The thermal infrared optical depth of mineral dust retrieved from integrated CALIOP and IIR observations

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Abstract

Recent studies reveal that a higher fraction of coarse mineral dust particles than that estimated by climate model simulations has been observed in the atmosphere, leading to a more significant positive (i.e., warming) longwave (LW) thermal infrared (TIR) direct radiative effect (DRE). However, the magnitude of this DRE remains highly uncertain because our understanding of the radiative properties, quantitatively represented by the optical depth of dust, especially information on the TIR, remains limited. This study presents a simple approach to retrieve the thermal infrared dust aerosol optical depth (DAODTIR) over oceans during nighttime using the observations from the Infrared Imaging Radiometer (IIR) and the Cloud-Aerosol Lidar with Orthogonal Polarization (CALIOP) onboard CALIPSO. For each cloud-free dust-laden profile identified by the IIR-CALIOP observation, a Lookup-Table (LUT) of the 10.6 μm IIR band brightness temperatures difference (dBT) under different DAODTIR with respect to their dust-free BTs is constructed based on the CALIOP retrieved dust vertical profile and pre-assumed dust scattering properties using a fast radiative transfer model. Then the DAODTIR is retrieved by projecting the IIR-observed dBT on the LUT. Sensitivity studies show that the DAODTIR retrieval at 10.6 μm is more susceptible to the dust particle size distribution (PSD) assumption than dust refractive indices. To estimate the uncertainty caused by PSD assumption, two DAODTIR retrieval products, one based on the dust PSD from the AERONET at Cape Verde and the other on an in situ measured PSD from the recent Fennec campaign, are provided. The retrieval uncertainty is mainly contributed by the BT difference between the observation and simulation using auxiliary atmospheric data. The climatology of the retrieval from 2013 to 2019 shows confident spatiotemporal variations of DAODTIR with the global-averaged value of 0.006 and 0.008 based on different pre-assumed dust PSDs. Climatological results agree reasonably well with two independent DAODTIR retrieval products based on the Infrared Atmospheric Sounding Interferometer (IASI) over the active dust transport regions, such as North and Tropical Atlantic ($r = 0.904$ and $0.819$) and Indian Ocean ($r = 0.832$). The seasonal and interannual variation is also well-compared ($r = 0.758$) with AERONET coarse-mode AOD at 97 selected sites. The synergic CALIOP observation allows the retrieved DAODTIR to directly compare with the extrapolated DAODTIR from DAOD in visible (i.e., 532 nm), which helps evaluate the observational constraints on DAODTIR. This study offers a unique prospect of collocating active lidar and passive IR observations for retrieving dust DAODTIR.
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Abstract

Recent studies reveal that a higher fraction of coarse mineral dust particles than that estimated by climate model simulations has been observed in the atmosphere, leading to a more significant positive (i.e., warming) longwave (LW) thermal infrared (TIR) direct radiative effect (DRE). However, the magnitude of this DRE remains highly uncertain because our understanding of the radiative properties, quantitatively represented by the optical depth of dust, especially information on the TIR, remains limited. This study presents a simple approach to retrieve the thermal infrared dust aerosol optical depth ($\text{DAOD}_{\text{TIR}}$) over oceans during nighttime using the observations from the Infrared Imaging Radiometer (IIR) and the Cloud-Aerosol Lidar with Orthogonal Polarization (CALIOP) onboard CALIPSO. For each cloud-free dust-laden profile identified by the IIR-CALIOP observation, a Lookup-Table (LUT) of the 10.6 $\mu$m IIR band brightness temperatures difference ($\text{dBT}$) under different $\text{DAOD}_{\text{TIR}}$ with respect to their dust-free BTs is constructed based on the CALIOP retrieved dust vertical profile and pre-assumed dust scattering properties using a fast radiative transfer model. Then the $\text{DAOD}_{\text{TIR}}$ is retrieved by projecting the IIR-observed dBTT on the LUT. Sensitivity studies show that the $\text{DAOD}_{\text{TIR}}$ retrieval at 10.6 $\mu$m is more susceptible to the dust particle size distribution (PSD) assumption than dust refractive indices. To estimate the uncertainty caused by PSD assumption, two $\text{DAOD}_{\text{TIR}}$ retrieval products, one based on the dust PSD from the AERONET at Cape Verde and the other on an in situ measured PSD from the recent Fennec campaign, are provided. The retrieval uncertainty is mainly contributed by the BT difference between the observation and simulation using auxiliary atmospheric data. The climatology of the retrieval from 2013 to 2019 shows confident spatiotemporal variations of $\text{DAOD}_{\text{TIR}}$ with the global-averaged value of 0.006 and 0.008 based on different pre-assumed dust PSDs. Climatological results agree reasonably well with two independent $\text{DAOD}_{\text{TIR}}$ retrieval
products based on the Infrared Atmospheric Sounding Interferometer (IASI) over the active dust transport regions, such as North and Tropical Atlantic (r = 0.904 and 0.819) and Indian Ocean (r = 0.832). The seasonal and interannual variation is also well-compared (r = 0.758) with AERONET coarse-mode AOD at 97 selected sites. The synergic CALIOP observation allows the retrieved DAOD\textsubscript{TIR} to directly compare with the extrapolated DAOD\textsubscript{TIR} from DAOD in visible (i.e., 532 nm), which helps evaluate the observational constraints on DAOD\textsubscript{TIR}. This study offers a unique prospect of collocating active lidar and passive IR observations for retrieving dust DAOD\textsubscript{TIR}.

