EGUsphere, referee comment RC1
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Comment on egusphere-2022-78

Anonymous Referee #1

Referee comment on "An improved near-real-time precipitation retrieval for Brazil" by Simon Pfreundschuh et al., EGUsphere, https://doi.org/10.5194/egusphere-2022-78-RC1, 2022

An improved near real-time precipitation retrieval for Brazil

By Pfreundschuh et al.,

The paper presents a convolutional neural network architecture for IR precipitation retrieval over Brazil. The training data are from IR and GPM combined retrievals. The framework is extended such that it can provide uncertainty of the retrievals. The estimates are compared with ground-based gauge data to validate the retrievals. The paper is well written and is of high-quality. I have the following comments.

Major comments:

- Validation only with a month of gauge data is not sufficient for clamming those improved results in the abstract. Seasonal to annual validation results are needed to make those claims.
- A single storm retrieval is missing. It is imperative to show the output of the algorithm in retrieval of a single or multiple storms and compare the results with the combined GPM retrievals as a reference. One retrieval snapshot speaks very clearly about the skill of the algorithm in reconstructing the training data and retrieve spatial structure of precipitation.
- Error metrics are only represented cumulatively. The expectation is that paper presents the quality of retrievals for an individual storm in terms of detection accuracy (e.g., probability of detection, miss) and then focuses on estimation quality metrics at different time scales from a storm scale to monthly and seasonal.
- This needs to be clarified whether the training data were only over Brazil or not. If this is the case, then the provided improved statics are not of surprise. This issue needs to be stated in the abstract.

- The way the paper explains the Bayesian retrieval is confusing. First, what is the prior distribution? Just obtaining uncertainty of estimates does not mean that the approach is Bayesian, and we can call the distribution a posterior. We can quantify uncertainty in a frequentists sense. It seems that the approach counts the number of retrievals associated with Tbs within bins. Then the bin with maximum is labeled. The problem is then defined as classification problem and the output of the softmax function is considered as the posterior distribution of the retrievals. Even though, I found the approach creative, I am not convinced that it is a Bayesian approach.
- It is claimed that spatially aware CNNs provide more accurate retrievals than pixel-level DNNs. The reason is not discussed, and no evidence is provided.
- In equation 2, when the prior probability approaches to a small number, the likelihood ratio can be extremely large. The correction numbers in Fig. 4 are too large. Please explain why such a large difference might exist in the retrievals that need such a large correction factor. For correcting probability distribution we can use a simple CDF matching!
- The resolution of IR is higher than microwave data. In this sense, you have redundant samples. How were those samples treated in the training?
- Explanation of the uncertainty quantification is too complex. Please consider simplifying the text and provide improved explanations.

Some minor comments

- Why both the second and third configurations are needed. They are just different in resolution.
- Line 160. Provide reasoning.
- Line 185”. The range is too wide! The training GPM combined precipitation can range from 0.1 to 200 mm/hr. Why 1000 mm/hr?