We thank you for taking the time to review the manuscript and for your helpful comments. We have revised the manuscript in response to your comments. We believe that the manuscript has been greatly improved thanks to your suggestions.

This is a very interesting paper utilizing state of the art satellite data from active and passive remote sensing sensors together with models in order to characterize aerosol optical properties globally, by clustering to aerosol types and relevant aerosol properties.
The novelty and the strength of the paper is the use of the less uncertain inputs from both satellite sensors and combine it in a model run, globally.

Introduction

I miss the state of the art on aerosol global climatologies based on Kinne et al and other AEROCOM related publications.Also, Amiridis et al., for calipso.　In addition, publications discussing dust only ODs based on MODIS-CALIPSO-MERRA2 synergies have been presented by Gkikas et al..

We added the following description of aerosol data sets in Sect. 1.
"Based on the recent sophisticated numerical models with aerosol modules, and space- and ground-based observations, the data sets of aerosol composition climatology have been developed. The Modern-Era Retrospective analysis for Research and Applications version 2 (MERRA-2; Gelaro et al., 2019), and the Copernicus Atmosphere Monitoring Service Reanalysis (CAMSRA; Innes et al., 2019), and the Japanese Reanalysis for Aerosol v1.0 (JRAero; Yumimoto et al., 2017) are the reanalysis data sets by data assimilation schemes. The Max-Planck-Aerosol Climatology version 2 (MACv2; Kinne et al., 2019) is a climatology data set created by merging the data of the Aerosol Robotics Network (AERONET; Holben et al., 1998) and MAN (Smirnov et al., 2009) ground-based sun-photometer networks onto the ensemble mean of AeroCom models (Kinne et al., 2006). These data sets provide the global distributions of major aerosols, such as, sulfate, organic carbon, BC, dust, and sea-salt. The ModIs Dust AeroSol (MIDAS; Gkikas et al., 2021) data set is the global map of dust at fine resolution ($0.1^{o} \times 0.1^{o}$), and is created by the aerosol optical depth derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) and the dust fraction of the MERRA-2 reanalysis. Amiridis et al. (2015) develop LIVA (Lidar climatology of Vertical Aerosol Structure for space-based lidar simulation studies), which is a three-dimensional multi-wavelength global aerosol and cloud optical data set. This data set is based on the Cloud-Aerosol Lidar with Orthogonal Polarization (CALIOP) on board the Cloud Aerosol Lidar Infrared Pathfinder Satellite Observations (CALIPSO) satellite (Winker et al., 2010), and the ground-based networks of European Aerosol Research Lidar Network (EARLINET; Bösenberg et al., 2003; Pappalardo et al., 2014) and AERONET."

In addition, the distinction of the aerosol types with mixing possibilities in the atmospheric is a basic assumption of the paper and it have to be accompanied by studies elaborating on different approaches of aerosol typing definition efforts.

In Sect. 1, we described the assumption of aerosol compositions in the remote sensing as follows: "In the previous remote sensing methods of aerosol compositions, there are two approaches in assuming aerosol components. One is the CALIOP-type categorization, such as, clean marine, polluted continental, and smoke, etc. These types are based on the aerosol characteristics observed in the typical scenes. The other is the similar categorization to the numerical models, i.e., sulfate, organic carbon, BC, DS, and SS. We adopted the latter approach because the external mixing of these components is applicable to various scenes, and the τ_a and extinction coefficient (α_a) of each component are suited for the comparison with the numerical models and the data assimilation. In this study, aerosols are assumed to consist of four components with different sizes, light-absorbing features, particle mixtures, and shapes. We defined these components as WS, light-absorbing particles (LA), DS, and SS. WS is defined by an external mixture of sulfate, and organic carbon, etc., because both the sulfate and organic carbon are fine and less light-absorbing particles, and it is difficult to estimate sulfate and organic carbon separately from the MODIS and CALIOP measurements. LA is defined by an internal mixture of WS and BC. The details of the assumed aerosols are described in the Sect. 3. In this study, the global three-dimensional distributions of these components were estimated from the CALIOP-MODIS retrieval."

Schematic of the retrieval.

Looking at the figure 1 scheme. I was wondering how the optimized x step is achieved, only for part of the aerosol properties or satellite based observations used for the matching at the convergence stage. Or some more clarity needed on the paragraph lines 135 to 144.

