“Improving GOES Advanced Baseline Imager (ABI) Aerosol Optical Depth (AOD) Retrievals using an Empirical Bias Correction Algorithm”. Hai Zhang et al.

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Summary

Current operational retrievals of AOD from radiances measured by the ABI sensor on aboard of GOES 16 exhibit a diurnal bias (sun angle dependency) associated to the surface reflectance of the pixel under observation. This study introduces this problem and proposes an ad-hoc correction to the retrieved AOD. A correction is developed by collocating GOES AOD retrievals over selected Aeronet sites (mostly in the East of USA). Only days with low and constant (through the day) Aeronet AOD values are used to ensure that the GOES deviations are caused by the solar angle changes and not from aerosol loading variations. The differences are then assessed and a correction based on those differences (which in turn are a function of geometry and NDVI) is created. The correction is assumed to be valid through the full ABI swath and then applied to retrieved AODs. The corrected AODs are validated against Aeronet during a 6-month period. The correction successfully improves the satellite-Aeronet AOD comparison. While the improvement is clear and it may result in a more accurate operational product, this analysis does not address the actual problem the causes the bias (a non-adequate surface reflectance data base) and presents an ad-hoc correction. In addition, I find that this study has important methodological defects and I do not recommend the paper for publication in this form.

Overall there are two major concerns about this work.

First, this a very empirical approach where the root of the problem is not addressed, namely the angular dependence of the surface reflectance as a function of sun angle. Although the authors do acknowledge that this is the real issue and they are working on it, they are content to use an ad-hoc approach by forcing the retrieved AOD to match the ground truth AOD. While this may be a reasonable practical correction, it does not show any new scientific approach (alternatively the authors do not highlight what is novel in doing this) and it does not attempt a correction on the actual measurement (observed radiances) based on physical principles (such as a modeled BRF) and using radiative transfer. With this regard, the work does not offer anything new.

This is an approach in addition to the traditional approach based on physical principles. The uncertainty in BRF model is transferred to AOD. Improving AOD is the same as improving BRF. The approach in this paper solves the problem in AOD space instead of BRF space, which is different from traditional approach. The traditional approach uses AERONET matchup dataset to generate surface reflectance relationships and then assume these relationships can also be applied to surfaces at other places where AERONET stations are not present. Even at the AERONET sites, the surface reflectance relationships have large uncertainty. The bias correction algorithm proposed here can reduce those uncertainties. More importantly, it does not rely on AERONET surface and therefore can be applied anywhere else without assuming everywhere else is the same as AERONET.

The empirical bias corrections to retrieved AODs is not new. The NASA MODIS Dark Target AOD algorithm corrects AOD using a bias correction algorithm over urban areas using post processing of AODs for areas where urban land percentage is greater than 20% (Gupta et al., 2016). There are other MODIS AOD correction algorithms as well developed by users for their own applications (e.g., Lary et al., 2009). In fact, compared to these bias correction algorithms, our approach is better because it is internally consistent and does not rely on any external dataset. Moreover, the bias correction preserves the original AOD data file, and it is “self-correcting”, meaning if the physical AOD algorithm improves the bias correction will automatically adjust to the new values.

Second, the validation is carried out by comparing the corrected retrievals against observations from the same instrument used for creating the correcting term. This is not adequate and it puts an asterisk on the goodness of the correction. At least these new corrected AODs need to be validated against an independent set of observations.

The comparison is between the correction before correction and after correction to show the improvement. The 30-day AOD used is assumed to contain information of the bias. For most of the days of validation, except the first 30 days, we use the 30-day period data before the day to get the AOD bias, which is independent from the data being corrected. The following figure shows the scatter plots of the validation using the data with the first 30 day removed, and therefore the bias corrected ABI AOD data are totally independent from the data used for obtaining the AOD bias. The conclusions remain the same as in the paper.

