

Line 171: Mention the batch size, number of epochs / early stopping, learning rate, and other details on training (restore best weights, etc.). Add figures of the training and test loss for each epoch until training is stopped for each of the three models to the appendix.

Response:

Thank you for your comment. We have included the requested training details in the revised manuscript. Specifically, we used eight A800 GPUs to train the models with a batch size of 512 and 100 epochs. The learning rate was initialized at 1e-3 and adjusted using an InverseTimeDecay schedule. Early stopping was applied, and the best weights were restored during training. This information has been included in the revised manuscript in **Lines 201-203**.

Additionally, we have added the loss curves for training and testing across epochs for each of the three models in the appendix. Thank you for your valuable suggestion, which has helped improve the clarity and transparency of our methodology.

Line 173: Clarify why the published code has a different loss than MSE (sum of squared errors: tf.reduce_sum(tf.square(y_true_filtered - y_pred_filtered))) in line 58 of training_cnn.py.

Thank you for pointing out the discrepancy regarding the loss function used in our published code versus what is stated in the manuscript. Upon review, we realize that our manuscript's description may have caused some confusion. To clarify:

In **line 58 of training_cnn.py**, the actual loss function implemented is **Sum of Squared Errors (SSE)**, defined as:

```
tf.reduce_sum(tf.square(y_true_filtered - y_pred_filtered))
```

This is consistent with the published code. However, in the manuscript, we referred to the loss as "MSE," which was imprecise. We appreciate your feedback, and we will revise the manuscript to explicitly state that **SSE** was used as the loss function.

The reason for choosing SSE over MSE is based on findings from our previous studies. In the context of radar reflectivity reconstruction, the following characteristics of the task make SSE more appropriate:

1. **Emphasis on Overall Reconstruction Error**: Reflectivity reconstruction involves capturing the full profile's structure across all vertical levels. SSE directly sums up the reconstruction error across all samples and levels without normalization, ensuring that significant deviations in key regions are not diluted.
2. **Sensitivity to Sparse High Values**: Reflectivity profiles often feature sparse but crucial high values (e.g., during precipitation events) embedded in a majority of background values. SSE's quadratic nature amplifies the contribution of these high-value regions, leading the model to focus on reconstructing these physically meaningful regions more accurately.
3. **Handling of Imbalanced Vertical Distributions**: Reflectivity values tend to exhibit significant vertical variability, with lower levels often containing larger and more impactful values for precipitation and hydrometeorology. SSE effectively accounts for these variations by prioritizing larger deviations without introducing explicit weighting mechanisms.

We have clarified in the revised manuscript in **Lines 203-210** to clarify the above rationale and explicitly state that the loss used in our code and experiments is **SSE**.

Line 174: It would be good to separate the description of experiments from the model architecture chapter. The paragraphs of each experiment repeat large parts of the introduction and do not belong to the methodology section.

Response:

Thank you for your suggestion. We agree that the detailed explanations of the three experiments were somewhat redundant in the methodology section. In the revised manuscript, we have streamlined this section by retaining only the descriptions of the different inputs for each experiment. This ensures clarity and avoids unnecessary repetition while maintaining focus on the methodology.

We appreciate your feedback, which has helped improve the structure and readability of the manuscript.

Line 193: Explain how the model output advances weather forecasting techniques and links to hydrometeors simulated by weather models.

Line 225: See comment on line 193.

Response:

Thank you for your comment. Upon review, we recognize that the original statement regarding the advancement of weather forecasting techniques was unclear and, at this stage, speculative. As the operational applicability of the reconstructed reflectivity profiles remains to be further evaluated, we have removed the related discussion from the manuscript to avoid overstating the findings.

Line 231: It would be good to split non-precipitation in land and ocean as well; see comment on line 86. How does the model perform in coastal regions where parts of the passive channel are affected by land?

Response:

Thank you for your suggestion. We agree that splitting non-precipitation cases into land and ocean categories, as well as analyzing coastal regions where passive channels are influenced by land, provides valuable insights into the model's performance. We have filtered these samples and included them in the evaluation. The results have been added to Table 3 in the revised manuscript, along with the corresponding analysis.

We appreciate your feedback, which has significantly improved the thoroughness of our evaluation.

Table 2: Reduce the precision of metrics to those digits that are significant. The names of the experiments are wrong; all are named "baseline." The F1 score is the same for land and ocean for all three models. Is that correct?

Line 254: How does the F1 score vary between land and ocean? See comment on Table 2.

