Response to Reviewer 1:

The data set presented contains measured microwave and infrared brightness temperatures, corresponding quality flags and retrieved integrated products on a minutely time resolution. In addition, retrieved temperature and relative humidity profiles are given on a 10 min time resolution. Both types cover the time period of Apr 2013 - Dec 2022.

In the presented article, the authors describe a multi-year data set of quality-controlled microwave radiometer observations, including comparisons to simulated brightness temperatures using atmospheric profiles from reanalysis. Two different retrieval approaches are presented, applied to cloudy and clear sky conditions, respectively, and compared to the retrieval approach provided by the manufacturer with respect to radiosonde data. Furthermore, a statistical analysis is carried out including a temperature trend and inversion analysis connected to air pollution.

The study presents a valuable data set with a high temporal resolution and the performed statistical analysis provides insights in long-term developments of the thermodynamic structure of the lower troposphere as observed from a ground-based remote sensing instrument. However, the argumentation for choosing different retrieval approaches for clear sky and cloudy conditions remains unclear. In addition, more information on the provided retrieval by the manufacturer is needed to ensure that a fair comparison is made in terms of underlying training data and radiative transfer methods. Instead the newly developed approaches could be compared for cloudy and clear sky cases. Also, the retrieval seems to be trained on observations rather than simulated data. Therefore the article / data set could be accepted after revision. All major and minor points, corresponding to the data set and manuscript, supporting this decision, are listed in detail below.

We thank the reviewers for their constructive comments and suggestions. Detailed, point-by-point responses to all comments are provided. All corresponding revisions have been incorporated into the revised manuscript.

Manuscript Major points:

1. How do the DNN and OE retrievals compare to radiosondes in all sky or clear sky / cloudy conditions? This comparison would add more insights rather than comparing it to the retrieval from the manufacturer (where additional information is missing). Also, the argumentation of using different approaches is unclear.

Reply: Thank you for this insightful comment. We agree that a direct comparison of the OE and DNN retrievals against radiosonde observations under different sky conditions is essential to better demonstrate the performance and applicability of the proposed methods.

In the revised manuscript, we have clarified this aspect and emphasized that both retrieval schemes are independently validated against radiosonde measurements, rather than relying solely on comparisons with the manufacturer-provided LV2 product. Specifically:

(1) Clear-sky conditions (OE retrieval): The OE method shows strong agreement with radiosonde profiles throughout the 0–10 km layer. The mean bias remains within approximately ±0.8 K for temperature and ±6% for relative humidity, with RMSE values generally below 3.6 K and 20%, respectively. These results demonstrate that the OE approach effectively constrains the retrieval using physical radiative transfer and prior information, leading to robust performance under clear-sky conditions.

(2) Cloudy-sky conditions (DNN retrieval): Under cloudy conditions, where the assumptions of the OE method are often violated (e.g., inaccurate cloud screening and forward model limitations), the DNN-based retrieval provides significantly improved agreement with radiosonde observations. The mean bias is close to zero for temperature across most altitudes, and the RMSE is substantially reduced, particularly in the boundary layer and upper troposphere. Similar improvements are observed for humidity profiles.

Importantly, this choice is not merely empirical but is motivated by the fundamental limitations of each method. The OE approach relies on an accurate forward radiative transfer model and well-defined prior information, which are generally valid under clear-sky conditions but become unreliable in the presence of clouds due to uncertainties in cloud properties and radiative effects. In contrast, while a DNN model can flexibly learn complex nonlinear relationships from data, it does not explicitly enforce physical consistency and may be less constrained under clear-sky conditions where physical models are reliable.

Therefore, using a single retrieval approach for all atmospheric conditions may lead to suboptimal performance. The adoption of separate OE and DNN methods is a deliberate strategy to ensure that each method is applied within its domain of validity. To clarify this rationale, we have revised the manuscript (at the end of Section 3) to explicitly state that:

"From an application perspective, the OE and DNN approaches are employed as complementary rather than competing methods. The physically based OE method performs optimally under clear-sky conditions where forward radiative transfer modelling is highly reliable. Conversely, the DNN model demonstrates enhanced robustness under cloudy conditions by implicitly capturing the complex, nonlinear relationships between TBs and atmospheric states. By applying each method under its respective optimal conditions, this condition-dependent strategy yields retrieval results that are consistently closer to independent radiosonde observations than the generic operational RPG-LV2 product across all sky conditions."