**Keywords:** Aerosol, Dust, Thermal infrared, IIR, CALIOP
1. Introduction

Mineral dust (hereafter referred to as dust for short) is a major component of atmospheric aerosols, originating mainly from arid and semi-arid deserts, dry lake beds, and areas with extreme soil moisture deficits and reduced vegetation cover (Choobari et al. 2014). Once aloft, dust aerosols may be carried by winds for long-range transport of an intercontinental scale, such as the trans-Atlantic transport of North African dust (Chiapello and Moulin 2002; Di Biagio et al. 2021), transport of dust plumes from the Arabian Peninsula over the Arabian Sea and the Indian Ocean in summer, and trans-pacific transport of Asia dust in spring (Goudie and Middleton 2006). Meanwhile, they can influence the Earth-Atmosphere system's radiative energy budget and thermodynamic structure through aerosol-radiation interactions (ARI). Over dark ocean, the scattering effect of dust dominates its interactions with shortwave solar radiation (referred to as "SW"), leading to a negative (i.e., cooling) SW direct radiative effect (DRE_{SW}) at the top of atmosphere (TOA). Different from most other aerosol types that are small in size (below 1 μm), dust, whose particle size distribution (PSD) is in surface, volume and mass usually dominated by the coarse mode (diameter > 1 μm), also has significant radiative effects in the longwave (referred to as “LW”), where the absorption effect is dominant, resulting in a positive (i.e., warming) LW DRE (DRE_{LW}) (Torres et al. 1998; Yu et al. 2006). The net radiative effect of dust, as the sum of DRE_{SW} and DRE_{LW}, has significant impacts on the planetary energy balance (Tegen et al. 1996; Yu et al. 2006; Song et al. 2018), as well as regional weather and climate variability (Tegen and Lacis 1996; Evan et al. 2006). Despite this qualitative understanding, quantitative estimates of dust DRE remain highly uncertain. Several recent studies argued that most global climate models (GCMs) tend to underestimate the fraction of coarse dust particle as a larger amount of them have been observed (Adebiyi and Kok 2020; Kok et al. 2017; Ryder et al. 2013b). As a result, GCMs,
in turn, overestimate dust DRE$_{SW}$ and underestimate DRE$_{LW}$ (Kok et al., 2017; Di Biagio et al., 2020). In addition to the DRE, dust can also alter various micro- and macro-physical properties of clouds and their evolution and lifetime through aerosol-cloud interactions (ACI). Moreover, dust storms and plumes can degrade air quality and generate adverse impacts on human health (Griffin, 2007; Querol et al., 2019).

To better quantify the aforementioned influences of dust on radiation, cloud and air quality, we need continuous observations of dust spatial and vertical distribution and key optical and microphysical properties, broadly represented by the aerosol optical depth (AOD) of dust (DAOD). Presently, satellite-based remote sensing is the only way to obtain such observations on a global scale. Over the last few decades, numerous techniques have been developed to retrieve aerosol properties, in particular the AOD, from satellite observations, such as the Moderate Resolution Imaging Spectroradiometer (MODIS), the multi-angle imaging spectroradiometer (MISR), the Visible Infrared Imaging Radiometer Suite (VIIRS), the Cloud-Aerosol Lidar with Orthogonal Polarization (CALIOP) and the Cloud-Aerosol Transport System (CATS), etc. Most of these techniques operate in the visible (referred to as "VIS") to near-infrared spectral region because most aerosols, such as smoke and sulfate, only have significant radiative effects in the VIS (Satheesh and Moorthy 2005). However, as mentioned above, with a large amount of coarse particles, dust also interacts with radiation in the thermal infrared (referred to as “TIR” for brevity) spectral region, allowing the retrieval of DAOD based on TIR observations (Sokolik et al. 1998).

Satellite-based retrievals of the DAOD in TIR (i.e., DAOD$_{TIR}$), are essential and highly useful for many purposes. First, the VIS retrieval requires solar illumination and is therefore only available during the daytime. In contrast, the TIR retrieval does not have such limitations, available at both daytime and nighttime. Second, as shown in Capelle et al. (2014), merely extrapolating the
retrieved AOD in VIS to TIR without any observational constraint can lead to substantial error and uncertainty. Therefore, with a better satellite-based dust TIR retrieval, the dust extinction spectrum from VIS to TIR can be improved by connecting the retrieval from both spectra (Klüser et al. 2012). Third, the DRE\textsubscript{LW} of dust is more sensitive to the coarse mode of the dust and, therefore, more directly connected to the DAOD\textsubscript{TIR} rather than the DAOD\textsubscript{VIS} (Capelle et al. 2014; Peyridieu et al. 2010). For example, Song et al. (2018) showed that two dust models, one with a larger size and less absorptive VIS refractive index, and the other with a smaller size and more absorptive VIS refractive index, can have almost identical DRE\textsubscript{SW} provided the same retrieved DAOD\textsubscript{VIS}. However, the two have pretty different DRE\textsubscript{LW} because of the difference in DAOD\textsubscript{TIR} extrapolated based on the assumed dust models, attesting to the need for observation-based retrievals of DAOD\textsubscript{TIR}.

