An improved near real-time precipitation retrieval for Brazil

Response to reviewer comments

1 Comments from reviewer 2

1.1 Specific comments

Reviewer comment 1:

What is the purpose for the 4-km experiments given that the ABI has a native resolution of 2 km?

Author response:

The principal motivation for the 4-km experiments is that the current operational algorithm, HYDRO, operates at this resolution. Running the operational retrieval at 2-km resolution quadruples the computational and storage requirements. The 4-km experiments thus serve as a baseline to assess the benefits of running the retrieval at a higher resolution.
Furthermore, the GPM combined retrieval, which is used to generate the training data, has a comparably low resolution of 5 km. Therefore, it is not evident that the retrieval can benefit from the increased resolution of the input data.

Changes in manuscript:

- We will reformulate the section that introduces the retrieval configurations and clearly motivate them.

Reviewer comment 2:

Line 152: The availability of sunlight does not affect the other IR and WV bands, only the availability of VIS bands. Therefore, it does not justify the use of only a single IR channel. Please clarify the reasoning here.

Author response:

Only the IR window channel is used for the $\text{Hydronn}_{4,\text{IR}}$ configuration because the same channel is used by the HYDRO and PERSIANN CCS retrievals. Therefore the $\text{Hydronn}_{4,\text{IR}}$ configuration can be used to assess the benefit of neural-network-based retrieval over the traditional power-law-based retrieval. Moreover, because this channel has been continuously available on a long sequence of geostationary sensors, it is suitable for the generation of precipitation records and used, for example, in GPM IMERG (Huffman et al., 2020) and the PERSIANN CDR datasets (Ashouri et al., 2015).

Changes in manuscript:

- We will extend the section that introduces the $\text{Hydronn}_{4,\text{IR}}$ configuration to clearly state this motivation.

Reviewer comment 3:

Lines 155-156: How are the values of the visible and near-IR bands treated by the CNN to differentiate daytime from nighttime scenes? Or is this something the CNN does without any intervention?

Author response:

The CNN is trained with input from all GOES channels regardless of the time of the day. Therefore, it learns to handle both day- and night-time observations, and no intervention is required to handle them.

Changes in manuscript:

- We will add a sentence to the description of the training scheme to mention this feature of the CNN retrieval.

Reviewer comment 4:

Sections 3.3 and 3.4: The description of the CNN needs much more detail to be understood by readers who are not experts on CNNs.

Author response:

We will extend the description of the CNN model upon which Hydronn is based.

Changes in manuscript:

- Section 3.3, which describes the neural network model used by Hydronn, will be extended.

Reviewer comment 5:

Lines 181-183: Please briefly define terms such as cross-entropy loss, logits, and softmax activation that would probably be unfamiliar to most readers.

Author response:

We will add definitions of these terms to the manuscript.

Changes in manuscript:

- Definitions of the terms 'cross-entropy loss', 'logits' and 'softmax activation' will be added to Sec. 3.4 of the manuscript.

Reviewer comment 6:

Line 165: Why is downsampling done for the 2-km retrievals rather than the 4-km retrievals? Shouldnt́ it be the other way around?

Author response:

Hydronn$_{2,\mathrm{All}}$ ingests GOES observations at resolutions of 500 m, 1 km and 2 km, which means that the network has to handle three input streams of different sizes. The additional downsampling layers in the Hydronn$_{2,\mathrm{All}}$ retrieval are required to reduce the size of the 500 m and 1 km inputs so that they can be combined with the observations at 2 km resolution. Since the network applies learnable transformations before and after the downsampling layers, it can actually learn to make use of the information at 500 m and 1 km resolution. This would not be the case if the observations were down-sampled prior to feeding them into the network.
The inputs for the 4 km retrievals are down-scaled prior to feeding them into the network. Therefore no additional downsampling layers are required to reduce the size of the input to that of the output.

Changes in manuscript:

- We will extend the description of the neural-network architecture to better explain the role of the downsampling layers.

Reviewer comment 7:

Line 167: Please provide references to support this assertion about the number of internal features relative to other architectures.