2.The analysis and data set should be separate for the different approaches to ensure a meaningful interpretation, and it should be made clear which retrieval approach and conditions (cloudy / clear sky) were used for the statistical analysis in Chapter 4 and in the final data set.

Reply: We fully agree with the reviewer that a clear distinction between the two retrieval approaches (OE for clear-sky and DNN for cloudy-sky) is essential for a meaningful physical interpretation. In the revised manuscript, we have addressed this as follows:

(1) We have added a preamble to Chapter 4 (and specific notes in each subsection) to explicitly state which retrieval method and sky conditions were used for each analysis.

(2) In Sections 4.2 and 4.3, for the seasonal diurnal variations (Fig. 9) and

atmospheric inversion studies (Figs. 10–11), we utilized the merged dataset (OE for clear-sky and DNN for cloudy-sky) to ensure continuous temporal coverage, which is critical for boundary layer statistics.

(3) For the final dataset structure, we have also clarified in the "Data Availability:" section that the final dataset provides both individual flags and the merged high-quality profile product, allowing users to separate them if needed.

3.l. 283: the retrieval training should be conducted with multi-year simulated TB (from ERA5), but observed TB from 2019 are mentioned. This needs to be checked and clarified.

Reply: We thank the reviewer for raising this important point. We confirm that the DNN model was intentionally trained using actual observed TBs rather than simulated TBs, and restricted to a single year (2019).

Unlike physical retrievals that rely on radiative transfer models, a key advantage of empirical machine learning models is their ability to implicitly learn and adapt to real-world instrument characteristics (e.g., specific noise patterns and minor calibration nuances). Training the DNN with actual observed TBs mapped to high-quality ERA5 profiles (Cao et al., 2026) allows the network to capture these real-world instrumental features, bypassing the uncertainties inherent in forward modeling (especially under complex cloudy conditions).

Using a single, representative year (2019, which contains a complete seasonal cycle) for training was a deliberate strategy to ensure rigorous model validation. By isolating the training phase to one year, we can apply the trained DNN to the remaining 9 years (2013–2018, 2020–2022) as a strictly independent, long-term test dataset. This temporal out-of-sample testing effectively prevents overfitting and robustly proves both the generalizability of our DNN model and the long-term stability of the MWR instrument.

We have clarified the rationale for this experimental design in the revised manuscript (L338-342).

4.The authors should add more information on the retrieval methods (e.g. utilized auxiliary data, noise) and on the radiative transfer method (e.g. absorption models). Was it tested against line-by-line models?

Reply: We sincerely thank the reviewer for these insightful questions. We have substantially expanded the description of our retrieval setup in the revised manuscript to address these points. Specifically, we have clarified the following:

(1) Forward Model: We described the radiative transfer model used in this study, namely the non-scattering microwave radiative transfer model nonScatMWRadTran (Löhnert and Crewell, 2003). The manuscript now explicitly states that the gas absorption parameterization is based on the (Rosenkranz, 1998) model, with updates to the 22.235 GHz water vapor line width (Liljegren et al., 2005) and water vapor continuum absorption (Turner et al., 2009).

Following the reviewer's suggestion, we also added a benchmark evaluation against the MWRT model (Liu, 1998), which has previously been validated against line-by-line radiative transfer simulations (e.g., MonoRTM) for microwave radiometer observations at the XH site (Zou et al., 2021). Using 212 collocated radiosonde profiles with identical atmospheric inputs, the comparison demonstrated excellent agreement between nonScatMWRadTran and MWRT, with RMSEs below 0.12 K for the oxygen channels and below 1.5 K for the water vapor channels.