Although satellite based TIR observations are abundant, quantitative retrievals of the TIR dust optical properties are still limited compared to the VIS products due to two major challenges. First, the radiative signal of dust in the TIR is generally weaker due to the relatively small DAOD\textsubscript{TIR} compared with, for example, clouds. As a result, the noise from atmospheric absorptions in TIR can lead to significant DAOD\textsubscript{TIR} retrieval uncertainties. The second challenge is that a reliable TIR-based retrieval of DAOD requires precise a knowledge of the dust layer’s vertical location and corresponding temperature profile. For these reasons, most of the current DAOD\textsubscript{TIR} retrievals are based on observations from hyperspectral sounders, such as the Infrared Atmospheric Sounding Interferometer (IASI) and the Atmospheric Infra-Red Sounder (AIRS) (Klüser et al. 2012; Peyridieu et al. 2010; Pierangelo et al. 2004). The high spectral resolution of these instruments allows a careful channel selection in atmospheric window bands to achieve a better signal-to-noise ratio for the retrieval. The observed spectra also provide enough information
content to retrieve both DAOD_{TIR} and dust layer's vertical location. For instance, Pierangelo et al. (2004) demonstrated that DAOD at 10 μm and dust mean altitude could be retrieved by matching the BT difference between the computed and the observed BT in 8 selected channels. Later, Klüser et al. (2011) modified this method to utilize observed dust TIR spectra from IASI operating since 2007 by using the Singular Vector Decomposition (SVD) method to retrieve both DAOD_{TIR} and dust altitude. The 10+ years of IASI-based near-global retrievals of DAOD_{TIR} have proved to be an instrumental dataset for studying dust transport and radiative effects and evaluating dust simulations in climate models (Capelle et al. 2018). Beyond the DAOD_{TIR}, Cuesta et al. (2015) developed a new method to retrieve dust vertical profile for major dust outbreaks. Despite these successes, hyperspectral-based dust retrievals also face several challenges and limitations. First, hyperspectral sounders usually have a coarser spatial resolution (e.g., IASI ~ 12 km) than TIR imagers (e.g., IIR ~ 1 km resolution). At this scale, a large fraction of their observations could be contaminated by sub-pixel clouds and thereby overestimated the dust extinction signal (Kaplan 2013; Martins et al. 2002; Xia et al. 2004). Secondly, the retrieval of dust altitude is usually less accurate than what can be achieved by active sensors such as CALIOP and CATS. The inaccurate dust vertical height would, in turn, affect the accuracy of DAOD_{TIR} retrieval. Moreover, the development of a hyperspectral retrieval algorithm that usually involves numerous bands can be rather challenging.

This paper explores an alternative method to retrieve nighttime DAOD_{TIR} over oceans (as explained in section 2.2) based on the integrated observations from CALIOP and the Infrared Imaging Radiometer (IIR) onboard the CALIPSO mission. As an active lidar, CALIOP provides accurate information on the vertical location of dust and cloud masking. The IIR provides observations in three TIR bands, from which the DAOD_{TIR} can be retrieved. In comparison with
the hyperspectral-based methods, our algorithm is unique and has several advantages. First of all, the high sensitivity of CALIOP to clouds and the small spatial resolution of IIR (i.e., 1 km) enables a better cloud masking to avoid potential contamination by sub-pixel clouds. Second, as explained later, the unique depolarization observation of CALIOP provides a way to detect a dust layer and specify its vertical profile. With this advantage, the DAOD$_{TIR}$ can be retrieved from a single IIR band using a relatively simple algorithm, although a few a priori assumptions of dust properties, such as dust particle size, shape and complex refractive index, are needed. In the rest of this paper, we introduce the integrated IIR/CALIOP observation and the radiative transfer model in section 2. The implementation of the DAOD$_{TIR}$ retrieval algorithm is explained in section 3. Section 4 shows the spatiotemporal patterns of the retrieval results and the comparison with IASI retrievals and ground-based AERONET measurement, followed by the summaries and conclusions for the remarks in section 5.
2. Data and model

2.1 CALIOP and IIR observations

The CALIOP level-2 retrieval algorithm detects aerosol layers and records their top and bottom heights and layer integrated properties using a "feature finder" algorithm and cloud-aerosol discrimination (CAD) algorithm (Kim et al. 2018; Liu et al. 2019; Liu et al. 2009). The extinction of an identified aerosol layer is then derived from the attenuated backscatter profile using a priori extinction-to-backscatter ratios (i.e., lidar ratios) based on aerosol sub-types (Young et al. 2018; Young et al. 2013). The aerosol sub-type is determined based on the estimated particulate depolarization ratio (DPR), the color ratio, the layer attenuated backscatter, and the detected aerosol layers height (Kim et al. 2018). Note that the CALIOP operational aerosol product does not provide the specific dust extinction profile when dust is mixed with other types of aerosols (e.g., polluted dust and dusty marine). To alleviate this issue, instead of using the aerosol sub-type information, we mainly use the DPR along with the CAD score from the level-2 aerosol profile product ("CAL_LID_L2_05kmAPro") to estimate the portion of the attenuated backscatter profiles contributed by dust aerosols, and then to obtain the dust aerosol extinction profiles and column DAOD (see section 3.1 for detail). The derived dust aerosol extinction profiles further serve as the dust aerosol vertical distribution for the DAOD$_{TIR}$ retrieval.

The IIR provides measurements of the upwelling radiances in three TIR channels centered around 8.65, 10.6, and 12.05 µm with a medium spectral resolution of 0.9, 0.6, and 1.0 µm, respectively. The instantaneous field of view of IIR is 64 km x 64 km with a pixel size of 1 km by 1 km centered on the CALIOP ground track. The instrument is regularly calibrated using images from cold (about 4 K) deep-space views and a warm blackbody source of 25 °C. The calibrated radiances reported in the IIR Level 1b product are further represented by equivalent brightness
temperatures (BTs) computed using Planck's law and the relevant instrument spectral response functions (SRF) (see Figure 5 (black dash lines)) in the Level 2 product. Recent updates of the calibration corrected the residual systematic bias in the northern hemisphere. A detailed introduction of the IIR instrument and its calibration process is shown in Garnier et al. (2018). The noise equivalent differential temperature and calibration accuracy was assessed by the Centre National d’Etudes Spatiales (CNES) (Garnier et al. 2012). The instrument exhibits an intrinsic 1-sigma noise equivalent to 0.2~0.3 K for a scene temperature of 210 K that improves to 0.1~0.15 K at 250 K and above (see Table 1 in Garnier et al., 2012). In this study, the cloud-free dust-laden cases are rarely lower than 250K. Taking the calibration short term instability (0.1 K) into account, we estimated random measurement uncertainties for each 1-km IIR pixel with ± 0.15 K, ± 0.2 K and ± 0.17 K in the three IIR channels, respectively.