Response:

Thank you for your comment. In the revised manuscript, we have addressed the concerns regarding Table 2. We have corrected the experiment names, reduced the precision of metrics to reflect only significant digits, and clarified the results. Additionally, we have decided to exclude the F1 score from the analysis to avoid potential confusion, as it did not provide meaningful distinctions between land and ocean cases.

Line 234: In general, the melting layer is below 3 km in mid-latitudes, which are also covered by the satellite. Why does the RMSE show a peak at 4-5 km only and not at lower heights?

Response:

Thank you for your comment. Currently, we do not have access to PMR-specific melting layer products. Therefore, we referred to the analysis presented in the work by Hu et al. (2024), which investigates the quasi-global climatological features of the melting layer over the latitude range of 65°S to 65°N by Utilizing the detection from the Dual-frequency Precipitation Radar onboard the Global Precipitation Measurement Mission Core Observatory during 2018-2022.

Their study shows that a larger amount of ML occurs more frequently in tropical regions (30°S–30°N), especially in the Asia-Pacific region (fig. 1d). The melting layer height varies with latitude, being higher in tropical regions (30°S–30°N) and lower in mid- and high-latitudes (fig. 1a and d). Specifically, in tropical areas (0°–30°N), the top of the melting layer is generally distributed between 4–5 km, and the bottom height is primarily between 2–4 km. This finding aligns with our results.

In the revised version of the manuscript (**Line 243**), we have incorporated the referenced work by Hu et al. (2024). By including this reference, we aim to make our analysis more robust and provide a clearer context for the RMSE peak at 4–5 km.

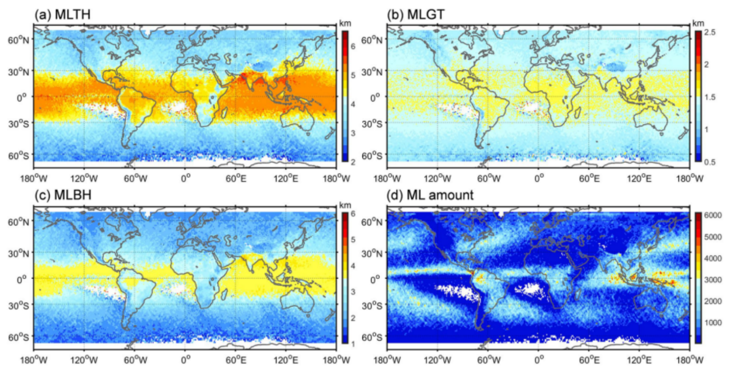


Fig. 1 Global geographical distributions of mean melting layer top height (**a**), melting layer geometric thickness (**b**), melting layer bottom height (**c**), and melting layer amount (**d**) detected by GPM DPR from 2018 to 2022 (plotted at 1° ×1° grid resolution)

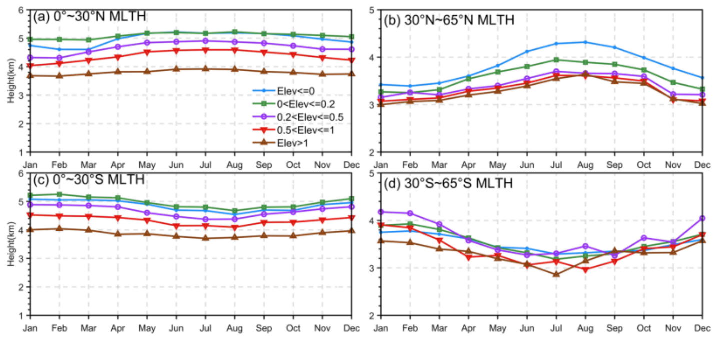


Fig. 6 The monthly mean of the top height of the melting layer detected by GPM DPR in five terrain areas (elevation ~0, 0~0.2, 0.2~0.5, 0.5~1, and 1~ km) at four typical latitudinal regions: (**a**) 0°~30°N, (**b**) 30°N~65°N, (**c**) 0°~30°S, (**d**) 30°S ~65°S

Hu, X., Ai, W., Qiao, J., and Yan, W.: Insight into global climatology of melting layer: latitudinal dependence and orographic relief, Theor Appl Climatol, 155, 4863–4873, https://doi.org/10.1007/s00704-024-04926-6, 2024.

Line 244: The scattering signal of precipitation at the 50-53 and 118 GHz channels is very small.