We found some mistakes in Fig. 1 and corrected them. The logarithmic transformation is applied to x and y and the objective function is minimized by the iteration in ln(x) space. Therefore, Equation 1 is modified. The convergence criterion is described in the revised manuscript.

Section 3.1.3 It is necessary to introduce a number of assumptions here, so the authors to my opinion have done a good work. A discussion on overall uncertainties of the method would be nice for the reader. Realistically these retrievals and assumptions work much better in different parts of the world and worse in others based on the aerosol field complexity. Could the authors comment on such aspects ?
For example standard deviations in figure 6 I presume, is a mix of "easier" retrievals spatially and more difficult ones that cause these standard deviations. Final effect will be lonked with more uncertain retrievals in some areas and less in others.

It is difficult to comment on that, but the comparison with the aerosol data set of Kinne (2019) provided information on the points. In Sect. 5.1 of the revised manuscript, we compared the global distribution of

SSA with the global map of SSA in Kinne (2019) in the revised manuscript. The comparisons of SSA showed good agreements of SSA in the central and southern parts of South America, and the southern part of Africa. These are famous biomass-burning regions. We think the assumptions regarding to LA would work better in these regions. However, the SSA was underestimated in the most parts of the land area.
We are now conducting the intensive validation study using the ground-based networks of AERONET, SKYNET (sun/sky photometer), and AD-Net (lidar) data. The validation study will show that our assumptions work better in different parts of the world and worse in others.

Figure 8. MODIS standard AOD have been used in various studies and has been extensively validated with AERONET data. (Moreover, MODIS itself use AERONET to retrieve (some kind of) uncertainty estimation over land and ocean). What is the novelty here with the use of Callipso in AOD only ? Is lower than MODIS standard global AOD more realistic ? And what improvements and errors are dealt here with the combined MODIS-Callipso retreival ?

The merged AOD of the dark target and deep blue algorithm in the MODIS collection 6.1 is slightly greater than the AERONET AOD (Shi et al., 2019). The AOD of the CALIOP has a negative bias (Kim et al., 2018). Our retrieved AOD exists between the CALIOP and MODIS standard products, and is better than the CALIPSO products. However, the bias of the CALIPSO and MODSI standard products is different by regions. We need further comparisons in the regional scale. We added these discussions in Sect. 5.1.

Figure 9 shows a very limited spatial varability of both parameters. First of all should be nice to increase the size and improve the quality of this figure as details can be already there but not visible.

The color bars of Figure 9 have been corrected to emphasize the spatial variations.

In general it would be nice to comment on difference the authors find compared with the Kinne aerosol climatologies. Discussion could be combined with figure 13 results.

In Sect. 5.1, we added the comparisons of SSA, AF, and compositions with the global maps of MACv2 (Kinne, 2019). The global distributions of SSA and AF matched well to MACv2, but the SSA over the most parts of the land area is smaller than that of MACv2. The underestimation of SSA is also seen in the comparisons with the AERONET (Fig. 13).

Figure 10 is the paper highlight and it needs technical improvements in order to be able to see spatial details and changes of the AODs.

The color bars of Figure 10 have been modified to emphasize the spatial variations.

Figure 14 is a very nice demonstration of aerosol shape effects.

Thank you very much.

I would see fig 14 to 18 in a supplement. But it is up to the authors to decide.

Figures 17 to 19 are important in this study, so only Figures 14 to 16 were moved to the supplement.

Fig. 19 should be discussed much more as properties like SSA are ery uncertain based on the figures 9 and 13.

In the revised manuscript, we discussed the overestimation of LA and its impact on the heating rate.

Major comment

How this method improve compared with other existing ones and what are the advantages that lead to it?

CALIOP provides the global 3-D distribution of aerosols, but the AOD is underestimated due to the low signal to noise ratio in the tenuous layers (Omar et al., 2013; Kim et al., 2018). The AOD of the MODIS has small positive bias (Shi et al., 2019). The synergistic retrieval using both CALIOP and MODIS observations provides the AOD close to the MODIS products, and the better global 3-D distribution of aerosols. In addition, our assumed aerosol components of WS, LA, DS, and SS are similar to the components defined in the numerical models with aerosol modules. The AOD and extinction coefficients of each component would be useful for the comparison with the numerical models, and the data assimilation. We added these descriptions in Sect. 1 and 6.