Table 1 lists all variables with the specific values from the Version 4 Level-2 CALIOP aerosol profile product and the Version 4 Level-2 IIR along-track product ("CAL_IIR_L2_Track") used in this study. Beyond the BT measurements, the CAL_IIR_L2_Track product also provides a background reference flag (defined as “Was_Cleared_Flag_1km”) to report the number of clouds seen by the 1-km IIR pixel that CALIOP also detected at single-shot resolution (i.e., 333 m) but that were cleared from the CALIOP 5-km layer products to improve the detection of aerosols at coarser spatial resolutions (Vaughan et al. 2005). It helps identify confident cloud-free aerosol profiles for the derivation of the vertical distribution of dust extinction. The level-2 CALIOP aerosol products have a 5-km along-track spatial resolution, while the level-2 IIR products are in 1-km resolution. To match these two datasets, we match the 5-km CALIOP segments to five successive 1-km IIR footprints.
Table 1 Variables of level-2 CALIOP and IIR products that are used in this study

<table>
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<th>Products</th>
<th>Variable</th>
<th>Value is used</th>
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</thead>
<tbody>
<tr>
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<td>Type_of_scene</td>
<td>Cloud-free clean sky (10)</td>
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<tr>
<td>CAL_IIR_L2_Track</td>
<td>Was_Cleared_Flag_1km</td>
<td>No single-shot cloud (0)</td>
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<tr>
<td></td>
<td>TGeotype</td>
<td>Open Water (1700)</td>
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<td></td>
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<tr>
<td></td>
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</tr>
<tr>
<td></td>
<td>(0.971, 0.984, 0.982)</td>
<td>at 8.65, 10.6, 12.05 μm</td>
</tr>
<tr>
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<td>IIR_Data_Quality_Flag</td>
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<td>Atmospheric_Volume_Description</td>
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</table>

2.2 The radiative transfer models and reanalysis data

The backbone of our DAOD\textsubscript{TIR} retrieval algorithm is the FAS\textsubscript{T} radiative transfer code with the Discrete Ordinate Method (FASDOM) developed by Dubuisson et al. (2005). This radiative transfer model (RTM) uses the correlated \( k \)-distribution method tailored to the IIR SRFs to calculate the atmospheric gas absorptions. With a full account for multiple scattering, the radiative transfer equation is solved by the coupled discrete ordinate radiative transfer code (DISORT) developed by Stamnes et al. (1988). The FASDOM code inputs include atmospheric profiles (temperature, water vapor and ozone), surface temperature, surface emissivity, aerosol layer location in atmospheric profiles, aerosol layer optical depth (OD) and spectral radiative properties.
(i.e., single-scattering albedo and asymmetry factor). The FASDOM code has been thoroughly evaluated by comparing the combined line-by-line and DISORT radiative transfer code. Simulations have shown that the accuracy is generally better than 0.3K (Dubuisson et al. 2005; Dubuisson et al. 2008).

Implementing the radiative transfer simulation for global satellite observations requires a reliable dataset of atmospheric states with relatively high spatial and temporal resolution. In this study, we use the instantaneous assimilated atmospheric profiles and surface temperature from Version 2 Modern-Era Retrospective analysis for Research and Applications (MERRA-2) as RTMs’ input. The atmospheric profiles from MERRA-2 “inst3_3d_asm_Nv” product have a gridded horizontal resolution of 0.5° latitude × 0.625° longitude and 72 pressure levels from the surface to 0.01 hPa with a 3-hour time step. The surface temperature from “inst1_2d_asm_Nx” product shares the exact horizontal resolution with a 1-hour time step. Detailed introduction is provided in Gelaro et al. (2017).

As explained later in section 3.3, the retrieval of DAOD\textsubscript{TIR} relies on the difference of brightness temperature (BT) at TOA between the cloud-free clean atmosphere (referred to as “BT\textsubscript{clean}”) and the cloud-free dusty atmosphere (referred as to “BT\textsubscript{dust}”). Thus, an accurate estimate of BT\textsubscript{clean} is a prerequisite for the accurate retrieval of DAOD\textsubscript{TIR}. In this regard, the algorithms based on hyperspectral observations have an obvious advantage, i.e., they can select channels in atmospheric window bands to reduce the impacts of atmospheric profile uncertainties. In contrast, the much broader spectral response of IIR bands makes them more susceptible to atmospheric profile uncertainties. To understand the magnitude and impacts of this uncertainty, we performed a careful radiative closure benchmark study. First, we used the "cloud-free clean" scene type in the "CAL_IIR_L2_Track" product to select those cloud-free and low-aerosol-loading profiles. Ideally,
without the impact of cloud or aerosol, the simulated $BT_{\text{clean}}$ based on MERRA-2 atmospheric profiles and FASDOM should agree with the observed $BT_{\text{clean}}$. Of course, they could differ significantly in reality because of various uncertainties, including instrument noise, uncertainty in MERRA-2 profile, and/or radiative transfer error. Therefore, the difference between simulated and observed $BT_{\text{clean}}$ provides us a reasonable estimate of the impacts of these critical uncertainty sources on our dBT LUT. The results from this radiative closure study are shown in Figure 1.