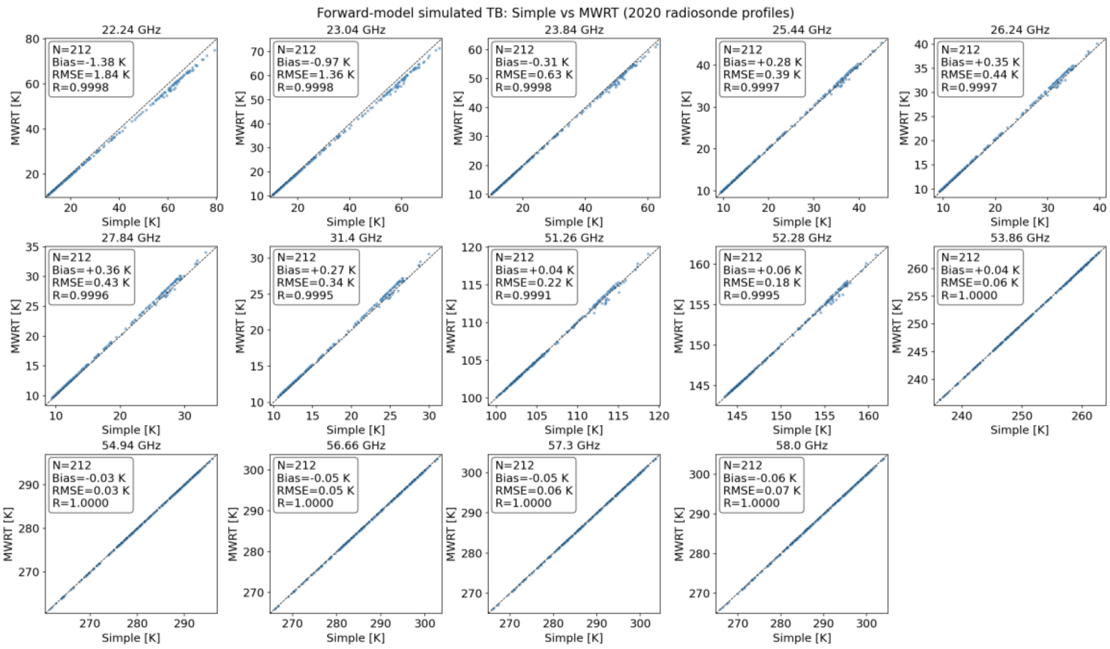

Figure R1. Comparison of simulated brightness temperatures between nonScatMWRadTran and MWRT using 212 collocated radiosonde profiles for the K-band water vapor channels and V-band oxygen channels.

(2) Retrieval Setup: The total effective observation error covariance matrix (S_e) is constructed as a diagonal matrix, assuming uncorrelated observation errors among channels. In this setup, the diagonal elements represent the total effective observation variance, which comprehensively accounts for instrumental thermal noise, calibration uncertainties, and forward-model errors. Based on the clear-sky observation-minus-simulation (O-B) residual statistics and the quality assessment of TBs detailed in Section 3.2.2, the prescribed observation error standard deviations (the square root of the diagonal elements of S_e) were specified as 2.0, 2.2, 1.8, 1.3, 1.4, 1.0, and 1.0 K for the seven K-band water vapor channels (22.24–31.40 GHz), and 1.5, 1.7, 1.2, 0.8, 1.0, 1.0, and 1.0 K for the seven V-band oxygen channels (51.26–58.00 GHz), respectively. In addition, the background error covariance matrix (S_a) was constructed separately for each season (DJF, MAM, JJA, and SON) using long-term statistics derived from collocated radiosonde observations during 2016–2019.

(3) Auxiliary Data: We clarified that local radiosonde data provided the necessary prior probability distribution (covariance matrix) for the OE retrieval.

These additions are now included in Section 3.3.1 of the revised manuscript.

Minor points:

1. More information on the site could be presented (e.g. map)

Reply: Done.

