Atmos. Meas. Tech. Discuss.,
doi:10.5194/amt-2019-327-AC3, 2020

Atmospheric Measurement Techniques Discussions

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AMTD

Interactive comment

Interactive comment on "Low-level liquid cloud properties during ORACLES retrieved using airborne polarimetric measurements and a neural network algorithm" *by* Daniel J. Miller et al.

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Received and published: 11 February 2020

Author Response: AMT-2019-327

We would like to thank the reviewers for their thoughtful comments. In response to the reviewer's suggestions we will make several important clarifications in the paper text. In addition to this, we will update the paper to include links to the public dataset.

1. There are two aspects here that require response separately: First, the two retrieval approaches have different error sources and different information; and Second, that combining the two types of datasets is sensitive to error sources in each, making it

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Discussion paper

difficult to disentangle impacts.

a) Two Approaches: The reviewer is correct to note that the different retrievals come along with different sensitivities to different sources of error and uncertainty. In addition to this they are also sensitive to different effective sensing depths within the cloud, though this statement is largely dependent on that bands selected for the bispectral retrieval. For strongly absorbing bands 3.75, the differences in effective sensing depth are less severe. However, those statements being acknowledged, the work of Miller, et al. (2018), demonstrated that for the differences between the two retrievals (at high spatial resolution) tend to be minimal for unbroken clouds that are spatially homogeneous, optically thick, and have microphysically narrow cloud droplet size distributions. These statements also happen to be representative of the cloud regime marine boundary layer stratocumulus we observed throughout the ORACLES field campaign. In the paper we also discuss these different sources of conflict between the two retrievals and demonstrate in our analysis that they are still relatively similar to one another in figure 2.

b) Disentangling Impacts of biases: On this front, I think that our approach runs into difficulties as the reviewer has pointed out. It is certainly already difficult (though not impossible) to disentangle the sensitivities of machine learning approaches to the properties and sensitivity to error in input state vector. Some studies regarding the development of more understandable and physically traceable machine learning approaches have been more recently undertaken. McGovern, et al. 2019 is a good example of the kind of work being performed to address understandability of machine learning. However, this field has been growing extremely rapidly, and as a consequence it expanded a lot the paper well after the paper was already finished.

Despite being a possible source of difficulty, mixing the information content of the two radiometric techniques helps us to achieve the stated objectives of this work – namely to provide a quick a priori input to retrieval methods that already must mix radiometric and polarimetric information to address complicated remote sensing problems (i.e., simultaneous retrieval of aerosols above clouds). In ORACLES, smoke aerosols are commonly observed over clouds, and the intended objective of studying this dataset is to improve future simultaneous retrievals.

2. This is not something that we considered, but the proposed approach is certainly sensible. The reviewer is correct in noting that the most obvious difference between the corrected results and the uncorrected results is the linear offset of the effective radius retrieval. However, as we explored a lot of different sorts of network architectures we found that this one demonstrated the most significant improvement in the re RMSE from our previous study, Segal-Rozenhaimer, et al. 2018. In the previous study we were unable to get very sensible re retrievals and concluded that the approach probably wasn't very useful for re retrievals. In contrast to this conclusion, when we found in this work that there was only systematic high bias in the NN retrieval it was quite a positive revelation. Additionally, as we later indicate in the discussion section, it is possible to improve the neural network without this linear correction approach – but instead by applying atmospheric correction for gaseous absorption above the cloud prior to input to the neural network. We saw greater improvement in the initial output of the network after performing this correction, especially for ORACLES 2017 (and later 2018, not included in the paper), when the separation between cloud top and the airborne platform (NASA P3) was far more variable.

3. The weighting is strictly based on the RSP instrument uncertainty model and not on anything else. The impact of the forward model assumed geometry plane-parallel infinite slab (or rather 1-D radiative transfer), is not accounted for and is therefore treated as an assumption error. The reason this is the case is because there is not yet, to our knowledge, a generally accepted method for dealing with 3-D radiative effects in a single-pixel retrieval. Some techniques exist using iterative 3-D radiative transfer modeling, but require providing a whole cloud domain and performing all retrievals at the same time.

4. The explicit inclusion of above cloud aerosols in this research is part of our future

plans. However, because this was intended as a research algorithm to demonstrate our ability to perform and validate a new Neural Network cloud retrieval against existing algorithms – which also exhibit this source of error – tracking down this error source is outside the scope of this analysis. However, given that our comparison to the other RSP COT retrievals is rather good, it indicates that it is likely that the results of such a study would be very similar to those indicated in prior work by Meyer, et al. (2013). In that work, they showed that the bispectral retrieval of cloud optical thickness is biased low due to the presence of an absorbing above-cloud aerosol, but that there is minimal impact on the bispectral re retrieval. This indicates that the same impact would be present in the polarimetric cloud optical thickness retrieval.

To address this in the manuscript, we will revise the paper to more explicitly discuss the results of Meyer, et al. (2013) in the context of our work.

5. This was kind of puzzling, but we hypothesize that it is because the magnitude of the primary cloud bow is sensitive to both COT and ve when the COT is less than 3. Therefore this particular observation geometry has a non-linear dependence on two different retrieval variables. As a result of this joint dependency, the network manipulates the observed information in favor of reducing the uncertainty in either the COT or the ve and here it appears to favor the COT determination.

Some editorial changes: * As mentioned within the text of the manuscript, this study is intended as a required first-step toward the objective of a future machine learning approach for the simultaneous joint-retrieval of aerosol and cloud properties for ACA scenes. We wanted to demonstrate that we could use Machine Learning to address the cloud-only approach before we made the state space more complicated.

* Figure 6. Unit (microns) needed to be added to RMSE of effective radius in the legend. This figure will be modified before final publication to include units on the RMSE

*P. 15: ". . .after the RMSE in the ve(ff) evaluation after training is enough to span the possible state space an indication that this network cannot adequately retrieve ËĞ ve(ff)" This was correct as written, but we have clarified this sentence to make it more clear overall. We were attempting to say that because the RMSE of veff is larger than the range of the training set a retrieval of veff in this framework would have extremely low skill. Ideally the RMSE would be small relative to the range of the training grid, as is the case for effective radius and optical thickness.

"The results for tau and re are quite promising, but the results for ve are concerning. The RMSE for ve is larger than the range of training parameter space listed in Tables 1 and 2, an indication of both high uncertainty and very low precision. As a consequence, we do not consider this network capable of inferring adequate information about ve."

P. 28: "Please add reference to the statement - "This is unlike the other RSP retrievals, which typically make use of a limited wavelengths and either polarized or total reflectance observations."" References to both of the RSP retrieval papers have been added to the revised manuscript. These are Alexandrov et al. 2012a and Alexandrov et al. 2012b respectively (and have been cited throughout the paper). This also contains a typo and has been corrected to read:

"This is unlike the other RSP retrievals, which currently only make use of limited spectral information in each individual retrieval; both polarimetric retrievals use a single band (Alexandrov et al. 2012a, 2012b), and the bispectral retrieval uses a pair of bands."

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Interactive comment on Atmos. Meas. Tech. Discuss., doi:10.5194/amt-2019-327, 2019.