The radiative closure over land has a large discrepancy (up to $\pm 10 \text{ K}$) because of the high-varied surface emissivity and skin temperature around the TIR window spectrum over bright deserts (Zhou et al. 2013). Thus, in this study, we only consider retrieval over the ocean and mask the land regions. In addition, to focus on the simulation performance over the dust-concentrated region, the derived 2-year annual CALIOP DAOD at 532 nm (referred to as “DAOD$_{532\text{nm}}$”; the derivation process is explained in section 3.2) from 2007 to 2008 is used to define the area with noticeable dust loadings for the radiative closure testing. As shown in Figure 1a, the area with DAOD larger than 0.03 is defined as the dust-concentrated region over oceans.
Figure 1 The global distribution of the annual mean CALIOP DAOD (a), the BT\textsubscript{clean} difference of all-day dBT\textsubscript{clean} (IIR-FASDOM) at 8.65 μm (b), 10.60 μm (c) and 12.05 μm (d) over oceans from 2007 to 2008. The black contour line represents the annual mean CALIOP DAOD of 0.03 from 2007 to 2008.

Figures 1b, 1c and 1d show the BT\textsubscript{clean} difference between IIR and FASDOM (referred to as “dBT\textsubscript{clean}”) is within ±2.0 K at all three IIR bands. Out of the dust-concentrated region, the dBT\textsubscript{clean} has a positive bias, especially in the Southern Ocean. Although the cause of this bias is not fully understood, it could be a combination of several other factors, including biases in MERRA-2 data and/or issues in radiative transfer models. However, the radiative closure results over the dust-concentrated region are highly encouraging, i.e., with the annual mean difference primarily within ±0.1 K, indicating a good agreement between simulated and observed BT\textsubscript{clean}. Figure 2 provides a more quantitative perspective by separating the daytime and the nighttime cases over the dust-concentrated region. As shown in Figure 2b, the probability distribution function (PDF) of dBT\textsubscript{clean} over the dust-concentrated region for all three IIR bands follows a Gaussian-shape distribution for nighttime cases with the peak centered around zero (biases smaller than 0.05 K). However, the daytime cases in Figure 2a have a 0.25 K positive bias and ~0.15 K larger standard deviations. Similar bias in daytime is found and discussed in previous studies for both IIR and MODIS (Garnier et al. 2021; Garnier et al. 2017). The possible reason of the slight but systematic bias in daytime cases remains unclear if it is due to the IIR-CALIOP’s cloud-free clean masking or other reasons. Accordingly, we only use nighttime observations for the DAOD\textsubscript{TIR} retrieval in this study. Note that the random error of IIR measurement with 0.2 K is already included throughout the radiative closure benchmark. Therefore, the uncertainty from both observations and forward simulations can be represented by one standard deviation of the BT\textsubscript{clean} difference at each IIR channel.
Figure 2 The probability distribution function (PDF) of daytime (a) and nighttime (b) dB T (IIR-FASDOM) of BT\textsubscript{clean} at 8.65 μm, 10.6 μm and 12.05 μm over oceans from 2007 to 2008 for the dust-concentrated region as indicated in Figure 1.

3. Description of Retrieval Algorithm

3.1 The use of 10.6 μm channel for DAOD\textsubscript{TIR} retrieval over ocean

Although IIR has three bands with similar observational uncertainties as analyzed above, we choose to use only the 10.6 μm channel for the DAOD\textsubscript{TIR} retrieval over oceans during nighttime based on the following considerations. First of all, as will be shown later in Figure 5 (section 3.3), as well as in the atmospheric transmission spectrum (Dubuisson et al. 2005), the 10.6 μm channel contains a more extensive dust extinction and with higher atmospheric transmission than the other two channels, which means a better signal-to-noise ratio for the DAOD\textsubscript{TIR} retrieval. Secondly, as previous studies usually report the DAOD\textsubscript{TIR} retrieval results at around 10 μm (Capelle et al. 2014; Peyridieu et al. 2010), the choice of 10.6 μm channel will help us compare the result with these previous estimates. Finally, although the three IIR channels provide independent observations, they share similar BT differences due to the change of DAOD at their spectral range (see Figure
leading to insufficient information content regarding the spectral BT difference among the three IIR channels. Note that we can use a single channel to retrieve the DAOD$_{\text{TIR}}$ because CALIOP specifies the vertical distribution of dust. In contrast, hyperspectral IR observations need information at different wavelengths to simultaneously retrieve DAOD$_{\text{TIR}}$ and mean dust altitude as the dust layer height has the same order-of-magnitude of information content as DAOD$_{\text{TIR}}$ (Klüser et al. 2015; Pierangelo et al. 2004).

If on one hand the use of a single channel makes the DAOD$_{\text{TIR}}$ retrieval algorithm relatively straightforward, on the other it requires making more careful assumptions on dust properties, such as their size, shape and complex refractive index. Although this is a common practice in aerosol remote sensing due to the lack of information, the pre-assumed properties inevitably fall short of the variability of actual dust and therefore may lead to retrieval uncertainties. We test the sensitivity of the pre-assumed dust particle size and complex refractive index in our retrieval and analyze their contribution to retrieval uncertainties in sections 3.5 and 3.6. In future research, we will also explore the possibility of retrieving other dust properties in addition to DAOD$_{\text{TIR}}$ using more IIR channels and/or other IR observations from, for example, MODIS and AIRS.

### 3.2 Cloud masking and dust detection

An essential prerequisite for a successful DAOD$_{\text{TIR}}$ retrieval is reliable identification of cloud-free and dust-laden profiles and pre-knowledge of the vertical distribution of dust within the profile. This step of cloud masking and dust detection can be challenging for passive sensors with relatively coarse spatial resolution (e.g., AIRS and IASI). But the unique capabilities of CALIOP, together with the supplementary information from IIR, make this step relatively straightforward, as explained below.
We use the 5-km “CAL_LID_L2_05kmAPro” product from CALIOP and the 1-km “CAL_IIR_L2_Track” product from IIR. As aforementioned, the 5-km CALIOP segments are first collocated with the 1-km IIR pixels such that each CALIOP profile contains five IIR pixels.