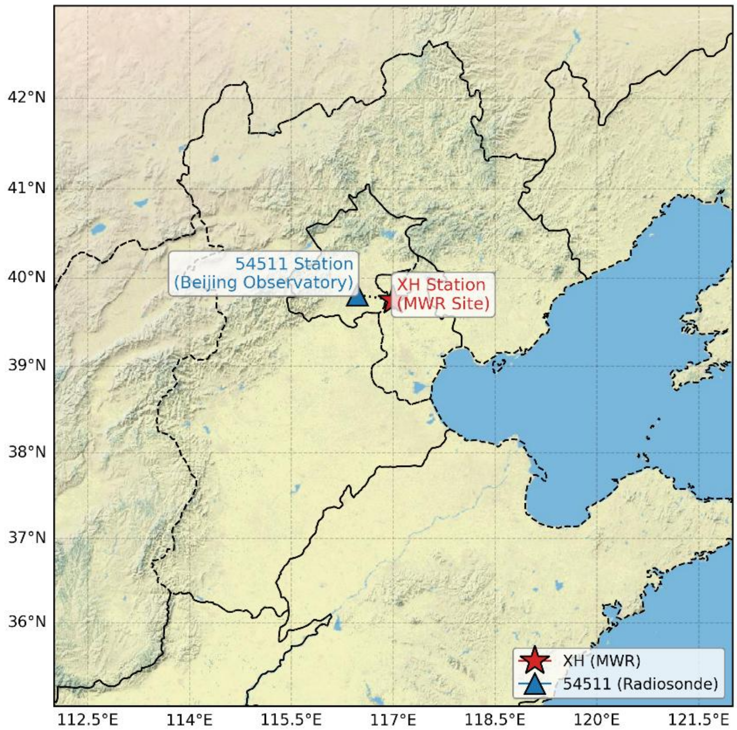

Figure 1. Geographical locations of the observation sites in the Beijing-Tianjin-Hebei region. The red star indicates the deployment site of the RPG-HATPRO ground-based microwave radiometer (MWR) at XH (39.75° N, 117.00° E). The blue triangle denotes the Beijing National Basic Meteorological Station (54511; 39.81° N, 116.47° E), which provides routine radiosonde profiles for data validation.

2. Were elevation scans available for improved temperature profiles?

Reply: We thank the reviewer for this insightful question. We acknowledge that the RPG-HATPRO MWR is capable of performing boundary-layer elevation scans, which can significantly improve the vertical resolution of temperature profiles in the lower troposphere. However, in this dataset, only zenith observations (90° elevation angle) were utilized.

3. The phrasing “weather type classification” is misleading, as it only contains a rain and cloudiness check and should be changed (e.g. to weather related information / flags) throughout the manuscript (e.g. l. 20).

Reply: Done.

4. l.28 (and others): Change “MWR’s self-developed products” to “retrieval approach

provided by the manufacturer". This also needs a more consistent naming, as "LV2" is too general.

Reply: Done. We have updated "MWR's self-developed products" to "retrieval approach provided by the manufacturer". Additionally, we agree that "LV2" is too general, and have adopted the more specific designation "RPG-LV2" for consistency.

5. l. 70: Statistical retrievals can also rely on e.g. model data (as in this study; not only radiosondes).

Reply: We thank the reviewer for pointing out this inaccuracy. We completely agree that modern statistical retrievals extensively utilize model data (such as reanalysis datasets or numerical weather prediction outputs), rather than relying exclusively on historical radiosondes. We have revised the text in the introduction in L70-72:

"Statistical approaches, such as multivariate regression and neural network algorithms, rely on comprehensive profile datasets obtained from historical radiosondes or atmospheric models to establish empirical relationships between observed TBs and atmospheric parameters".

6. l. 77: cited paper doesn't support statement and needs to be replaced to justify the decision of using multiple retrieval approaches for different atmospheric conditions.

Reply: We thank the reviewer for the correction. We have replaced the inaccurate citation (*Yan et al., 2020*) with *Maahn et al. (2020)* to properly justify the limitations of physical methods under cloudy/precipitating conditions due to hydrometeor scattering. The text is revised as follows in L76-79:

"While less dependent on large training datasets, physical methods are computationally intensive, especially under cloudy or precipitating conditions, as the complex scattering effects of large hydrometeors introduce severe non-linearity and convergence difficulties in the radiative transfer modelling (Maahn et al., 2020)"

7. l. 81: add reference "Rose, T., Crewell, S., and Löhnert, U.: A network suitable microwave radiometer for operational monitoring of the cloudy atmosphere, Atmos.

Res., 75, 183–200, 2005." for the RPG-HATPRO system.

Reply: Done.

8. l. 106: reference doesn't describe the specific retrieval developed for the presented study.

Reply: We have removed this reference.

9. l. 108: change "microwave window" to "radome". Also, how often was the radome replaced?

Reply: We have revised "microwave window" to "radome". The radome of the ground-based microwave radiometer was replaced every 6 months according to the instrument maintenance manual. Monthly inspection and cleaning were also carried out during the observation period.

10. l. 113: what is the distance to the radiosonde station?

Reply: The distance between the MWR site and the radiosonde station is approximately 50 km. We have clarified this in the revised manuscript.

11. chapter 3.1.1: this approach flags valid "extreme" events, whereas erroneous data with small deviations remain in the data set, which could cause a bias. This needs to be discussed.

