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Atmospheric Measurement Techniques Discussions

Interactive comment on "A 12-Year Long Global Record of Optical Depth of Absorbing Aerosols above the Clouds Derived from OMI/OMACA Algorithm" *by* Hiren Jethva et al.

Hiren Jethva et al.

hiren.t.jethva@nasa.gov

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The authors are thanking the anonymous reviewer for offering constructive comments, which have helped us improve the content of our manuscript.

Following is the one-to-one response to each comment made by the reviewer.

RC: Referee Comment AR: Author's Response

RC: Introduction: a couple of important papers in the field of above-cloud aerosol studies are missing in the introduction. They should be cited to give the readers a more comprehensive and complete overview of the field. Devasthale and Thomas [2011] is

among the first to study the occurrence of above-cloud aerosols.

AR: We realized that we missed these citations in the earlier version of the paper. Relevant papers, as suggested by the referee, are now added/cited at appropriate places in the revised paper.

âĂć Zhang et al. (2016) cited for direct radiative effects of aerosols above cloud. âĂć Min and Zhang (2014) cited along with the statement listing several parameters affecting radiative effects. âĂć Devasthale and Thomas (2011) cited along with the statement "Such situations are commonly observed from satellites over several oceanic and continental regions.." âĂć Devasthale and Thomas (2011) and Zhang et al. (2016) cited and mentioned in section 5.1 describing the results on frequency occurrence of ACA. âĂć Lu et al. [2018] now cited along with Wilcox [2012].

RC: I think a brief overview of the existing above-cloud aerosol retrievals algorithms for the passive sensors will give the readers a "big picture" and understand the relative position of this study. In particular, as the authors are aware, the following algorithms have been developed for POLDER and MODIS

AR: A discussion on the existing state of the active and passive-sensor based ACA algorithms are now added to the Introduction (2nd paragraph).

RC: Aerosol type identification (section 2.2.2.1): This part is very important, Because the retrieval algorithm uses different optical properties for different type of aerosols, i.e., dust or smoke. A misclassification can cause retrieval errors and uncertainties. However, the description of this paper is very brief. Some more details need to be added with proper references. For example, it should be mentioned whether and how the identification scheme is validated or evaluated. Has it been compared with CALIOP aerosol subtypes? Why different threshold of CO is used for northern and southern hemispheres?

AR: The aerosol type identification scheme in the OMACA has been directly adopted from the cloud-free OMAERUV algorithm. The scheme uses real-time observation of AIRS CO information in conjunction with OMI UVAI to discern the carbonaceous smoke aerosols from mineral dust, which otherwise not possible to detect using only near-UV measurements. The use of CO measurements also enables the identification of high levels of boundary layer pollution undetectable by near-UV observations alone. Since Torres et al. [2013] adequately describes the methodology and implementation of the scheme within OMAERUV, we didn't include a lengthy discussion on this topic in the present manuscript.

The different threshold values of CO in Northern and Southern hemispheres correspond to the average of AIRS CO climatological annual minima over major biomass burning/boreal ïňĄre activity regions. These values are 2.2x1018 in the Northern Hemisphere (NH) and 1.8x1018 for the Southern Hemisphere (SH), based on Yurganov et al. [2008, 2010]. The presence of carbonaceous aerosols is assumed if AI $\geq$ AI threshold (0.8) and CO $\geq$ CO threshold (2.2x1018 for NH and 1.8x1018 for SH) or when CO values larger than 2.8x1018 (2.5x1018) are observed in the Northern (Southern) Hemisphere regardless of AI considerations. Conversely, OMI pixels with observed AI $\geq$ AI threshold (0.8) and CO <CO threshold are assigned with the dust aerosol type. Threshold values in AI and CO represent noise and background levels in the respective measurements not necessarily associated with the free troposphere CO burden which is expected to co-exist with the lofted carbonaceous aerosols.

The straightforward way of discerning the absorbing aerosol type works efficiently in most cases, however, may break down under certain situations, i.e., when dust aerosols are present over regions characterized by high CO levels associated with pollution episodes other than the biomass burning smoke for which the scheme would assign absorbing aerosol type as smoke. Note that the aerosol type identification scheme doesn't account for the mixture of aerosols for which either smoke or dust aerosol type is assigned depending upon the threshold values of AI and CO.

A detailed regional-level comparison between CALIOP aerosol sub-type and that of the

OMAERUV hasn't been done, but we consider conducting the said analysis in the near future. A brief description of the aerosol type identification scheme is now provided in the revised paper in section 2.2.2.1.

RC: Single scattering albedo (section 2.2.2.1): the SSA is extremely important for ACA retrieval and DRE. I hope the information of aerosol type and the corresponding SSA will be part of the OMIACA so the users can use it in a consistent way with the AOD product

AR: We fully agree with the referee that the assumption of aerosol SSA above the clouds is extremely crucial for deriving accurate ACAOD retrievals as well as in the quantification of DRE. Section 2.2.2.1 describes how we take advantage of clear-sky SSA retrievals from the OMAERUV product and assign a representative SSA value for each region at a daily scale. In this regard, the OMACA stands alone among passive-sensor based ACA algorithms that currently rely on a fixed value of SSA [Jethva et al., 2013; Myer et al., 2015].

