Response to Reviewer 1

We thank the anonymous referee for very thorough and constructive comments. Below are our responses to the comments.

Reviewer 1

The work presented in this article is interesting and the authors invested a lot of work to enable a retrieval of cloud liquid water path (CLW) and total precipitable water (TPW) from measurements of MWTS and MWHS aboard FY-3D.
However, although the title of the paper suggested a focus on the retrieval scheme and a thorough analysis and validation of the results, this has been just briefly touched in section 4. The authors are aiming to use existing algorithms to retrieve CLW and TPW, which have been originally developed for another instrument. It is not clear whether the algorithm coefficients have been adapted or newly trained. I have to assume that this is not the case because it is not presented in the paper and that the original algorithm has been used unchanged. I therefore do not see a substantial new concept or approach to derive CLW and TPW from sounder data.

Response: So far, FY-3D's microwave sounding data still fails to effectively enter the assimilation system to serve the weather forecast directly. One of the very important reasons is that it lacks effective quality control methods to obtain observation points under clear sky.

The large-scale TPW and CLW distribution obtained by satellite inversion, in addition to being used for global cloud water resource assessment, another important function is to use as cloud detection criterion for quality control in satellite data assimilation.

The main purpose of this paper is not to propose a new TPW and CLW inversion method, but to extend the application of FY-3D microwave sounding data by using existing TPW and CLW inversion methods so that it can be successfully assimilated into the numerical weather prediction (NWP) system.

The method adopted in this paper is the TPW and CLW inversion algorithm that has been successfully applied to multiple satellite data (AMSU and ATMS), and the inversion results have been widely used as satellite data quality control in NWP systems, such as GSI and GRAPES.

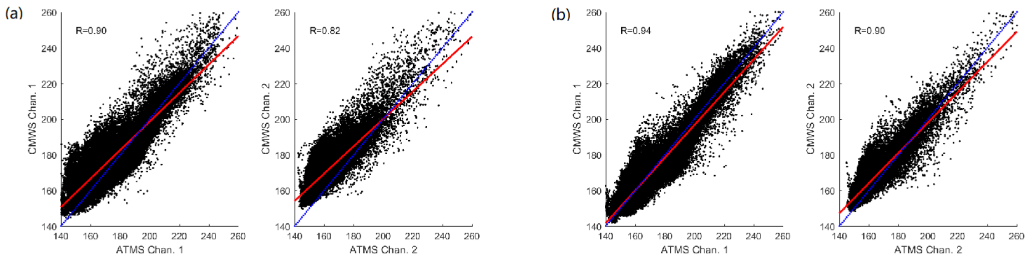
Except for the two missing channels, FY-3D contains all the sensor channels of ATMS, and their channel parameters are basically the same. Through cross calibration, the

CMWS data generated based on FY-3D has very similar observation results to ATMS, so the inversion algorithm suitable for ATMS can be transplanted into CMWS.

The verification of the results is very limited. Basically, just two days of retrieved data from two different instruments are compared visually. Unfortunately, a thorough statistical analysis and validation of the results over a sufficient period of time is missing.

Response: We added some quantitative assessments in the revised manuscript. A total of five days of data were selected as data sources from different months. Since ATMS and CMWS have different field of view (FOV) and satellite transit times, to perform pixel-to-pixel accuracy assessments, we need to collocation all pixels to ensure that the same pixels are evaluated. Successfully matched pixel pairs need to meet the following parameters: imaging time difference is less than 30 minutes, space distance is less than 15KM, satellite height angle difference is less than 10°, and scanning angle difference is less than 20°. After collocate all the ocean pixels from 60°S to 60°N, a total of 180,906 pixels were used for quantitative evaluation.