Author response:

We reconsidered the sentence in question an decided to remove it from the manuscript. The principal reason for this is that by correcting a bug in our training code we were able to increase the number of features used in the NN architectures. In retrospect, we also consider the sentence imprecise and not really helpful for the reader.

Changes in manuscript:

- We will remove the sentence in question from the manuscript.

Reviewer comment 8:

Line 178: What in particular makes it easier to compute this sum on the binned PDF than on the quantiles? Please explain this more thoroughly.

Author response:

The principal reason for this is that we are not aware of any other way to calculate the distribution of the sum of two independent random variables.
Therefore, if a distribution is given in terms of a sequence of quantiles, it would be necessary to (1) use the quantiles to calculate the PDF of the distribution, (2) calculate the binned PDF of the sum of the variables, and finally (3) compute the desired quantiles of the resulting distribution.
If, on the other hand, the retrieval results is already a PDF in binned form, the sum can be calculated directly.

Changes in manuscript:

- We will extend the explanation of the calculation of the sum of the retrieval results to make the advantage of the binned PDF format clearer.

Reviewer comment 9:

Line 186, 442: Please explain what the degeneracy of (low) quantiles means.

Author response:

Non-raining pixels, which are assigned a precipitation rate (PR) of exactly $0\,\mathrm{mm\,h^{-1}}$, cause a discontinuity in the CDF of the distribution of precipitation rates. Since this makes it impossible to invert the CDF, not all quantiles are well defined. For example, it is impossible to determine the 25th percentile of the CDF of a pixel that is assigned a raining probability of 50 % because the CDF is 0 for all PR < 0 and larger than 0.5 for all PR ≥ 0.

Changes in manuscript:

- We will add an explanation of the degeneracy of quantiles to Sec. 3.4 in the manuscript.

Reviewer comment 10:

Line 189: What is the rationale for creating outputs for 128 bins if only 14 quantiles are used?

Author response:

The retrieval results of Hydronn are represented as a binned approximation of the posterior PDF. The number of bins must be such that the full range of possible output values is covered and that the bins are sufficiently fine to ensure that they can accurately represent the posterior PDF in the region where most of its mass is located. Since it is impossible to know a priori where the mass will be located, Hydronn employs a relatively fine grid across the full range of possible output values.
A posteriori, the PDF can be represented more compactly using quantiles. To ensure that these quantiles, but also the mean, mode and samples of the posterior distribution, can be calculated with high accuracy, Hydronn such a high number of output bins.

Changes in manuscript:

- We will extend Sec. 3.4 to more clearly motivate the choice for number of output bins.

Reviewer comment 11:

Line 193: What does inference mean in this context?

Author response:

In the field of machine learning, 'inference' refers to the application of a statistical model to unseen data. It is used to distinguish the actual usage of a machine-learning model from its training process. In this case it means during the retrieval processing.

Changes in manuscript:

- We will add an explanatory phrase to the sentence in question.

Reviewer comment 12:

Line 196: What does posterior mean in this context?

Author response:

The posterior distributions here are just the results of the retrieval for each observation.

Changes in manuscript:

- We will rephrase the sentence in question to make it clear what is meant with 'posterior'.

Reviewer comment 13:

Lines 203-204: Why specifically will assuming that the retrieval uncertainty is temporally independent cause the uncertainty to decay for consecutive identical observations?

Author response:

Our assertion that the retrieval uncertainty of independent measurements decays is based on the following reasoning:
Given a sequence of random variables $X_1, \dots X_n$ with finite mean and finite and bounded variance, let $\sigma_{\text{max}} = \max\{\text{Var}(X_1), \dots \text{Var}(X_n)\}$ denote the maximum variance of any of the distributions. It is then possible to derive the following upper bound for the variance of the mean of the random variables:

$$\text{Var}(\frac{1}{n}\sum_i X_i) = \frac{1}{n^2}\sum_i \text{Var}(X_i) \tag{1.1}$$

$$\leq \frac{1}{n^2} n\sigma_{\text{max}} \tag{1.2}$$

$$\leq \frac{\sigma_{\text{max}}}{n} \tag{1.3}$$

Note that (1.1) holds because of the independence of the random variables. This means that the variance of the mean of the random variables will always be lower than that of the distribution with the highest variance and decay as more observations are included in the mean.