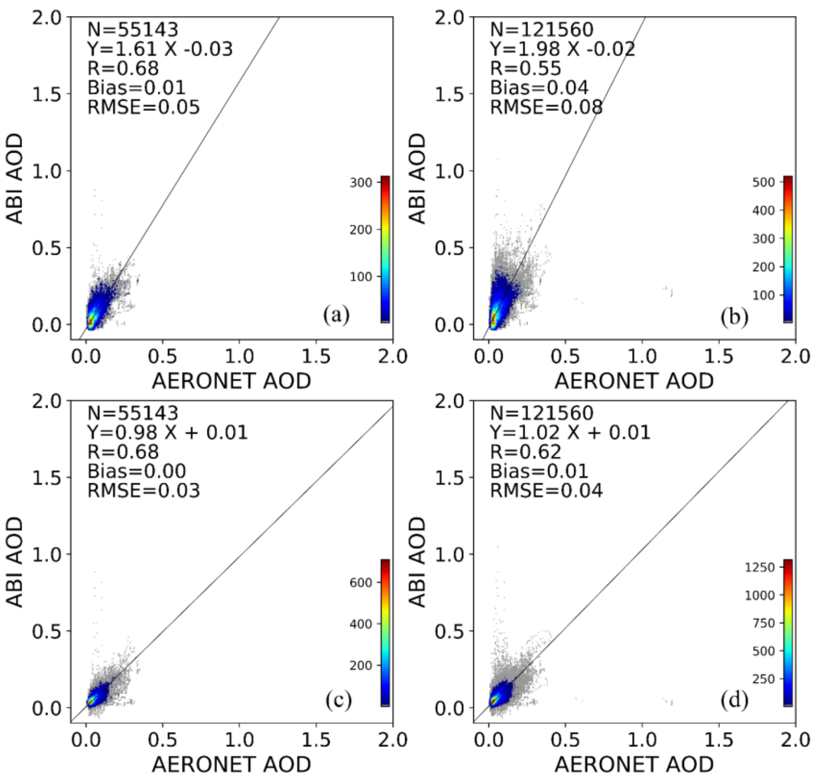

Figure A. Scatter plots of GOES-16 ABI AOD vs AERONET AOD for September 5, 2018 to December 31, 2018 across the CONUS domain: (a) high quality ABI AOD before bias correction, (b) top 2 qualities ABI AOD before bias correction, (c) high quality ABI AOD after bias correction, and (d) top 2 qualities ABI AOD after bias correction. In the plots, N is the number of matchups, R is the correlation coefficient, and RMSE is the root mean square error.

Also, note that in comparing figures 4c and 4d, there is a clear improvement in high AODs (~>0.5) whereas for lower AODs values, the scattering increases in figure 4d.

Figure 4c and 4d are both after correction AOD. One is high quality and the other is high and medium quality. Figure 4d has more data points than 4c and they don't have one-to-one correspondence. Therefore, they should not be compared for improvement of bias correction. The correct comparison is between Figure 4a and Figure 4c, and between Figure 4b and Figure 4d. (Figure 4 changes to Figure 5 in the revised paper).

This raises the question on whether the correction should be applied across the board to all aerosol loadings. This is relevant to AQ studies given that the vast majority of aerosol loadings are below AODs ~< 0.5, it is very desirable to have those levels of loading well characterized.

We plotted comparisons of AOD errors vs AERONET AOD for different AOD loadings in Figure 7 in the revised paper. The bias corrected AOD are shown to have reduced bias for all the AOD ranges for the top 2 (high and medium) qualities AOD. For high quality AOD, bias correction reduces bias in the highest two AOD bins, with center around 0.3 and 0.57. In the range [0.1, 0.3], bias correction over corrects and introduces negative mean bias with slightly larger magnitude than the original mean bias, around 0.01 in magnitude differences. In the range [0,0.1], AOD mean biases are close to zero both before and after correction, but the bias correction AOD error has smaller standard deviation.

It should be noted that this critique does not preclude or advise against the application this correction to the operational product. However, the material here presented does not have the depth required for a scientific report.

The algorithm is an effective tool to evaluate and correct the AOD bias from geostationary satellites. If you agree that the algorithm works, we should have it published so the other researchers can benefit from the improvements and use this data in their studies/applications. For example, apply it on AOD product from other geostationary satellite platform or other retrieval algorithm.

We hope the new results added to the revised paper also adds more depth to the material presented. We believe that even though an empirical "technique" for correcting biases in a specific product is presented, the approach and its evaluation presented do have merits in its application to other AOD products as well, and thus others could benefit from its publication.

References

Gupta, P., Levy, R. C., Mattoo, S., Remer, L. A., and Munchak, L. A.: A surface reflectance scheme for retrieving aerosol optical depth over urban surfaces in MODIS Dark Target retrieval algorithm, Atmos. Meas. Tech., 9, 3293–3308, https://doi.org/10.5194/amt-9-3293-2016, 2016.

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