Cloud screening is done in two steps using the two collocated products. In the first step, we use the vertical features mask ("Atmospheric_Volume_Description") from the "CAL_LID_L2_05kmAPro" product to filter out any 5-km profiles that contain cloud layers or stratospheric aerosol. It should be noted that even after the first step screening, ~59% of the remaining CALIOP 5-km segments are still partly cloudy (i.e., containing sub-pixel clouds, see Table 2). It results from the “hiding” single-shot cloud in the 5-km CALIOP segments. Therefore, in the second step of cloud masking, we use the “Was_Cleared_Flag_1km” to find the cloud-free 1-km IIR pixels within those partly cloudy 5-km CALIOP pixels and assign them pre-quality assurance (pre_QA) flags with discerptions in Table 2. Note that post-quality assurance (post_QA) flags are also assigned for the retrieval result, explained in section 3.6.

After cloud masking, the next step is to identify dust and specify its vertical profile. As the first step of dust detection, we use the extinction control flag (“Extinction_QC_Flag_532”) in the CALIOP product to select only reliable retrievals (i.e., Extinction_QC_Flag_532 =0, 1, 16 or 18 (Winker et al. 2013; Yu et al. 2015)). Then, we further select from the remaining profiles those with the cloud-aerosol discrimination (CAD) score between -100 and -90 to ensure the profile is confidently aerosol (Liu et al. 2009; Yu et al. 2010).

Table 2 The pre- and post-quality control flags assigned in the retrieval process.
<table>
<thead>
<tr>
<th>QA flag</th>
<th>Value</th>
<th>Description</th>
<th>Number of Samples in 2013</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
<td>All 1-km pixels in a 5-km profile are cloud-free aerosol</td>
<td>767040 (40.62%)</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>Part of 1-km pixels in a 5-km profile are cloud-free aerosol</td>
<td>828445 (43.87%)</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>None of 1-km pixels in a 5-km profile are cloud-free aerosol</td>
<td>292788 (15.51%)</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>retrieved DAOD / CALIOP DAOD &lt; 2.0</td>
<td>1796767 (95.16%)</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>retrieved DAOD / CALIOP DAOD &gt;= 2.0</td>
<td>59013 (3.12%)</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>A 5-km profile with dBT (BT_{dust} – BT_{clean}) &gt; 0</td>
<td>32493 (1.72%)</td>
</tr>
</tbody>
</table>

As mentioned in section 2.1, the extinction profile classified as dust, polluted dust and dusty marine from the V4 CALIOP operational product contains the dust mixture with other non-dust aerosols, such as air pollution and marine aerosols. Because of their small size, these aerosols have very little extinction in the TIR region, even though they have a notable contribution to the visible extinction.

For our DAOD{TIR} retrieval, we need to know the vertical profile of only dust aerosols. For this purpose, we apply a widely used technique to first derive a vertically resolved fraction of dust backscatter (\(\beta_d\)) to total backscatter (\(\beta\)), i.e., \(f_d(z) = \beta_d(z)/\beta(z)\) from the following equation:

\[
f_d(z) = \frac{(\delta(z)-\delta_{nd})(1+\delta_d)}{(1+\delta(z))(\delta_d-\delta_{nd})}
\]  

(1)

where \(\delta_d\) and \(\delta_{nd}\) are the pre-assumed particulate DPR of dust and non-dust aerosols. Following Yu et al. (2015), the lower and upper limits of \(\delta_{nd}\) are set to 0.02 and 0.07 and \(\delta_d\) to 0.20 and 0.30, respectively. The \(f_d\) upper bound is estimated based on the combination of \(\delta_d = 0.2\) and \(\delta_{nd} = 0.02\) and the lower bound based on \(\delta_d = 0.3\) and \(\delta_{nd} = 0.07\). The value of \(f_d\) is set to be 1 when \(f_d > 1\) and 0 when \(f_d < 0\). For simplicity, the final \(f_d\) is set to the mean value of the upper and lower bounds. Lastly, using the derived \(f_d\) and pre-assumed lidar ratio for pure dust, i.e., \(S_d = 44\)
sr at 532 nm, we convert the aerosol backscatter profile ($\beta(z)$) from the CALIOP aerosol profile product to dust extinction profile $\sigma_d(z) = S_d \cdot f_d(z) \cdot \beta(z)$), and further the DAOD$_{532\text{nm}}$ from the column $\sigma_d$. It is important to note that the $\sigma_d(z)$ is used for scaling the input layer OD with a given DAOD$_{\text{TIR}}$ in FASDOM to represent the vertical distribution of dust. In other words, the assumption of $S_d$ is irrelevant on the DAOD$_{\text{TIR}}$ retrieval but impacts the absolute value of DAOD$_{532\text{nm}}$. Moreover, we assume that the dust properties, e.g., size and refractive index, are the same within a dust layer. This assumption can lead to uncertainties as dust particles can become stratified during transport because of vertical sedimentation processes (Yang et al. 2012). We leave the investigation of this uncertainty to future research and assume it is a second-degree level compared to other sources, e.g., radiative transfer uncertain, dust size and dust refractive index.

The corresponding cloud-free 1-km IIR BTs are eventually averaged back to 5 km footprints. For example, if a partly cloudy 5-km CALIOP pixel has three cloud-free 1-km IIR pixels, then the input BTs for the DAOD$_{\text{TIR}}$ retrieval is based on the mean value of the three cloud-free IIR pixels. The retrieval results are, therefore, in 5 km spatial resolution along the CALIOP track.