Reply: We acknowledge that small-magnitude instrumental drifts or subtle erroneous data remain undetected by this 3σ check. However, these hidden biases are not ignored; they are systematically identified and eliminated in the subsequent, more rigorous QC steps—specifically, during the Observation-minus-Background (O-B) consistency checks using the radiative transfer model (as detailed in Section 3.1.3). We have added a dedicated paragraph at the end of Section 3.1.1 (L156-160) to explicitly discuss these limitations:

"While this statistical 3σ threshold serves as an efficient gross error check, it has inherent limitations. Genuine extreme meteorological events may be flagged as outliers;

however, such events typically involve precipitation and wet-radome conditions, which inherently invalidate standard MWR profiling. Conversely, undetected minor erroneous data (e.g., small instrumental drifts) remaining within the 3σ range are systematically identified and eliminated in the subsequent consistency checks to prevent long-term biases."

12. l. 143: 4 hours seem to be too long; was a blower/heater system deployed with the instrument?

Reply: Yes, the instrument is equipped with a continuously operating blower/heater system. While the radome typically dries within an hour, the severe sub-zero winters in Xianghe significantly slow down evaporation. Therefore, 4 hours was adopted as a strictly conservative maximum threshold to guarantee no residual moisture affects this decadal climate dataset. We have clarified this in the text (L164-167):

"Although an active blower/heater system is deployed, sub-zero winter temperatures can slow evaporation. Following cleaning, TB values generally return to normal within 1–2 hours, but this process can take and up to 4 hours in winter. Based on maintenance logs, TB observations recorded within 4 hours after radome cleaning are flagged as abnormal (n1 = 1 in Table 1) to conservatively ensure data purity."

•13.l. 160: change "stability" to "variability"

Reply: Done.

14. chapter 3.1.3 b): how is CBH derived/retrieved from IRT?

Reply: We thank the reviewer for pointing this out. In this study, the CBH is not derived using a custom algorithm; rather, it is directly obtained from the standard data product provided by the RPG instrument's built-in operating software. The manufacturer's proprietary algorithm estimates the CBH by comparing the downwelling infrared sky temperature measured by the IRT with the ambient atmospheric temperature profile to determine the condensation level. We have clarified the source of the CBH data in the revised manuscript to avoid any ambiguity (L193).

15. l. 181: is 1 min the chosen output resolution, or are temporally higher resolved values averaged?

Reply: ~1 minute is the chosen native output resolution configured in the instrument's software. It is not a post-processed average of higher-resolution data. We have clarified this in the text (L206).

16. l. 189: add "model uncertainties" to the argumentation

Reply: Done.

17. l. 193: add "or bias from input data"

Reply: Done.

18. l. 201: He et al. (2021) don't show a comparison of radiative transfer models

Reply: Done.

19. l. 212: more details on the data matching should be presented

Reply: We thank the reviewer for this suggestion. We have expanded the text to explicitly describe the spatiotemporal matching process between the 1-minute MWR observations and the hourly model data. The temporal window and the alignment strategy are now clearly defined in L237-240:

"In the comparison study, a spatiotemporal synchronization approach was applied. Specifically, to match the 1-minute MWR observations with the hourly forward-modeled TBs, the single 1-minute MWR measurement closest to the exact hour of the simulation was selected. Subsequently, data pairs with anomalous deviations were removed using the 3σ criterion based on the Root Mean Square Error (RMSE)."

20. l. 238: how are LWP & IWV retrieved? Retrieval approach from the manufacturer? Was an often applied LWP offset correction carried out?

Reply: We thank the reviewer for the clarification request. The IWV and LWP values included in this dataset were directly obtained from the manufacturer's standard products. As the primary focus of this study is on the quality control of TBs and the retrieval of thermodynamic profiles (T and q), no additional post-processing, such as the LWP offset correction, was applied to these auxiliary parameters.

However, we did the IWV comparisons between MWR and CEMEL Sun photometer at XH, the results show that high precision of retrieved MWR IWV (Wang et al., 2025). Since both LWP and IWV are retrieved from MWR first 7 Channel covering the absorption of water vapor and liquid water. Under the quality assurance of TB observations from all microwave channels, the accuracy of the integrated water vapor (IWV) retrieval products can be used to indirectly verify the validity of the liquid water path (LWP) data from the microwave radiometer (MWR).

We have clarified the data source and processing in the revised manuscript (L265-266).

21. l. 250-257: this part is repeated from the introduction and could be removed

Reply: Done.

22. Table 4: change to "Available samples after QC"

Reply: Done.

23. chapter 4.1: could the different occurrence of clouds and rain be linked to atmospheric conditions in the different years? Maybe using findings from other studies to provide more context.