First, we compared the brightness temperature simulation accuracy of Ch1 and Ch2 when FY-3D observations are used as input in the machine learning model. Figure R1 shows scatter plots between ATMS and CMWS of two corresponding channels. The scatter results for five different dates are shown in (a) to (e), respectively. Subplot (f) represents the total scatter results. Overall, the accuracy and stability of the two simulated channel are satisfactory. According to the five-day observation results from different months, the correlation coefficient of Ch1 is more than 0.9, and the correlation coefficient of Ch2 is also close to 0.9. It should be pointed out that the results of machine learning using FY-3D observations as input will definitely be lower than the accuracy of quantitative evaluation using ATMS measurements as input. This is because the cross calibration between ATMS and FY-3D will inevitably introduce some new errors. Quantitative evaluation results can be found in Table R1. The mean absolute errors of the two channels between ATMS and CMWS are 6.74 and 5.73K, respectively.



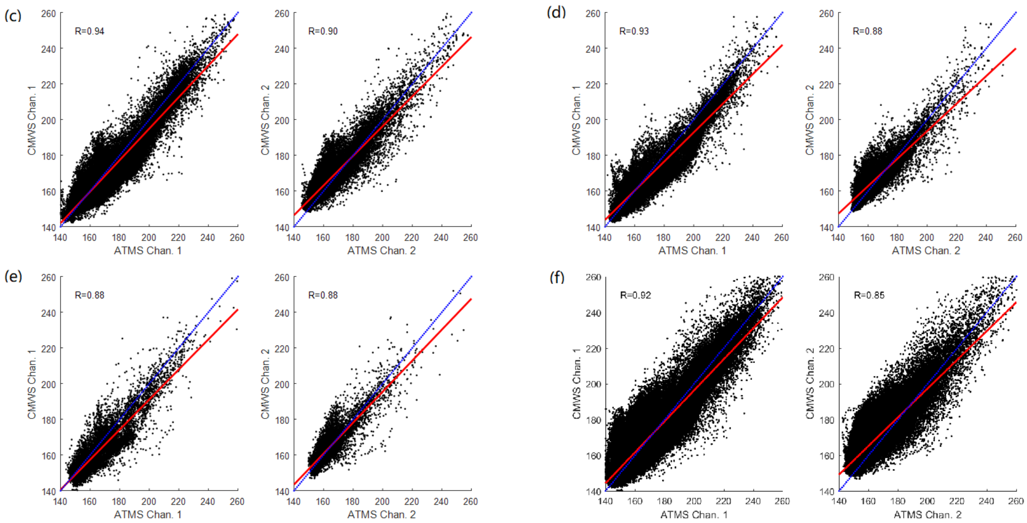
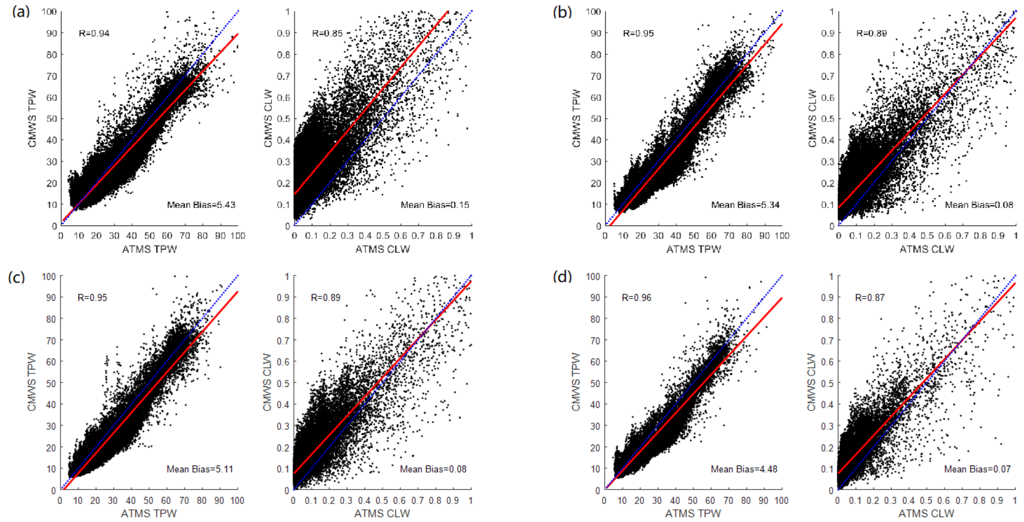


Figure R1. Scatter plots for ATMS channels and CMWS channels. (a) June 2, 2018, (b) July 2, 2018, (c) August 2, 2018, (d) September 2, 2018, (e) October 2, 2018, (f) All collocation pixels.