Response:

Thank you for your feedback. We have removed the phrase “the scattering signal of precipitation” in the revised manuscript to address this issue and avoid potential misunderstandings. We appreciate your careful review and constructive suggestions.

Line 260: Explain why these events are "challenging" for the model. Those are strong precipitation events with clear passive microwave signatures.

Response:

Thank you for your comment. While strong precipitation events often exhibit clear passive microwave signatures, they remain challenging for deep learning models due to their extreme nature. These events typically involve highly complex and dynamic atmospheric conditions, which can introduce significant variability and non-linear interactions that are difficult for the model to generalize. Additionally, extreme precipitation often pushes the model beyond the range of conditions it has encountered during training, further impacting its performance.
We will clarify this in the revised manuscript in **Lines 278-281** to provide a more detailed explanation of the challenges associated with these events.

Line 280: The discussion following this line is very vague and subjective. I recommend quantifying the comparison between PMR and the reconstructed profiles and providing a difference and scatter plot between the observed profile and the predictions.
Line 303: Provide a quantitative comparison between observation and prediction.

Response：

Thank you for your suggestion. We have incorporated two quantitative metrics (RMSE and MBE as) and scatter plot to evaluate the reconstruction performance of different models for the specific case study.

The discussion on the melting layer could be supported by comparing it with reanalysis data.

Response：

We appreciate your suggestion to incorporate reanalysis data into our discussion of the melting layer. However, our primary objective was to assess the model's capability to reconstruct the vertical structure of reflectivity, particularly the position of high-reflectivity features such as the bright band. The bright band serves as an indirect indicator of the melting layer, and its accurate representation in our modeling framework already implies a reasonable portrayal of the underlying thermodynamic structure. This correspondence between the observed and reconstructed reflectivity profiles allows us to infer that the model has captured the melting layer's position effectively without explicitly computing it. Direct comparison with reanalysis data, such as the zero-degree-level fields, falls outside the scope of our current analysis. Nevertheless, we acknowledge the value of such comparisons and will consider them in future studies to further validate and refine the model's performance.

Figure 5: Use the same x-axis among the columns to make them comparable, ideally starting at 0 for RMSE and STD. How was the yellow area in a and d calculated, considering that the melting layer varies with latitude? In panels g and I, the polarization model performs worse than the model without polarization close to the surface. Why?

Response：

Thank you for your suggestions. We have revised Figure 5 to use a consistent x-axis across all columns, starting at 0 for RMSE and STD, to facilitate comparison. Regarding the yellow shaded area in panels a and d, it represented the empirically estimated range of melting layer heights. However, as it was not based on a specific calculation and could potentially lead to misunderstanding, we have removed this shaded area in the revised figure to avoid confusion.

Line 294: What is meant by "vertical resolution," and how was it determined?
Line 354: Clarify if resolution means vertical or horizontal.

Response:

Thank you for pointing this out. We agree that the term "vertical resolution" may be misleading. While the reconstructed reflectivity profiles have the same resolution as the actual observations in terms of their vertical discretization, the inherent ambiguity of the passive microwave signals used as input affects the final output accuracy. This can lead to limitations in capturing finer details, such as the exact height of high-reflectivity regions like the melting layer.

We have revised the manuscript to avoid the use of "vertical resolution" and provide a more precise explanation of the factors influencing the reconstruction accuracy. Thank you for highlighting this important clarification.

Line 295: Add a reference to the precipitation amount.

Response：

Thank you for your comment. We have revised the text to include a detailed description of the precipitation amount during the "23·7" BTH extreme rainfall (BTHER) event, based on the findings of Zhao et al. (2024).

Zhao, D., Xu, H., Li, Y., Yu, Y., Duan, Y., Xu, X., and Chen, L.: Locally opposite responses of the 2023 Beijing–Tianjin–Hebei extreme rainfall event to global anthropogenic warming, npj Clim Atmos Sci, 7, 1–8, https://doi.org/10.1038/s41612-024-00584-7, 2024.

Line 296: Mark the regions mentioned in the text inside the map.

Response:

Thank you for your suggestion. We have added the location markers for the regions mentioned in the text to the map in the revised version of the manuscript to enhance clarity and alignment between the text and figures.

Line 321: Add ground-based radar data to the data section.