Looking at its importance, the values of aerosol SSA above-cloud assumed in the OMACA algorithm for the three wavelengths, i.e., 354, 388, and 500 nm, are already reported in the product. The corresponding SDSs are named as "InputSSA354", "InputSSA388", "InputSSA500". Additionally, the aerosol type associated with each valid ACA pixel is also stored in the product as "AerosolType". Refer to the complete list of SDS stored in each OMACA HDF-EOS file in Appendix I.

RC: Look-up-tables (section 2.2.24): How is cloud effective radius considered in the LUT? Is it assumed as a constant? Note that the assumption of CER could have impacts on the COD retrieval. Some discussion is needed to clarify this.

AR: In LUT calculations, clouds are assumed to be liquid in phase and follow the standard C1 size distribution [Deirmendjian, 1969]. The effective radius of C1 water cloud droplet distribution is assumed to be a constant value of 6.0 microns. To answer the reviewer's concern, we carried out a sensitivity analysis, similar to the ones presented in Table 3, 4, and 5, in which the errors in both ACAOD and aerosol-corrected COD were calculated following the perturbation approach around the assumed CRE value of 12.0 μm. The table attached to this response lists the errors in aerosol-corrected COD due to the range of uncertainty in the assumed cloud CRE. The analysis was performed assuming reference cloud CRE of 12 μm and for the ACAOD values of 0.5 and 1.0 (388 nm).

The errors in COD retrievals due to the uncertainty in CRE follow asymmetric behavior to the perturbation around the assumed state. While a large underestimation in CRE of -8 μm produces negative errors of $\sim$10%-11% in the retrieved COD, an overestimation in CRE of +8 to +12 μm yields positive errors of much smaller magnitudes ($\sim$1%-2%). The spatial distribution of MODIS monthly cloud CRE over the Southeastern Atlantic Ocean, as shown in Figure 11 of Meyer et al. (2015), exhibits spatial variations with smaller droplets (CRE 7-11 μm) concentrated closer to the coast and relatively larger size droplets (11-17 μm) retrieved away from the coast. Given the fixed value of CRE equals 6.0 μm assumed in the OMACA cloud LUTs, the observed variations from MODIS would produce <2% error in the retrieved aerosol-corrected COD.

The corresponding errors in ACAOD due to the uncertainty in cloud CRE are found to be marginal. For an ACAOD>0.5, an uncertain assumption in cloud CRE by $\pm$8 μm results in ACAOD errors <2% with much smaller magnitudes at higher aerosol loading. This is because at larger ACAODs the aerosol absorption effects dominate over that resulting from varying effective radius of liquid droplets leaving other major algorithmic assumptions, i.e., SSA, ALH, and AAE to determine the resultant uncertainty in ACAOD retrievals.

This analysis implies that near-UV wavelengths don't offer a strong sensitivity to the variations in cloud droplet size rather the cloud signal is predominantly driven by the optical thickness. Due to the lack of information on cloud droplet size from OMI, we adopted the standard C1 cloud model validated and used in numerous studies for all cloud LUT calculations.

The description provided above is now added to the section 3 of the revised paper.

RC: Partly cloudy pixels: the footprint size of OMI is 13x24 km (338km2). At this scale, there cloud be a lot of partly cloudy pixels. One of my main questions/concerns is about the treatment of the partly cloudy OMI pixels. It seems to me the OMIACA algorithm is applied to both overcast pixels and partly cloudy pixels, correct? How is the subpixel cloud fraction determined? How are the partly cloudy pixels treated in the LUT and radiative transfer simulations? How is the UVAI of clear-sky part of the partly cloudy pixel different from that of the cloudy part, and what is the meaning of the "observed" UVAI for the partly cloudy pixel? I would strongly recommend the authors to add a separate and dedicated sub-section to discuss the treatment of partly cloudy pixels in the OMIACA algorithm.

AR: OMACA algorithm performs retrievals for each pixel of size 13 x 24 km-square at nadir independently. As the referee has correctly pointed out, there is a possibility of encountering partly cloudy pixels, especially for measurements with lower reflectivity (388 nm) values. The algorithm quality flags reported in OMACA product precisely reflect these observed conditions (Table # 1 QFlag values 0, 1, and 2). Due to the coarser resolution of OMI pixels, there seem to be is no direct way to infer the sub-pixel cloud variability using only OMI measurements. Therefore, we have used the OMI-MODIS joint cloud product, OMMYDCLD, post-retrievals for all analyses reported in the manuscript. The OMMYDCLD product, as already explained in the original manuscript in section 2.2.3, provides the statistics of the MODIS 1-km cloud product (MYD06) on each collocated OMI footprint.