Reviewer comment 14:

Lines 279-280: This is true, but it would be very scientifically interesting to see the relative degree of improvement during the day and night e.g., to quantify the value of the visible and near-IR data.

Author response:

We agree with the reviewer that this would be an interesting question to investigate. However, we fear that a simple comparison of retrievals during day and night time would be misleading due to the confounding effect of the pronounced daily cycle of precipitation. A fairer comparison may be to add an additional retrieval configuration to the study. However, considering the associated computational cost and that the objective of our study was maximizing the accuracy of the precipitation retrievals, we consider this to be outside the scope of our study.

Reviewer comment 15:

Line 342: Why does assuming dependent retrieval errors lead to the uncertainties being overestimated?

Author response:

That the assumption of dependent retrieval errors causes uncertainties to be estimated can be seen from the fact that the calibration curves in Fig. 10 lie above the diagonal. This means that the retrieved confidence are too wide, which causes the true precipitation value to lie withing them more often that is expected based on the interval.
The observation that the assumption of dependent retrieval errors leads to an overestimation of the uncertainties is therefore primarily an experimental result. The likely reason for this is that the true errors are not completely dependent but include an independent component that causes the real uncertainties to decay.

Changes in manuscript:

- We will extend the discussion of Fig. 10 to reflect the above reasoning.

Reviewer comment 16:

Lines 361-362 and 473: How precisely does varying the probability threshold have a calibrating effect on the retrieval results?

Author response:

Upon reconsidering the statements in question, we have come to the conclusion that our results don't provide any evidence of a calibrating effect. We will therefore remove the statements from the manuscript.

Changes in manuscript:

- We will remove the statements from the manuscript.

Reviewer comment 17:

Lines 378-379: What probability threshold was tuned, and why was a FAR close to IMERG the criterion for doing so?

Author response:

Due to its probabilistic nature, Hydronn is able to predict the probability that the precipitation at a given pixel exceeds a certain threshold. This probability can be used to detect strong precipitation by choosing a probability threshold above which a pixel is assumed to contain heavy precipitation. The probability threshold can be used to tune either POD or FAR to an arbitrary value. In practice, the threshold should be chosen according to the application at hand. Since purpose of the evaluation was the comparison to IMERG, we tuned the FAR to that of IMERG.

Reviewer comment 18:

Table 4: Why precisely does correcting when assuming independent errors actually degrade the POD, FAR, and CSI relative to the uncorrected version?

Author response:

We think that the degradation of POD, FAR, and CSI for the assumption of independent retrieval uncertainties is due to an error in the calculation of the correction factors. The calculation of the a priori distribution of hourly accumulations assumed fully independent samples of the a priori distribution of instantaneous precipitation estimates. Since this neglects the dependence that is introduced by the temporal coherence of the satellite observations, it likely caused the correction factors to be incorrect.
We will adopt a different approach for calculating the correction factors in the revised version of the manuscript to see whether this improves the results.

Changes in manuscript:

- We will adopt a corrected approach to calculate the correction factors.
- We will rewrite Sec. 3.6 to reflect these changes.

Reviewer comment 19:

Figure 13: The use of grayscale for the rain rates and colors for the errors makes the plots very hard to read. Would it be possible to instead plot the satellite rain rates in color and plot the corresponding gauge values using the same color scheme? Similar values would have very little contrast whereas large errors would produce sharp contrasts.

Author response:

We agree with the reviewer that Fig. 13 contains too much information for a single plot. We will replace it in the revised manuscript with two plots showing accumulation maps and a scatter plot comparing the accumulations against the gauge measurements.

Changes in manuscript:

- We will revise Fig. 13 to only show an interpolated map of the gauge measurements and the accumulation maps obtained from the different retrievals.
- We will add a figure showing a scatter plots of the gauge-measured and retrieved precipitation accumulations.