Response:

Thank you for your suggestion. We have added a description of the ground-based radar data in the data section in **Lines 115-121**. Specifically, we utilized the dual-polarization radar from the China Next Generation Weather Radar (CINRAD/SA) network for comparison with the land precipitation reflectivity reconstruction results. The CINRAD/SA products have a radial distance resolution of 250 m and an azimuthal resolution of 1 degree. The Volume Coverage Pattern 21 (VCP21) scan mode was selected, which sweeps 9 elevation angles of 0.5, 1.5, 2.4, 3.4, 4.3, 6.0, 9.9, 14.6, and 19.5 degrees in 6 minutes (Teng et al., 2023). Based on the interpolation method used in Xiao and Liu (2006), we transformed the radar data from spherical coordinates into a unified Cartesian coordinate system, creating a 3D grid. The radar data were then stitched and organized to generate the CAPPIs (Constant Altitude Plan Position Indicator) data used in this study.

Line 321: What does "consistent" mean? It is not obvious from Fig. 9 and Fig. 8b. Plot both data in one figure with the same geographic extent and color bar. Ideally, a simple scatter plot should be made to show that the model and observation agree.

Response:
Thank you for your suggestion. In response to your comment, we have merged the two figures into one, ensuring that they share the same geographic extent and color bar for direct visual comparison. Additionally, we have revised the manuscript to provide a more precise analysis of the reconstructed reflectivities and their comparison with ground-based radar observations (**Lines 370-374**). This includes specific statements about areas where precipitation is detected and the position of reflectivity maxima to make the comparison more explicit.

We agree that a quantitative comparison, such as a scatter plot, between the ground-based radar reflectivity and the reconstructed spaceborne radar reflectivity would offer valuable insights. However, due to differences in radar wavelength, spatial resolution, and scanning geometry, such a quantitative comparison requires significant additional effort. This includes aligning the datasets, compensating for different measurement characteristics, and addressing inherent discrepancies.

Given the scope and time constraints of this work, we are unable to provide this analysis in the current manuscript. However, we plan to address this in future work by focusing on a more detailed quantitative evaluation of the reconstructed reflectivity profiles, particularly in regions beyond the PMR's actual scanning area, to further validate the model's performance.

Line 353: What is meant by representative training dataset? Why is the data used here not representative?

Response:
At line 353, we initially referred to having a "representative training dataset," which may have been misleading. The data used in this study were collected within a one-month period (2023-10-23 to 2023-11-31), and, as a result, the dataset did not fully capture the variability and diversity of global precipitation scenarios, particularly for land-based precipitation in the Northern Hemisphere. This limited data coverage reduces the model's ability to generalize well to a wide range of conditions, as it has fewer samples from certain environments (e.g., less land precipitation data from the Northern Hemisphere). To clarify this point, we have

removed the term "representative" from the revised manuscript. In future work, we plan to incorporate a more diverse and extensive dataset spanning multiple seasons, regions, and precipitation types, which will help improve the model's generalization capabilities.

Line 363: Mention snow scattering as well.

Response:
Thank you for your suggestion. We have included a mention of snow scattering in the revised manuscript as requested.

Line 369: What exactly is the advantage of GANs and diffusion models compared to the method selected here? This needs more explanation, potentially linked with the introduction where previous work is presented.

Response:
Thank you for your suggestion. The generative models have demonstrated remarkable capabilities in capturing fine-grained details and generating realistic outputs in various fields, which makes them relevant for radar reflectivity reconstruction as well.
GANs are particularly known for their ability to model complex data distributions and produce high-quality, detailed reconstructions. As shown in the work of Leinonen et al. (2019), a CGAN framework was applied to generate two-dimensional cloud vertical structures that would be observed by the CloudSat satellite-based radar, using only four input variables derived from MODIS (cloud top pressure, cloud optical depth, effective radius, and cloud water path). The CGAN in their study was capable of generating sharp and realistic images that closely resembled radar reflectivity fields. Furthermore, it demonstrated robustness to missing input data by effectively interpolating into regions with data gaps and was able to exploit spatial structures in the input data to infer features such as multilayer clouds. This example highlights how GANs, particularly CGANs, can leverage their generative capacity to recover subtle spatial variations and infer complex structures in atmospheric systems.
Diffusion models, on the other hand, provide an alternative generative modeling framework that excels in generating high-resolution and diverse samples. These models gradually transform noise into a structured data distribution through an iterative denoising process, allowing them to capture fine-scale spatial details and subtle variations that are often challenging for traditional deterministic methods. Their ability to preserve high-resolution information during generation makes them particularly suitable for reconstructing spatially complex systems, such as precipitation structures observed in radar reflectivity profiles.
While our current method adopts a deterministic approach to reconstruct radar reflectivity profiles, which ensures computational efficiency and straightforward implementation, it may face challenges in capturing finer-scale features or handling under-sampled regions. By contrast, generative models such as GANs and diffusion models have the potential to address these limitations by providing more nuanced reconstructions and effectively dealing with missing or noisy input data. In the context of PMR reconstruction, leveraging these models could improve the quality and resolution of the reconstructed reflectivity profiles, particularly in cases involving complex precipitation systems or incomplete data coverage.

