Overview

This paper presents a algorithm for use on the microwave imager instrument aboard FY-3G to retrieve profiles of temperature and humidity. The algorithm is a convolutional neural network (CNN) that was trained with ERA5 data, and because it is in the microwave part of the spectrum it can retrieve all sky conditions. Neural network retrievals are actively being improved in the literature, especially multidimensional algorithms such as convolutional neural networks, so this paper in its ideas is suitable for publication in AMT.

From what I can discern, the validation here is strictly whether the CNN is able to reproduce the input data based on the sample learning period. While it is good to utilize this as a check of the algorithm behavior, there should be a validation performed with observations from alternative sensors/algorithms or ground-based observations (including ground-launched radiosondes).

Response:

Thank you for your insightful feedback on our validation methodology. We acknowledge the need to strengthen transparency and have clarified our current work's scope. Specifically, quantitative metrics (e.g., RMSE) for different model architectures are presented in **Appendix A, Table A1** of the revised manuscript. These serve as preliminary model-selection indicators during development, without in-depth interpretation, as the study prioritizes demonstrating the framework's feasibility over exhaustive benchmarking. Additionally, the scarcity of in situ marine observations and spatiotemporal mismatches with FY3G retrievals currently limit robust maritime validation. In follow-up research, we will systematically address these via spatio-temporal alignment algorithms and high-resolution satellite datasets to ensure comprehensive cross-environment evaluation.

Why was relative humidity (RH) chosen over water vapor mixing ratio or specific humidity? While I am not arguing that RH is invalid to retrieve, RH is not an absolute quantity and is dependent on temperature (which entangles retrieval of waver vapor and temperature). RH makes it more difficult to compare results against other literature in the microwave remote sensing community. Retrieving a water vapor value specifically would make the two values more distinct and provide better illumination of what channels are sensitive to which physical values.

Response:

Thank you for your comment on RH selection. This choice is grounded in two key considerations. First, as a standard ERA5 output, RH offers direct usability as label data and aligns with meteorological operational practices, ensuring compatibility with public observations and model inputs. Second, this study represents an initial effort to develop a temperature-humidity joint inversion model using FY-3G/MWRI-RM full-channel data. While RH's temperature dependence introduces complexity, it enables exploration of dynamic temperature-humidity interactions (e.g., synergies between 118 GHz and 183 GHz channels; see Sections 4.2 and Conclusions in the revised manuscript). We agree that specific humidity retrieval would enhance physical clarity and plan to expand the model's output to include water vapor parameters in future work, alongside error propagation analysis to decouple temperature-humidity contributions.

The indication that 183 GHz provides higher information content for temperature sounding than all but one 118 GHz channel is a surprise to me (this statement is based on my interpretation of Figure 5 along with corresponding text). One citation is given for the reasoning behind this but is unfortunately in another language and inaccessible to me. Also, L239-242 states water vapor attenuates the signal (and cites a paper describing an infrared retrieval paper), which seems contrary to the stated conclusion. Detailed information about this analysis methodology and better tying the conclusions to relevant principles should be provided.

Response:

To deepen the analysis of 183 GHz channel sensitivity, we have enhanced both physical explanations and literature integration. Through gradient backpropagation and perturbation experiments (Sections 4.1–4.2), we clarify that the 183 GHz water vapor channel indirectly constrains temperature via vapor-radiation feedback: in high-humidity regions (e.g., boundary layers), water vapor's absorption/emission modifies radiation transfer, influencing temperature through latent heat release. In contrast, the 118 GHz oxygen channel directly senses mid-upper tropospheric temperature gradients, with humidity impacts mediated by dynamics like vertical advection and atmospheric stability. Furthermore, we replaced some Chinese references with English counterparts and added discussions on temperature-humidity coupling (**Lines 209–215** in Section 4.1; **Lines 279–284** in Section 4.2 of the revised manuscript). The "model weight diffusion in convolutional layers" describes potential propagation of 118 GHz temperature-sensitive features to humidity parameters via spatial feature mixing, a phenomenon warranting further study with physics-constrained neural networks.

The methodology explanation does not line up with explanations in the results sections. Up until section 4.2, I thought the retrieval was only over ocean (viz. L137) given that the training database was constructed from ocean only profiles and the validation dataset is part of the training database. The appendix plots also show only over ocean data. Yet Section 4.2 describes land cover characteristics when discussing the humidity retrieval performance. More detailed information about the database construction (perhaps a spatial map of where the database is compiled from) should be provided and the text clarified to line up with the methods.

