Response to reviewers

General comments to authors：

The authors introduced a new method in the manuscript to obtain continuous relative humidity profiles by integrating data from Raman LiDAR, microwave radiometer, and satellite sources. And it was validated through five months of observation data from north to south in China, which showed a high consistency with radiosonde data. Monthly statistical analysis and case studies also demonstrated the applicability of this method. I think this manuscript can be published in the journal Atmospheric Measurement Techniques. But before that, I think it is necessary to answer the following questions and make minor modifications.

Specific comments：

1. In the introduction section: the authors mentioned that the observation data from China's Fengyun (FY) satellite is rarely used for comprehensive inversion of relative humidity information, but did not mention the use of satellite data from other countries for inversion of relative humidity information. Please supplement this section.

Reply: Thank you for the comments. We have included more references to the use of satellite data from other countries for relative humidity information inversion in the Introduction part.

2. The author mentioned in the introduction section (lines 69-76) that many literature studies have introduced data from Raman lidar and microwave radiometer to obtain continuous RH profile data, but did not elaborate on the differences between your method and theirs. This will confuse readers: where is your new method new? Please provide a supplementary description for this section.

Reply: Yes, some work has focused on the integration of Raman lidar and MWR for RH retrieval. However, most of their algorithms primarily utilize statistical methods, performing data fusion between different instruments based on long-term time-series data from individual locations. While these approaches are suitable for observations at single stations, they lack universality when applied to scenarios requiring data integration from multiple sites or broader geographical coverage. Moreover, replacing instruments or equipment may also introduce additional inconsistencies. Compared to these existing techniques, our new method not only incorporates satellite data but also dynamically determines optimal fusion coefficients, enabling device model independence and geographical adaptability. Thus it eliminates constraints imposed by equipment specifications or observation locations, ensuring broad applicability across diverse scenarios.

We have provided a more detailed description for this part (in section 1 and section 3).

3. In section 2.1, when it comes to Raman differential absorption and setting the signal-to-noise , the description is unclear.

Reply: The threshold value of the signal-to-noise ratio is set as 3 based on our extensive comparisons with radiosonde data from CMA's long-term observations. The results indicate that selecting lidar signals with signal-to-noise ratios (SNR) >3 can significantly improve the consistency between retrieved RH profiles and radiosonde measurements. We have clarified it in this section.

4. In the Instrumentation section, line 118 mentions' The uncertainty of the instrument can reach a confidence level of 95.5%. '. This description is confusing.

Reply: We have deleted the sentence.

5. In the Methods and Evaluation section, the core steps of the dynamic optimal stitching algorithm (Figure 2) mentioned, such as correction coefficient calculation and weight allocation, lack mathematical formulas or quantitative descriptions. Suggest adding specific algorithm formulas and detailed explanations in the text rather than in the figure.

Reply: We have included the calculation of the correction coefficients by adding the mathematical formulas and descriptions in this part. Because the weighting coefficients are dynamically determined by comparing the deviations from other measurements with the reference of radiosonde, it can guarantee the independence of each device and observing site. It highlights that the new algorithm is real-time calibrated.

6. There is a formatting issue with Table 2, please make the necessary changes.

Reply: We have corrected it.

7. I noticed that after introducing the observation results of LiDAR, the maximum correlation coefficients R of the collaborative algorithm in HHHT, YB, and QY were 0.90, 0.91, and 0.93, respectively, which is very good. However, the RMSE of each instrument's individual data and sounding data exceeds 20% (Table 3). Does this indicate poor reliability of the data? What do you think about this?

Reply: We have checked the data and found that the precipitation data has not been removed from our dataset. This has led to the relatively larger RMSE. We have removed the precipitation data and recalculated the data.

8. At the end of section 4.1, the author analyzed the sources of errors. There are many sources of error analysis that lead to data uncertainty, such as the consistency of observation equipment? What is the uncertainty caused by regional differences? What is the physical essence that leads to differences here? There are many things worth pondering, which is why I recommend publishing this manuscript. It is meaningless to simply analyze these data differences.

Reply: Thank you for the comments. For the error sources, in addition to the theoretical measurement errors of the instrument, the errors also stem from the other sources. First, although all instruments are co-located in the ground, radiosondes deviate at higher heights, and uncertainty increases if clouds are present. Second, satellites provide gridded data, requiring the selection of ground observation points closest to its grid's latitude and longitude, which introduces uncertainty. Finally, errors during the retrieval process (e.g., neural networks for MWR) are also unavoidable.

The results in three observing sites (HHHT, YB and QY) show a similar RMSE with a value of 10% -12 %. It indicates the relatively good regional universality of the synegetic algorithm. Though there is no obvious uncertainty caused by regional differences, we found that QY exhibits the predominant seasonal feature throughout most heights. In contrast, no discernible seasonal characteristics in RH profiles are observed in HHHT or YB. Thus we believe diverse atmospheric circulation patterns and geographical environments could result in regional variations in RH values.

We have clarified it in the section 4.2.

9. The case analysis relies on ERA5 reanalysis data to provide the weather circulation situation (Figure 7), and the results generated by the synergetic method with Figure 8 lack correlation explanation. This is very confusing.

Reply: Thank you for the comments. We have chosen new cases and rewritten the case analysis. In the revised version, we analyzed the RH evolution in two severe convection cases. By comparing the characteristics of the height-time RH, we find that the RH in the middle troposphere is critical for distinguishing between hail and heavy precipitation. These two new cases can better demonstrate the importance of obtaining accurate spatio-temporal RH information for weather prediction.

10. The conclusion section is cumbersome and not concise, please rephrase.

Reply: We have shortened the conclusion part to make it more concise.