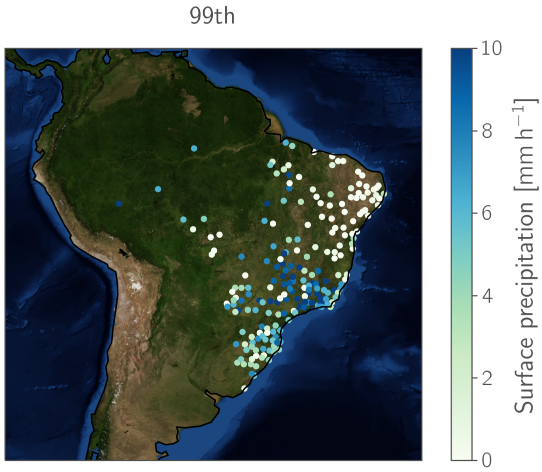

Figure 1.1: 99th percentile of hourly precipitation during December 2020. Points show the locations of the gauges used for the evaluation during December 2020. The coloring shows the 99th percentile of the distribution of hourly precipitation

Reviewer comment 20:

Line 432 and Fig. 15: Please define more precisely what the 99th percentile of the distribution means. If each point in Fig. 15 is the 99th percentile of all of the rainfall values for a particular gauge location during the month of Dec. 2020, why are there so many values $<$ 5 mm/h? Is it the dry season in some of these locations?

Author response:

Figure 15 does, in fact, show the 99th percentile of the rainfall values for each gauge location for December 2020. Although December is generally the beginning of the rain season in many parts of the country, the 99th percentile of the hourly precipitation remains below 5 mm for several stations.
As can be seen in Fig. 1.1, most of them are located in the semi-arid east of the country which makes these results plausible. In addition to this, the precipitation in December 2020 was below average in large parts of the country (Source in Portuguese: Grupo de Previsão de Tempo CPTEC/INPE, 2020).
Nonetheless, some of the stations in the western parts of the country exhibit very low values for the 99th percentile of the distribution of precipitation. This indicates that some of thos measurements may be faulty.

Changes in manuscript:

- We will reformulate the description of Fig. 15 to make it clear that the displayed quantity corresponds to the 99th percentile of the distribution of hourly precipitation accumulations for each gauge station.

Reviewer comment 21:

Lines 435-436: Are there any specific assertions in the published literature that HYDRO and PERSIANN-CCS were both developed to correctly represent heavy precipitation at the presumed expense of skill for lighter precipitation?

Author response:

We would like to thank the reviewer for commenting on this statement, whose formulation we consider problematic in hindsight. A more suitable statement would be that HYDRO and PERSIANN CCS were developed with a focus on convective precipitation at the expense of retrieval skill for stratiform scenarios. This is also acknowledged in the published literature.

Regarding HYDRO:

The HYDRO retrieval is based on the Hydroestimator, which is in-turn based on the Autoestimator. The study by Vicente et al. (1998) presents the original form of the Autoestimator. Regarding the data used to derive the regression curve that relates IR brightness temperatures and precipitation rates the manuscript states:

> The original set of observations, collected during the months of March to June 1995, was composed of 120 pairs of IR cloud-top temperatures and radar- derived rainfall estimates with 4 km by 4 km pixel resolution. Only convective rain systems were considered.

Although the algorithm includes corrections to adopt the relation to other meteorological regimes, the methodology exhibits a bias for convective precipitation, which is also acknowledged in the conclusions of the paper:

> Independent and qualitative studies not shown in this paper have demonstrated that in contrast to the reasonable performance of the technique for well-defined and short duration convective systems, poor results are common for stratiform cloud systems

Moreover, the study by Scofield and Kuligowski (2003) (titled 'Status and Outlook of Operational Satellite Precipitation Algorithms for Extreme-Precipitation Events') that introduces the Hydroestimator states:

> All of the estimates display relatively little bias for cold-top events, which is not surprising given that they were calibrated for such events and the assumptions behind satellite QPE algorithms generally work best for cold-top events.

Regarding PERSIANN CCS:

The available literature on the PERSIANN CCS algorithm indicates that the original cloud classes and T_B-precipitation curves are based on collocations from just a single summer month over the western CONUS (Hong et al., 2004):

> After completing the cloud-patch feature extraction, the system is calibrated using GOES infrared images and radar-rainfall maps for June 1999 over the region of 25 °N 45 °N and 100 °N130 °W (both datasets are mapped to 0.04° latitude × 0.04° longitude scale).