Reply: We agree with the reviewer that linking the observed weather identifier frequencies to the regional climatic context adds significant value. In the revised manuscript, we have expanded the discussion in Section 4.1 (L460-467):

"Second, excluding 2013, the frequency of clear-sky occurrences at XH has shown a gradual decline in recent years, especially from 2018 to 2021, when the clear-sky frequency dropped to below 50%, with the corresponding frequency of cloudy conditions increasing to around 40%. This trend aligns with recent findings that summertime low-level cloud cover has significantly increased across China over the past two decades. Such an increase is closely associated with regional vegetation greening, which enhances surface evapotranspiration and provides local moisture supply for cloud formation (Zhang et al., 2024a). The occurrence of precipitation, except for the anomalously high value in 2013, remained relatively stable in other years, generally around 5%. In addition, uncertain samples have been consistently controlled at about 10%, except in 2017, where it approached 20%, likely due to insufficient instrument maintenance or supervision."

24. Figure 7: the temperature from the AWS could be added

Reply: We thank the reviewer for this excellent and highly constructive suggestion. We carefully evaluated the inclusion of the AWS near-surface temperatures to validate the trends. However, after rigorous quality control, we found that the AWS record exhibits temporal inconsistencies and uneven data availability during parts of the study period, which would affect the robustness of long-term trend comparisons.

Furthermore, as part of our comprehensive revisions, we critically re-evaluated the entire long-term trend analysis section. Because the MWR observational data in certain early years were also relatively incomplete, we concluded that estimating a robust decadal trend might introduce unnecessary uncertainties. Therefore, to maintain methodological consistency and avoid potential sampling-related biases in the trend analysis, we have decided to completely remove the interannual trend analysis and the corresponding figure from the revised manuscript. Consequently, the AWS temperature series was not incorporated.

Nevertheless, the quality-controlled and temporally matched AWS observations were retained in the published dataset.

25. chapter 4.3: the generally "coarse vertical resolution" (limited information content) of MWR derived temperature profiles should be mentioned, especially regarding the EI layers. And what is the reason for increased STD in winter (Inversion Intensity)

Reply: We thank the reviewer for these important points:

(1) We have added a discussion at the beginning of Section 4.3 to acknowledge the relatively coarse vertical resolution and limited information content of MWR profiles, noting that this smoothing effect may lead to an underestimation of thin or sharp elevated inversion (EI) layers.

(2) We have also clarified the reason for the increased standard deviation (STD) of inversion intensity in winter. This high variability is attributed to the sharp contrast between extremely stable, stagnant periods (strong inversions) and well-mixed periods following frequent cold air outbreaks in the North China region during winter.

These changes are added in the revised manuscript in L502-504 and L522-524.

26. l. 456: how many cases are included in each bin?

Reply: We thank the reviewer for the suggestion. To provide a robust statistical basis for the mean and standard deviation shown in the error bands, we have updated Figure 11 to include the number of identified inversion layers (N) for both SBI and EI within each $PM_{2.5}$ bin. The updated X-axis labels now explicitly show N_{SBI} and N_{EI}.