Second, we compared the retrieved TPW and CLW using the same retrieval method for ATMS and CMWS, respectively. Figure R2 shows scatter plots of retrieved TPW and CLW based on ATMS and CMWS, respectively. Also, the scatter results for five different dates are shown in (a) to (e), respectively. Subplot (f) represents the total scatter results. The results of quantitative evaluation show that the correlation coefficients of TPW and CLW between CMWS and ATMS are 0.95 and 0.85, respectively, and the mean absolute errors are 5.14mm and 0.1mm. Moreover, the correlation coefficients and mean absolute errors during the five independent days are very close, which shows that the method proposed in this paper has good stability and robustness (see Table R1).



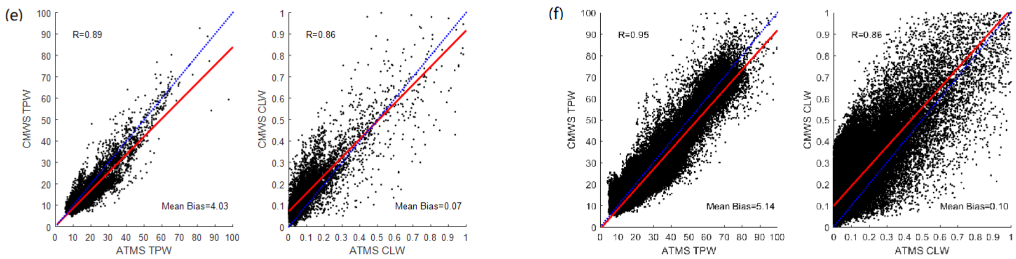


Figure R2. Scatter plots of retrieved TPW and CLW based on ATMS and CMWS, respectively. (a) June 2, 2018, (b) July 2, 2018, (c) August 2, 2018, (d) September 2, 2018, (e) October 2, 2018, (f) All collocation pixels.

Table R1. Quantitative evaluation results between ATMS and CMWS

Date (2018)	Matched pixels	Correlation Coefficient				Mean Absolute Error			
		Ch1	Ch2	TPW	CLW	Ch1 (K)	Ch2 (K)	TPW (mm)	CLW (mm)
June 2	54,831	0.90	0.82	0.94	0.85	7.27	8.66	5.43	0.15
July 2	53,322	0.94	0.90	0.95	0.89	6.75	4.4	5.34	0.08
August 2	40,565	0.94	0.90	0.95	0.89	6.24	4.60	5.11	0.08
September 2	22,955	0.93	0.88	0.96	0.87	6.37	4.62	4.48	0.07
October 2	8,936	0.88	0.88	0.89	0.86	6.61	3.77	4.03	0.07
Total	180,609	0.92	0.85	0.95	0.85	6.74	5.73	5.14	0.10

The authors concentrate on the simulation of two channels, which are not available on the two instruments but essentially needed to apply the selected algorithms. As these two channels are window channels, I do not expect that the surface emissivity characteristics of these window channels can be recovered from the sounding channels, as these do not see the surface. It is certainly possible to estimate parts of the atmospheric emission of the signal, because it is due to liquid water and water vapour. However, it would then be more appropriate to develop a new retrieval to directly derive CLW and TPW from the existing physical information in the given channel set. The additional step of estimating the surface channels is adding large uncertainties. This could be avoided by a direct retrieval.
Given these major general issues, I do not recommend to accept this paper for publication.

Response: For any FOV, although the observations of each channel are different due to different observation frequencies, there is a certain degree of connection between these observations. This is because the corresponding surface parameters and atmospheric environment at each observation point are exactly the same. It can also be seen from the distribution of the weighting function of all channels in ATMS that although Ch1 and Ch2 are window channels, the weighting distributions of Ch3, Ch4, Ch5 and Ch16 are very similar to those of Ch1 and Ch2, and other channels can also provide certain information in the lower layer (Figure R3). Therefore, we can establish the relationship between two low-frequency window channels and other channels of ATMS through the machine learning method for all FOVs.