3.3 A priori assumption of dust optical properties

The single band (i.e., 10.6 $\mu$m) DAOD$_{\text{TIR}}$ retrieval requires dust properties other than the dust altitude to be pre-assumed. This section introduces the dust particle size distribution (PSD), dust shapes, and dust complex refractive index (RI) that are used to derive the dust bulk scattering properties, including the extinction efficiency ($Q_{\text{ext}}$), single-scattering albedo (SSA) and asymmetry factor (g-factor).
As the retrieval is implemented over oceans only, it needs appropriate a priori dust PSDs obtained at dust-transport areas. Hence, we retrieve and report two sets of DAOD\textsubscript{TIR} retrievals based on two pre-assumed dust PSDs; as introduced further below, one is retrieved by AERONET measurements at Cape Verde (Dubovik et al. 2002), and the other is observed during the Fennec 2011 aircraft campaign (Ryder et al. 2013b). Song et al. (2018) used these two dust PSD to evaluate dust DRE over the tropical North Atlantic. Their result shows a remarkable difference of simulated DRE\textsubscript{LW} based on these two PSDs. Without the observational record in TIR, it is reasonable to have distinguished extrapolated DAOD\textsubscript{TIR} and, therefore, DRE\textsubscript{LW} based on the same DAOD\textsubscript{VIS} but different PSDs, especially in the coarse mode. Therefore, it is worth showing if similar impacts of dust particle size occur on the DAOD\textsubscript{TIR} retrieval.

The first PSD is based on AERONET climatology at Cape Verde (16°N,22°W) (referred to as "AERONET" PSD) averaged from 1993 to 2000 by Dubovik et al. (2002) to represent the transported dust PSD as it is from a dust-dominant site (Gama et al. 2015; Mahowald et al. 2014; Song et al. 2018). Note that the PSD retrieval artifact of AERONET measurements due to dust non-sphericity was corrected in our use of the AERONET PSD (Dubovik et al. 2002). Details of the AERONET PSD retrieval process can be found in Dubovik et al. (2000). The second set of dust PSD is taken from the Fennec field campaign during June 2011 over the eastern Atlantic Ocean, which is categorized as the airborne dust within the Saharan Air Layer (SAL) (referred to as “Fennec” PSD). This category is from the average of vertical profile observations excluding the marine boundary layer. It represents the airborne dust transported over the nearby eastern Atlantic Ocean with the remarkably disclosed larger particle sizes than measured previously in dust layers, as well as the AERONET PSD (see Figure 3). The errors due to sizing uncertainties have also explicitly been quantified (see Ryder et al. (2013a) for full details).
Figure 3 shows the size-normalized volume size distribution of AERONET PSD and Fennec PSD as the visual comparison. The coarse mode of AERONET PSD has the peak with diameter around 3 μm, while the diameter of the peak of Fennec PSD is larger than 10 μm. As the fine-mode PSD rarely (~10%) changes the dust extinction in TIR (Pierangelo et al. 2013), the difference of the coarse mode between the two PSDs mainly impacts the DAOD\textsubscript{TIR} retrieval.

For the dust RI, we use a state-of-art database developed by Di Biagio et al. (2017) (referred to as "Di-Biagio" database). It has laboratory-measured RIs for dust aerosols generated from natural soil samples collected in 19 arid and semi-arid sites from 8 regions globally, including northern Africa, the Sahel, eastern Africa and the Middle East, Eastern Asia, North and South America, southern Africa, and Australia. Compared with other older dust RI databases in the literature, e.g.,...
Volz (1973) and OPAC (Hess et al. 1998), the Di-Biagio database is more comprehensive and allows for the choice of regional dependent RI for DAOD\textsubscript{TIR} retrieval. As shown in Figure 4, in our algorithm, we divide the global ocean into seven regions and then assign one or more regional RI from the Di-Biagio database based on the dust transport model simulations (Griffin 2007; Querol et al. 2019). For each 5-km IIR pixel, we take the ensemble of RI for the region of influence and average the retrieved DAOD\textsubscript{TIR} corresponding to each assigned RI. Although this is a somewhat crude way, it still helps us capture the variability of dust RI to a certain extent. Moreover, as explained in section 3.4, the sensitivity of regional RIs to the radiative signal of dust at the IIR 10.6μm channel is relatively low.

![Dust Refractive Index (Di-Biagio Database) Regimes over Ocean](image)

Figure 4 The assigned eight ocean regimes corresponding to Di-Biagio RIs according to the dust transport simulation in Querol et al. (2019). The stars over land represent the location of the soil and sediment samples collected for the dust RIs. Each color of the stars represents the regime for which it applies.

For dust shape, studies on their impact on scattering properties have proved that spheroid assumption is a reasonable first-order approximation of the shape of non-spherical dust (Dubovik...
et al. 2006; Mishchenko et al. 1997). Consequently, we assumed a spheroid shape of dust particles with the size-independent aspect ratio distribution from Dubovik et al. (2006).

Dust bulk scattering properties (i.e., $Q_{\text{ext}}$, SSA and g-factor) for the different combinations of dust PSDs, RIs and shapes are calculated using the T-matrix code developed by Mishchenko (2000) as shown in Figure 5. We also calculate the $Q_{\text{ext,TIR}}/Q_{\text{ext,VIS}}$ (i.e., TIR/VIS) ratio as it is not only the key element to compare DAOD$_{\text{TIR}}$ retrievals with observations in VIS (e.g., CALIOP DAOD; see section 4.1) but also impacts the DRE$_{\text{LW}}$ calculation in climate models (Capelle et al. 2014; Kok et al. 2017). Because the variability of the real part of SW RIs in literature data is negligible at 550 nm (Ryder et al. 2019), we use one SW RI ($1.53-0.002i$ at 550 nm) from the OPAC database to calculate the $Q_{\text{ext,VIS}}$ with the given dust PSDs.