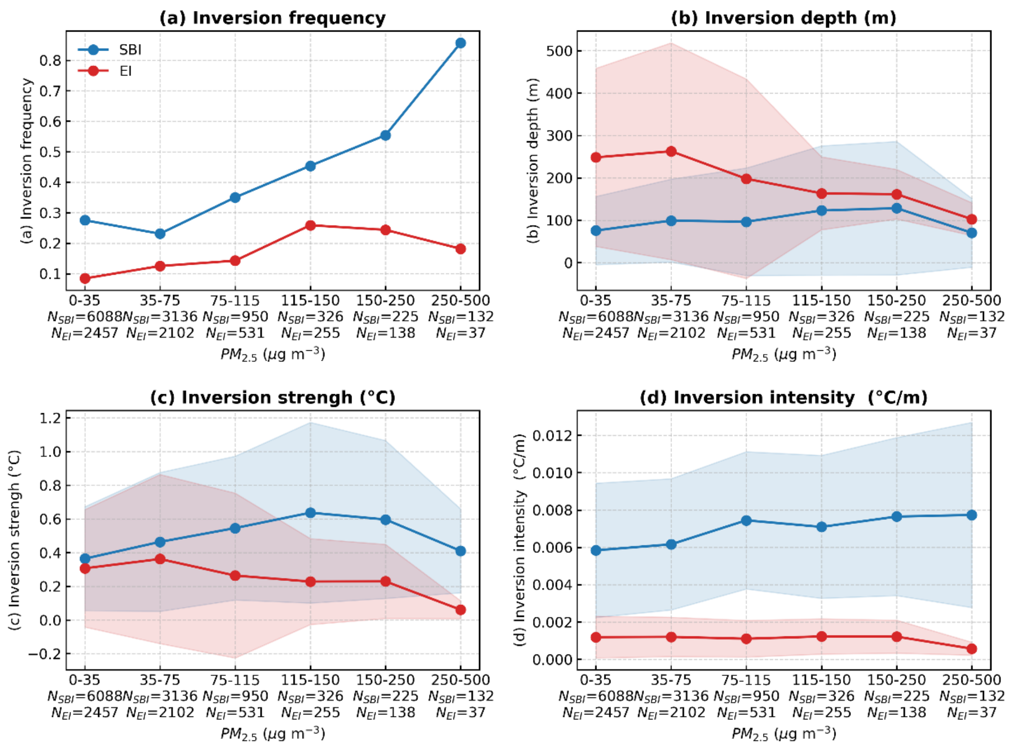

Figure 1: Statistics of inversion characteristics across different $PM_{2.5}$ concentration bins at XH during 2018-2019. Panels show (a) inversion frequency, (b) inversion depth, (c) temperature strength (ΔT), and

(d) inversion intensity (ΔT/depth) for surface-based inversions (SBI, blue) and elevated temperature inversion (EI, red). The specific number of inversion layers used for statistical analysis (N_{SBI} and N_{EI}) is indicated on the x-axis for each bin. Error bands indicate ±1 standard deviation.

Data set Major points:

1.All variables should have names and units

Reply: Thank you for this suggestion. We agree that all variables should have explicit names and units. In the revised data repository, we now provide this information in two dedicated README files, covering both profile products and brightness temperature/QC products:

(1) Profile datasets: README_profiles_with_method.md. This file documents variable names, definitions, units, time reference (UTC), height reference (m AGL), and retrieval-method labels for the merged profile datasets.

(2) Brightness temperature and QC datasets: README_BT_flag_units_v3.md.

This file documents variable meanings and units for the BT and flag files (including nflag and IRT-related variables), and clarifies unit conventions.

Therefore, variable naming and unit definitions are now explicitly provided across the full released dataset.

2.It should be made clear which retrieval method was used

Reply: Thank you for this comment. We agree that the retrieval method used for each profile sample must be explicit. We have now clarified this in both the data files and the documentation: A dedicated column retrieval_method is included in the merged profile datasets. This field explicitly indicates which algorithm produced each timestamp: OE for Optimal Estimation and DNN for Deep Neural Network.

3.Uncertainty estimates (e.g. from the optimal estimation method) should be included

Reply: We appreciate this suggestion. Actually, in Fig.6 and Fig.7, the shaded regions represent the interquartile range (IQR, 25–75%) of difference, reflecting the estimated uncertainty at each level.

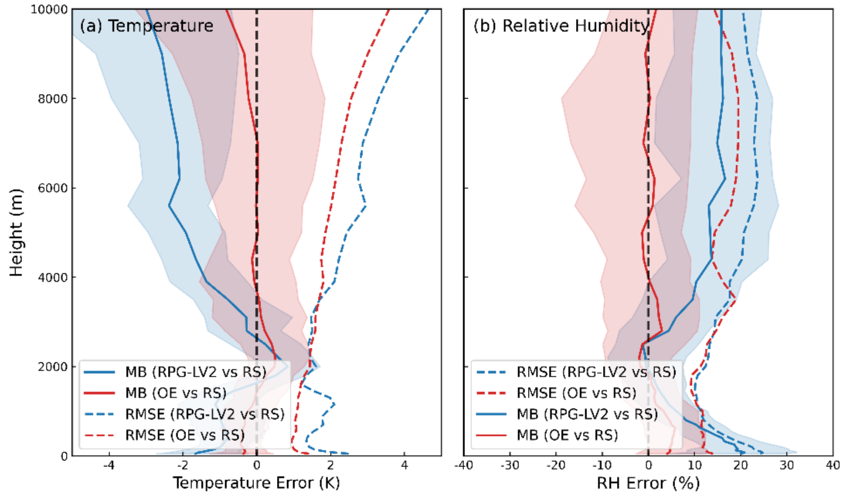

Figure 6: Vertical distributions of mean bias (MB) and root mean square error (RMSE) for RPG-LV2 and OEoptimal estimation retrieved temperature (a) and relative humidity (b) profiles compared with radiosonde profiles (RS) in 2020. Solid lines denote the median MB, dashed lines indicate the mean MB. The shaded regions represent the interquartile range (IQR, 25–75%) of difference, reflecting the estimated uncertainty at each level. A vertical dashed black line marks the zero-bias reference.