Since MWTS and MWHS contain all channel settings in ATMS except for the two low-frequency window channels, and the weighting function of these channels is also consistent with the corresponding channel in ATMS, we can match FY-3D data to ATMS level by cross calibration, thus realizing the prediction of missing channel values in FY-3D using ATMS training model.

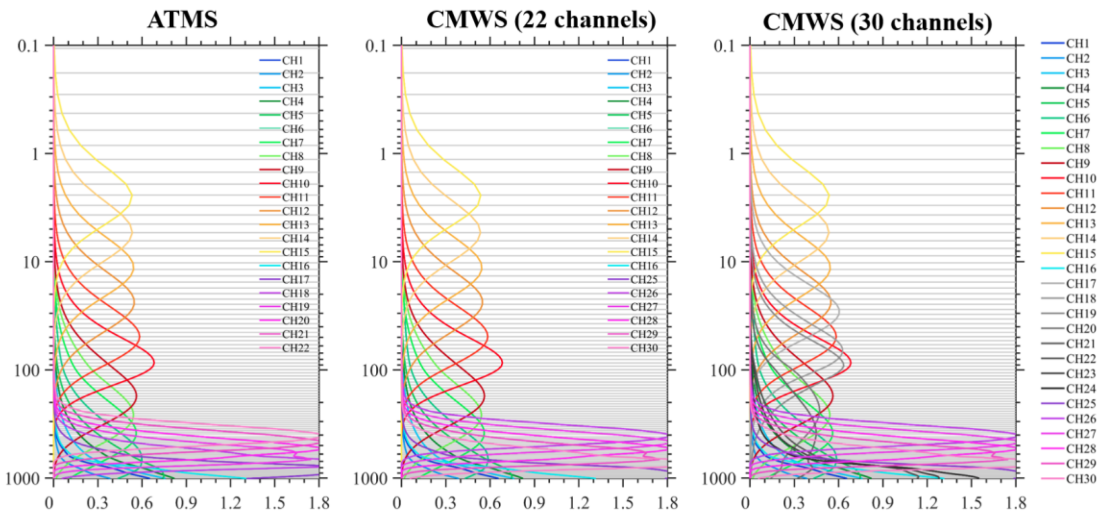


Figure R3 Weighting function of ATMS and FY-3D CMWS

We agree with the reviewer that it is best to retrieve directly from the microwave sounding data of FY-3D, but the information provided by other channels is not enough to invert TPW and CLW. Moreover, the quality control algorithm in the current NWP systems (such as GSI and GRAPES) is mainly based on the two channels (at 23.8 and 31.4GHz). That is, even if there is a newly developed TPW and CLW algorithm based on other channels, the effect of its application to the assimilation system is still uncertain.

Although the inversion of TPW and CLW through the two simulated channels will inevitably introduce some errors, after strict cross calibration and high-precision machine learning training, the correlation coefficients between TPW and CLW retrieved by two simulated channels and those retrieved by ATMS can still reach 0.95 and 0.85. Considering that our inverted TPW and CLW are mainly used for qualitative cloud detection and quality control during satellite data assimilation, the method proposed in this paper still has good application prospects at this stage to ensure that the microwave sounding data of FY-3D can effectively enter the assimilation system. Actually, based on the method proposed in this paper and the advanced radiative transfer modeling system (ARMS), the microwave sounding data of FY-3D has entered the GRAPES forecast system in China in real time.

The next FY-3 satellite FY-3E will soon be launched, in which two window channels (at

23.8 and 31.4GHz) will be added in the new microwave sounder. The simulation method proposed in this paper can also provide a good proxy simulation for FY-3E. After the FengYun satellite has the real observation data of these two window channels, we will carry out the inversion of TPW and CLW use physical inversion method (Weng et al., 2003), which should have higher retrieval accuracy than current statistical inversion method.

Weng, F., Zhao, L., Ferraro, R., Poe, G., Li, X., and Grody, N.: Advanced microwave sounding unit cloud and precipitation algorithms, Radio Sci., 38(4), 8068, doi:10.1029/2002RS002679, 2003.