Although an a bias correction based on passive-microwave data has been added to the operational algorithm (Karbalaee et al., 2017), the underlying estimation method seems to have remained the same.
Moreover, Nguyen et al. (2018) states

> Recent developments include integrating deep learning approaches, adding water vapor channel information (Tao et al., 2017), using PMW data for bias adjustment of PERSIANN-CCS (Karbalaee et al., 2017), incorporating MODIS and CloudSat information (Nasrollahi et al., 2013), and using probability matching methods to improve warm rainfall detection in PERSIANN-CCS.

indicating that the precipitation from warm clouds remains an issue for the algorithm. In summary, both retrievals were developed with a focus on convective precipitation. A likely better explanation for the improved accuracy in estimating extreme precipitation is therefore that by restricting the analysis to the high percentiles of the precipitation distribution the contribution from convective precipitation events is increased, which leads to the observed improved performance from the two retrieval algorithms.

Changes in manuscript:

- We will reformulate the sentence to state that HYDRO and PERSIANN CCS were developed with a focus on convective precipitation and struggle with precipitation from colder clouds.

1.2 Technical Comments

Reviewer comment 1:

Line 39: For consistency, it might be better to cite Schmit et al. (2018) instead of Schmit et al. 2005) since the former is cited in lines 65 and 129.

Author response:

Since Schmit et al. (2005) is a peer-reviewed publication, we are under the impression that it is more suitable as reference for the GOES ABI. We will therefore replace the existing citation of Schmit et al. (2018) with Schmit et al (2005).

Changes in manuscript:

- We will replace the references to Schmit et al. (2018) with Schmit et al. (2005).

Reviewer comment 2:

Line 46, 55, 93, 574-577: Scofield and Kuligowski (2003a) and (2003b) are the same paper.

Author response:

We would like to thank the reviewer for pointing out this mistake, which we will of course correct in the revised version of the manuscript.

Changes in manuscript:

- We will remove the duplicated reference.

Reviewer comment 3:

Line 54: Please cite Nguyen et al. (2020) here in reference to PERSIANN-PDIR.

Author response:

We will add the citation in the revised version of the manuscript.

Changes in manuscript:

- We will add the citation in the revised version of the manuscript.

Reviewer comment 4:

Line 64: Is Hydronn an acronym (e.g., Hydro-Neural Network) or does the name have a different meaning?

Author response:

Hydronn is the name of the retrieval algorithm. It is named after the character Hydron from the He-man comic series. It also functions as a portmanteau of the words Hydro and NN (for neural network) but we prefer both spelling and pronounciation of Hydronn over HydroNN, which is also why we did not introduce it in this way in the manuscript.

Reviewer comment 5:

Line 80: Replace consists with consist (measurements is plural).

Author response:

We will correct this in the revised version of the manuscript.

Reviewer comment 6:

Lines 85, 86, 88: Northwest should not be capitalized unless it is a proper name.

Author response:

We will correct this in the revised version of the manuscript.

Reviewer comment 7:

Line 86 Many readers may not know that Amazonas is the proper name for a state in Brazil, so the Brazilian state of Amazonas would be clearer.

Author response:

We will correct this in the revised version of the manuscript.

Reviewer comment 8:

Line 88: Replace manifest with e.g., is associated with.

Author response:

We will correct this in the revised version of the manuscript.

Reviewer comment 9:

Line 118: Replace available first with available only.

Author response:

We will correct this in the revised version of the manuscript.

Reviewer comment 10:

Line 135: replace criterion with approach.

Author response:

We agree with the reviewer that 'criterion' is not a suitable expression here. However, we think that 'interpolation' is actually more specific than 'approach', so will will use 'interpolation' in the revised version of the manuscript.

Reviewer comment 11:

Lines 133, 386, and elsewhere: please ensure that all dates in this manuscript match the format used in EGUsphere.

Author response:

We would like to thank the reviwer for pointing out this issue. We will of course correct this in the revised version of the manuscript.

Reviewer comment 12:

Line 150: A better wording would be a long time series of geostationary sensors.