Response:

Thank you for identifying the inconsistency in our data description. The term "land cover characteristics" was a typo; both training and validation datasets exclusively use oceanic observations (detailed in Section 2.2). We have corrected relevant paragraphs and removed land-data discussions, explicitly stated in the methodology: "To reduce preprocessing complexity, this study only selects oceanic data.", highlighted marine data coverage in **Appendix Figs. A1–A2**. Future research will extend to land scenarios via standardized surface parameter preprocessing (e.g., soil moisture, vegetation index).

Figures 3 (c-h) and 7 (c-h) are not very illustrative because of the density of points. Rather than shading by absolute error, a two-dimensional histogram should be performed and shading indicate the counts in the bins. Additionally, the line plotted on each subplot has no label -- whether it is a least squares fit or a 1-to-1 slope, that should be indicated in the figures. And speaking of least squares fit, are any fitting statistics available for the scatter plots?

Response:

Thank you for your thoughtful suggestions, which have been instrumental in enhancing the clarity and informativeness of our figures.

To address the density of points in **Figures 3(c–h)** and **7(c–h)**, we have replaced the absolute error shading with two-dimensional histograms, where color intensity now represents the count of data points in each bin. This modification improves visual interpretability by highlighting data distribution patterns while retaining error magnitude insights. Additionally, the black dashed line in each subplot is explicitly labeled as the "1:1 consistency line" to clarify that it denotes perfect agreement between retrieved and target values, rather than a least squares fit. To further quantify the scatter plot relationships, we have included three statistical metrics—Root Mean Square Error (RMSE), Bias, and Pearson correlation coefficient (r)—in the figure captions and corresponding discussions. These metrics systematically evaluate error magnitude, systematic deviation, and linear correlation, respectively, providing robust statistical support for our validation results.

For other figures, we have implemented the following improvements to ensure consistency and readability:

Figure 2: Font sizes were adjusted to enhance legibility across all text elements, ensuring key labels and annotations are easily distinguishable.

Figures 5 and 9: To emphasize critical channels, Channel 22 (118.75±1.2 GHz) and 26 (183.31±7 GHz) are now plotted with solid lines, while other channels use dash-dot lines for clear visual differentiation. This distinction highlights their unique roles in temperature-humidity retrieval as discussed in Section 4.2.

Figures 6 and 10: The layouts were revised to incorporate pressure-level distributions of percentage changes induced by perturbations. This addition clarifies how the model responds to input variations across different atmospheric layers, strengthening the mechanistic insights presented.

These adjustments collectively aim to align our figures with scientific visualization best practices, ensuring they effectively communicate the study's key findings while addressing the nuances raised in your feedback. We appreciate your guidance in refining our graphical representations.

In surveying the literature, much of the historical work mentioned was on infrared retrievals. More citations on microwave regime development should be included beyond why the regime is important for all-sky retrievals.

Response:

In response to your suggestion, we revised the introduction to enhance contextual depth:

Lines 55-68 in the revised manuscript: Expanded discussions on microwave remote sensing applications for atmospheric variable retrieval, integrating recent advancements and key studies to

underscore the research’s scientific significance.
This revision strengthens the rationale for our approach by connecting it to broader disciplinary progress.

Below is more specific copyediting feedback (which can be rejected where deemed), but overall the wording should be refined to focus on the scientific conclusions drawn from the results at hand without extra pomp or overbroad explanations.

Response:

We sincerely appreciate your meticulous copyediting suggestions, which have been invaluable in refining the manuscript’s clarity and scientific rigor. Below is a summary of the key revisions made to address your feedback, with a focus on enhancing readability, streamlining redundancy, and strengthening logical flow. All line numbers cited below correspond to the revised manuscript:
The original three-page introductory paragraph has been restructured into thematic subsections to improve navigability. We also expanded the literature review on microwave remote sensing (e.g., added citations in **Lines 55–68**) to better contextualize our approach, while adjusting the description of neural networks to acknowledge their established role in the field (avoiding the implication of excluding them from “conventional” methods).
Lines180-187 and Lines254-263: We recognize the need to further integrate broad theoretical discussions with our specific findings, particularly regarding error sources and future mitigation strategies. These aspects will be prioritized in follow-up analyses, including planned investigations into physics-constrained neural network architectures to address model uncertainties.
Broad statements about remote sensing uncertainties were either tied to our specific results or condensed, with clearer links to future mitigation strategies.
Lines199–201: The parenthetical comment about "model.conv1" was expanded into a dedicated paragraph explaining the convolutional layer architecture and spatial dimension considerations, improving methodological transparency.