

## ***Interactive comment on “Can machine learning correct microwave humidity radiances for the influence of clouds?” by Inderpreet Kaur et al.***

### **Anonymous Referee #2**

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Review of Kaur et al., “Can machine learning correct microwave humidity radiances for the influence of clouds?”

#### General Comments

The authors present a novel approach (quantile regression neural networks) to screening microwave brightness temperature observations near 183 GHz for cloud influence and constructing estimated “noise-free clear-sky” observations that could be used in data assimilation applications. The article is clear, concise, and well written, and the topic is relevant and important. I recommend publication after the following minor comments and corrections are addressed.

#### Minor Comments

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As I understand it, this study uses only simulated measurements (either with or without hydrometeors included), even for MWHS-2 for which actual measurements are available. This should be made clearer, especially given line 66, which states that no “background” data is required for the method. I’d also like to see a bit more discussion about whether the results you present should be expected to hold for real data. An assumption that you are making is that your forward model can represent real clouds with enough fidelity that a model trained on simulated data will still work on real-world data. Can you point to any evidence to back up this assumption? Have you tried comparing the histograms of model-simulated Tbs with real-world MWHS-2 Tbs?

What is the computational cost of the QRNN method compared to simpler cloud-clearing filters? Could it feasibly be implemented into existing NWP models given current computational constraints?

Lines 135-143: Why the large difference in number of cases simulated for ICI (220,000) vs. AWS (143,000), if they are both coming from the same population of CloudSat profiles? For the training dataset, you use about 75% of total cases for MWHS-2, about 80% of cases for ICI, and about 84% of cases for AWS. Why this difference in proportions?

Line 340: “With a test dataset of 70 000 samples, we cannot represent the far wings of the distribution accurately.” Couldn’t one apply this same reasoning to Figures 2,3, or 8, which have density values below  $10^{-4}$  included?

Figure 13: I wonder if there might be an easier, more concise way to evaluate whether the uncertainty intervals are properly calibrated. Namely, could you simply calculate how often the true value falls within the  $\pm 2\sigma$  uncertainty range, for each of the uncertainty bins (0-3K, 3-8K, 8+K) that you’ve included on the plot? If this percentage is significantly less than 95%, it would suggest that your uncertainties are too small, while if it were closer to 100% it would suggest your uncertainties are too large. Even if you don’t get rid of Fig. 13, I think this would be useful information to include in the

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paper.

Lines 498-499: “. . . other underlying uncertainties not considered here.” Whether here or elsewhere in the paper, I think you should talk a bit more about what these other uncertainties are (radiative transfer model errors should certainly be discussed), and what effects they might have on your results.

Typos

Line 26: The phrase “weather satellites are since some time equipped” is confusing to me. I suggest “weather satellites have for some time been equipped. . .”

Line 51: I believe you are missing the word “on” between “predicated” and “Gaussian.”

Line 154: Should 85% be changed to 84%? That would be +2 sigma for a normal distribution.

Line 455: “. . . provide coverage to the humidity channels in, lower and mid troposphere” This is confusing – get rid of the comma and add the word “the” instead?

Line 494: “QRNN predictions are weighted mean. . .” I think this should say, “QRNN predictions are the weighted mean. . .”

Line 508: Missing “the” before “same”

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Interactive comment on Atmos. Meas. Tech. Discuss., doi:10.5194/amt-2020-464, 2020.