Minor points:

4.The data repository site lacks details about file contents (such as variable names, units, metadata), exact instrument location and information on how the products were derived

Reply: Done. We added a detailed README and variable dictionary to the repository. These files now include variable names, units, metadata, exact site coordinates (39.75°N, 116.96°E), and a concise description of the product derivation workflow (TB quality control, cloud classification, and retrieval strategy).

5.Time is encoded in two ways in the *cflag.csv files, which could be confusing

Reply: We removed the duplicated datetime column and kept only one time representation (Year/Month/Day/Hour/Minute/Second in UTC) in the revised files.

6.Is there a difference between "Rainflag" and "n2"? Could one of them be omitted?

Reply: Thank you for the comment on the precipitation flag definition. In the revised release, we keep both Rainflag and n2 in the TB+flag files. Rainflag is retained for direct consistency with the original MWR product stream, while n2 is retained for consistency with the multi-identifier QC framework used in this study. For samples where n2 is available, n2 and Rainflag are equivalent (0: no precipitation; 1: precipitation). For branch-terminated cases (e.g., n1=1, within 4 hours after cleaning), n2 can be NaN by QC design, whereas Rainflag remains available as the native precipitation indicator.

7.Are there two IR channels? IRT2 is not mentioned in the manuscript (and has a different unit than IRT1)

Reply: Yes, two IR channels are included. We clarified this in the metadata and explicitly distinguished their units: IRT1_K (Kelvin) and IRT2_K (Kelvin). We also updated the variable documentation accordingly.

8."cflag" is not defined in the manuscript

Reply: We agree that this was an oversight. As “cflag” is an unnecessary variable for this specific data product, we have removed it entirely from the updated dataset.

9.Why do some quality flags show NaN

Reply: Thank you for the comment. We re-checked all yearly files (2013-2022) and confirmed that NaN values are intentional outputs of the QC decision tree, not random missing values. Importantly, NaN occurs in branch flags (n2/n3/n4), while nflag itself has no NaN values.

Specifically:

(1) When n1 = 1 (within 4 hours after instrument cleaning), n2, n3, and n4 are not evaluated and are set to NaN; nflag = 3.

(2) For precipitation cases (n2 = 1), n3 and n4 are not evaluated and are set to NaN; nflag = 2.

(3) For non-precipitation cases with cloudy sigma-c condition (n2 = 0, n3 = 1), n4 is not evaluated and is set to NaN; nflag = 1.

We have added this clarification to the dataset documentation and explicitly state that these NaNs mean “not applicable by design.”

“**Table 1.** Multi-Identifier for TB observations and the meanings of its values

Identifier	Value	Checking Condition	Meaning
n_1	0	$\lvert TB(n) - \mu \rvert \leq 3\sigma$ and not within cleaning window	Normal
	1	$\lvert TB(n) - \mu \rvert > 3\sigma$ or ($\lvert TB(n) - \mu \rvert \leq 3\sigma$ and within 4 hours after cleaning)	Abnormal
n_2	0	*Rainflag* = 0	No precipitation
	1	*Rainflag* = 1	Precipitation
	NaN	n_1 = 1 (branch terminated)	Not applicable by design
n_3	0	$\sigma_c \leq a + b \cdot IWV$	Clear-sky
	1	$\sigma_c > a + b \cdot IWV$	Cloudy
	NaN	n_1 = 1 or n_2 = 1 (branch terminated)	Not applicable by design
n_4	0	CBH<500m or CBH>8000 m	Clear-sky
	1	500 m <CBH<8000m	Cloudy
	NaN	n_1 = 1, or n_2 = 1, or n_3 = 1 (branch terminated)	Not applicable by design
nflag	0	n_1=0, n_2=0, n_3=0, n_4=0	Clear-sky
	1	n_1=0, n_2=0, (n_3=1 or n_4=1)	Cloudy
	2	n_1=0, n_2=1	Precipitation
	3	n_1=1	Other/uncertain

Note: NaN values in n_2-n_4 indicate branch-terminated checks and are not random missing data, while *nflag* contains no NaN values.”

References:

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