In the revised manuscript, we have referred to the works of Leinonen et al. (2019) to make our discussion more profound **(Lines 425-430).**

Line 372: "fully replicate" sounds as if it is, in principle, possible to create a radar reflectivity profile from passive microwave observations equivalent to a radar observation with the right AI method. I suggest to rewrite this. It is impossible to retrieve unique information on each height bin from the limited information of passive microwave observations.

Response:
Thank you for pointing this out. We agree that our original wording may have been too absolute. It is indeed not feasible to fully replicate radar reflectivity profiles from passive microwave observations due to the inherent limitations in the vertical resolution and information content of passive microwave data. We have revised the statement to reflect this limitation more accurately and acknowledge that while AI methods can reconstruct radar-like profiles with useful detail, they cannot fully replace the unique vertical information provided by active radar observations. We have clarified in the revised manuscript in **Lines 430-434**.

However, it would be interesting to see which channels provide information on the height level of the reflectivity profile. Could this be seen when computing the Jacobian of the model with 35 input channels?

Response:
Thank you for your suggestion. We agree that analyzing the contribution of each channel to the height levels of the reflectivity profile, for instance by computing the Jacobian of the model with respect to the 35 input channels, is a valuable approach. Such an analysis can indeed reveal which channels provide the most information regarding the vertical structure of the reflectivity.
We are currently conducting related work to extract gradient-based information to assess the influence of input channels on the output reflectivity profiles. However, due to time constraints, we were unable to include this analysis in the present study. We plan to incorporate this analysis in future work, as it can provide deeper insights into the role of individual channels and further improve the interpretability and performance of the model.
Thank you again for your valuable suggestion, which will help guide our ongoing and future research.

Technical corrections
Line 7: What does "VPR" stand for? I suggest using "reflectivity profiles." and not "VPR."
Line 15: The start of the sentence should be a capitalized letter.
Line 22: Mentioning nations is distracting. Remove them throughout the manuscript.
Line 25: See comment on line 22.
Line 28: Remove the word "wideband."
Line 32: Rephrase the beginning of the sentence to more neutral wording like "To further

advance global precipitation observations."
Line 49: Remove the word "strong."
Line 56: The year in the reference is missing.
Line 61: See comment on line 18.
Line 73: Does "precipitation measurement radar" refer to PMR or any radar?
Line 90: The "HIW" acronym is not needed.
Line 93: See comment on line 22.
Line 96: DPR is written instead of PMR.
Line 104: Replace "frequency points" with "channels."
Line 112: Move this to the data availability section.
Line 128: Remove the word "detrimental."
Line 165: Remove the word "advanced."
Line 168: Remove the word "enriched."
Line 249: Replace "precipitation reflectivity" with "radar reflectivity."
Line 294: Replace the word "fuzziness."

Response：Thank you for your careful scrutiny, we have revised it accordingly!

Line 18: The acronym "AWR" is rarely used. Use "radar" instead.

Response:
Thank you for your suggestion. While "radar" is indeed commonly used, we adopted the term "Active Microwave Sensors (AMW)" following its usage in recent literature, such as in the works of de Roda Husman et al. (2021) and Sharifnezhadazizi (2022). These references employ the term to emphasize the distinction between active and passive microwave sensors in remote sensing applications. However, we understand that clarity and common terminology are crucial for broader readership. We will revise the manuscript to use "radar" instead, ensuring consistency and accessibility for the audience.

de Roda Husman, S., Lhermitte, S., and Wouters, B.: Towards Improved Spatio-Temporal Resolution Surface Meltwater Detection on the Antarctic Ice Shelves from the Synergy of Active and Passive Microwave Remote Sensing, 2021, C52B-04, 2021.
Sharifnezhadazizi, Zahra, "Data Fusion and Synergy of Active and Passive Remote Sensing; An application for Freeze Thaw Detections" (2022). *CUNY Academic Works*.