An analysis using the OMMYCLD product over the Southeastern Atlantic Ocean for the period of Jun-July-Aug 2007 revealed a well-constrained non-linear relationship between the MODIS-derived COD times the geometric cloud fraction and LER388. A threshold of LER388 of 0.25 adopted for the best quality retrievals (QFlag=0) compares to the COD times geometric cloud fraction of 3-4. Conversely, given the geometric cloud fraction of unity, the minimum COD retrieved by OMACA would be in the range 3-

4. Retrievals assigned with QFlag=1 further extends the LER388 to 0.20 allowing pixels with relatively lower reflectivity with much stronger absorption (larger UVAI) above the clouds [Jethva et al., 2013, Figure 6, Aug 12, 2006 case study].

Currently, the OMACA algorithm is designed to perform inversion over fully overcast pixels. The LUTs are generated assuming fully cloudy conditions and do not explicitly treat partly cloud pixels. To avoid a large fraction of partly cloudy pixels, therefore, we adopted the geometric cloud fraction thresholds calculated using OMMYDCLD product of 0.5 and 0.75 for the FOACA (Figure 5, 6, 7) and AOD/COD analyses (Figure 8, 9, 10, 11).

We will consider using the OMMYDCLD product in the OMACA processing in the next upgrade of the algorithm. We believe that most of the explanation provided here on this concern is already described in the original version of the paper in section 2.2.3 and 2.2.4.

RC: Sub-pixel COD variation: A related question is whether and how the algorithm accounts for the subpixel COD variation. What is the physical meaning of the "retrieved COD"? Is it a simple mathematical mean or some kind of weighted mean?

AR: As explained in the previous response, each OMACA retrieval corresponds to the respective pixel size derived using a single set of reflectivity and UVAI values. The retrieved values of ACAOD and COD, therefore, represent an overall condition observed in each pixel. It is hard to draw a conclusion that the observed condition is merely a mathematical mean or weighted mean of the sub-pixel cloud variability as the TOA reflectance versus COD relationship exhibits a non-linear behavior especially at higher values of CODs.

RC: Spatial distribution of ACA: As mentioned above Zhang et al. (2016) studied the global distribution of different types of ACA. Actually, Figure 5 agrees reasonably well with the Figure 2 of Zhang et al. (2016). In addition, Zhang et al. (2016) also found significant amount of ACA over the north pacific due to the Asian dust and pollution.

This study should be cited here anda discussed.

AR: We referred to Zhang et al. [2016] paper which also shows similar cloudy-sky FOACA results over the global ocean derived using 8-year daytime CALIOP observations. Prior to Zhang et al. [2016] and our study, Devasthale and Thomas (2011) also conducted FOACA analysis using 4-years of CALIOP data. Both studies are now mentioned and cited in the revised manuscript.

RC: Figure 5 shows some ACA over the Southern Ocean in January and February. Is this true or some retrieval artifact?

AR: Most likely ACA over the Southern Ocean during the winter months inferred from our analysis is an artifact resulting from non-aerosol related enhancement in UVAI observed at certain geometry conditions that are associated with higher solar zenith and viewing zenith angles. Although these artifacts are largely removed from the best quality retrieval group (see Table 1 of the original manuscript) based on thresholds in geometry and are assigned a different quality flag (=3), some residual ACA pixels still reside within the group of good quality retrievals. One of the possible reasons for the non-aerosol related enhancement in the UVAI could be the presence of ice clouds over the Southern Ocean for which the effect of angular scattering is unaccounted for in the calculation of UVAI.

RC: It is interesting to see that the FOACA in Figure 5 and the ACA AOD in Figure 8 are highly correlated. Is this a coincidence or there may be some real connection between them? One could argue that the region with high FOACA does not necessarily have a larger ACA AOD. Do you agree? AR: It is assumed here that the reviewer is referring to the high-level of spatial consistency in FOACA and ACAOD maps. This is because of the OMACA algorithm's efficiency to quantitatively retrieve ACAOD and COD when the presence of absorbing aerosols over clouds is identified based on a set of LER and UVAI thresholds. We agree with the reviewer that high-frequency occurrence and large ACAOD do not necessarily correlate with each other. FOACA is simply a measure of the temporal occurrence of the aerosol-cloud overlap, whereas ACAOD is a quantitative measure of actual aerosol loading above the clouds.

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Theoretical error (%) in aerosol-corrected COD (388 nm) due to the uncertainty in the assumption of cloud effective radius

Error in cloud effective radius (μm)	*Assumed AOD (388 nm) = 0.5/1.0* *Reference cloud effective radius = 12.0 μm* **% Error in Aerosol-corrected COD (388 nm)**			
	COD=5	**COD=10**	**COD=20**	**COD=30**
-8.0	-11.31/-11.9	-10.28/-10.88	-9.13/-9.83	-10.11/-10.76
-6.0	-5.94/-6.54	-5.38/-5.94	-4.68/-5.29	-5.01/-5.62
-4.0	-2.85/-3.26	-2.57/-2.94	-2.18/-2.57	-2.25/-2.66
4.0	1.17/1.4	1.43/1.79	1.21/1.62	0.95/1.39
6.0	1.34/1.70	1.63/2.07	1.37/1.87	1.05/1.59
8.0	1.51/1.94	1.83/2.35	1.52/2.11	1.16/1.78
12.0	1.85/2.41	2.22/2.92	1.83/2.59	1.36/2.18

Fig. 1.