Author response:

We will change the formulation in the revised version of the manuscript.

Reviewer comment 13:

Line 350: Insert to before derive.

Author response:

We will correct this in the revised version of the manuscript.

Reviewer comment 14:

Line 354: Is retrieved meant rather than predicted?

Author response:

In the field of machine learning the term 'predict' is commonly used when a model is evaluated. We have therefore used the terms 'predict' and 'retrieve' interchangeably in the manuscript. We acknowledge that this may cause confusion for readers from meteorological backgrounds and will change the wording in the revised version of the manuscript.

Reviewer comment 15:

Line 354: Pixel should be plural.

Author response:

We will correct this in the revised version of the manuscript.

Reviewer comment 16:

Line 362: Is worse detection accuracy than at 5 mm/h meant here?

Author response:

Yes, this is what is meant here. We will reformulate the sentence to make this clear.

Reviewer comment 17:

Figure 12 caption: add at a rate of 5 mm/h to the end of the caption for clarity.

Author response:

We will adopt this change in the revised version of the manuscript.

Reviewer comment 18:

Line 387: Floodings should be singular or replaced with floods.

Author response:

We will correct this in the revised version of the manuscript.

Reviewer comment 19:

Lines 387, 404, 520: Is this citation and reference formatted correctly?

Author response:

According to the guidelines for referencing websites in AMT (`https://www.atmospheric-measurement-tec` `net/submission.html#references`), the reference should be formatted correctly except for the wording used for the last access date.

Changes in manuscript:

- We will change the wording for the last access date of the reference in question.

Reviewer comment 20:

Line 388: Replace were with was.

Author response:

We will correct this in the revised version of the manuscript.

Reviewer comment 21:

Line 394: Please indicate the location of Duque de Caxias in Fig. 13.

Author response:

The location of Xerém, which is the neighborhood in Duque de Caxias in which the rain gauge is located, is already indicated in Fig. 13. However, the manuscript does not clearly state the relation between Duque de Caxias and Xerém. We will reformulate the introduction of Sec. 4.3 to make it clear where the flooding occurred.

Reviewer comment 22:

Line 430: Replace by with of.

Author response:

We will correct this in the revised version of the manuscript.

Reviewer comment 23:

Line 431: Runoff is a single word.

Author response:

We will correct this in the revised version of the manuscript.

Reviewer comment 24:

Line 433: Station should be plural.

Author response:

We will correct this in the revised version of the manuscript.

Reviewer comment 25:

Line 434: Replace similar accuracy as with accuracy similar to.

Author response:

We will correct this in the revised version of the manuscript.

Reviewer comment 26:

Line 461: A more precise wording might be correct for variations in the distribution of precipitation rates in the training data relative to comparable ground validation data.

Author response:

We will adopt this suggestion in the revised version of the manuscript.

Reviewer comment 27:

Line 465: Replace stronger with more strongly.

Author response:

We will correct this in the revised version of the manuscript.

Reviewer comment 28:

Line 473: Replace small with low.

Author response:

We will correct this in the revised version of the manuscript.

Reviewer comment 29:

Line 475: Constant in time, space, or both?

Author response:

We will correct this in the revised version of the manuscript.

Reviewer comment 30:

Line 485: Please define GPM CO in line 69 so the acronym is already defined.

Author response:

We will reformulate this sentence to correct the use of acronyms in the manuscript.

Reviewer comment 31:

Lines 485-486: the latitude range of the GPM DPR is actually 65 °S to 65 °N when the instrument swath is accounted for.

Author response:

We will correct this in the revised version of the manuscript.

Reviewer comment 32:

Line 489: This is the first time that the CNN is described as a probabilistic regression approach; this concept should be introduced earlier in the manuscript.

Author response:

We will revise the manuscript to introduce the concept of probabilistic regression already in the introduction.

Reviewer comment 33:

Line 494: Delete the comma after resolutions.

Author response:

We will correct this in the revised version of the manuscript.

Reviewer comment 34:

Line 587: The Python Language Foundation should be considered as starting with P since The is ignored when alphabetizing entries.

Author response:

We will correct this in the revised version of the manuscript.

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