In the plots, red and blue color groups correspond to scattering properties based on AERONET and Fennec PSD, respectively. Each color group contains 19 lines corresponding to the 19 RI in the Di-Biagio database. By looking at the difference between two dust PSD groups using the Di-Biagio RIs, one can see, in Figure 5a, 5b and 5d, that the sensitivity of dust size to $Q_{\text{ext}}$, TIR/VIS ratio and g is more significant than that of dust RIs as the groups are completely separated, while the spectral variation of SSA in Figure 5c in two groups are more entangled. It is because the regional RIs mainly differ in the imaginary parts, while the real parts are almost identical at 10.6 µm (Di Biagio et al. 2017). However, the change of SSA with RI shows a limited impact on the radiative signal of dust, which is discussed in section 3.4. The grey and black bars in Figure 5 are the SRF (dash lines with right y-axis) integrated scattering properties centered at 3 IIR bands. The integrated SSA and g-factor of dust at 10.6 µm by IIR SRFs are finally used as the input of dust radiative properties in the FASDOM simulation for retrieving DAOD$_{\text{TIR}}$. 
Figure 5 The scattering properties (Qext (a), Qext ratio (b), SSA (c) and g (d)) calculated using the spheroid assumption by T-matrix. The blue lines and red dash-dot lines represent the result calculated by assuming the Fennec PSD and the AERONET PSD, respectively. Black and grey bars represent the convolved scattering properties using the IIR spectral response functions (SRF) (dash lines with right y-axis) at three bands, respectively (centered at 8.65, 10.6 and 12.05 μm).

3.4 The Retrieval framework

A flow chart of our DAOD$_{\text{TIR}}$ retrieval algorithm is given in Figure 6. With the IIR BT at 10.6 μm for the identified cloud-free dust profiles after the screening process introduced in section 3.2, the BT difference due to dust (referred to as “dBT”) is then obtained by subtracting the IIR observed BT$_{\text{dust}}$ with the FASDOM simulated BT$_{\text{clean}}$ using the collocated MERRA-2 assimilated atmospheric profiles (included temperature, water vapor and ozone profiles with height and
pressure profiles) and surface properties (included MERRA-2 surface temperature and surface emissivity from IIR Level-2 product). Afterward, with the a priori dust scattering properties calculated based on the assigned regional RIs, dust PSD and shape, and the CALIOP-derived dust vertical distribution, the look-up table (LUT) of dBT as a function of DAOD\textsubscript{TIR} is built simultaneously for each cloud-free dust profile. Finally, the corresponding DAOD\textsubscript{TIR} to the matched BT from LUT with the observational IIR BT can be retrieved. The following estimated absolute retrieval uncertainty and the post-filtering process are introduced in section 3.6.
As an illustrative example, we first applied the retrieval framework to a case in Figure 7. In Figure 7a, CALIOP observations reveal a dense dust layer from 3 km to 5 km above the ocean surface with some broken marine boundary layer clouds underneath it. Figure 7b shows the variation of IIR observed BT\textsubscript{dust} at 10.6 \, \mu m and the corresponding BT\textsubscript{clean} simulated by FASDOM. In this case, the 1-km IIR pixels can capture BT's rapid change due to the marine boundary layer cloud extinction. After applying the dust detection method presented in section 3.2, the identified cases maximally exclude the observed BT with cloud contaminations (blue dots on top of IIR BT in Figure 7b). Corresponding to the cloud-free dust cases, Figure 7c shows the comparison of dBT (IIR BT\textsubscript{dust} - FASDOM BT\textsubscript{clean}) with the derived CALIOP DAOD at 532 nm. Evidently, the IIR dBT has a negative correlation with the CALIOP DAOD for this scene, illustrating the sensitivity of IIR observation to the DAOD\textsubscript{TIR} retrieval at 10.6 \, \mu m. Because the case's location is in the North Atlantic affected by the Africa and Sahel regions in Figure 4, we use the dust RIs from Sahara and Sahel accordingly, in the calculation. Afterward, both Fennec PSD and AERONET PSD are used to obtain two sets of dust bulk scattering properties for the retrieval. Utilizing the dBT signal, Figure 7d shows the retrieved DAOD at 10.6 \, \mu m (referred to as “DAOD\textsubscript{10.6\mu m}”) for the dust with AERONET PSD (red dot line) and Fennec PSD (blue dot line). We found that the same dBT signal yields larger retrieved DAOD when using Fennec PSD's larger particle size than AERONET PSD. The explanation on this requires further understanding about the impact of bulk scattering properties regarding different dust PSD on the dBT signal, which is discussed in the next section.
Figure 7 a) The CALIOP total attenuated backscatter at 532 nm on July 18th, 2008, in Tropical North Atlantic (the orbit at upper left). b) The IIR BT$_{dust}$ at 10.6 μm (orange lines) and the FASDOM BT$_{clean}$ at 10.6 μm (red dash lines), respectively. c) The dBT (IIR-FASDOM) (green dots) and the CALIOP DAOD (red dots) of cloud-free dust-laden profiles corresponding to the left and right y-axis, respectively. d) The retrieved DAOD$_{10.6 \mu m}$ using Fennec PSD (blue lines) and AERONET PSD (red lines).

3.5 Sensitivity of the retrieval to assumed dust particle size and dust refractive indices
In FASDOM simulation, the variation of the input SSA and g-factor due to the change of dust PSD and RI yields different simulated $B_{\text{dust}}$, hence, different $d_{\text{BT}}$ LUT. In the retrieval framework, with the same observed $d_{\text{BT}}$, the change of LUT leads to different retrieved DAODs corresponding to the change of dust PSD and RI. Therefore, investigating how dust PSD and RI impact the $d_{\text{BT}}$ simulation by changing the dust scattering properties (see Figures 5c and 5d) helps understand the DAOD$_{\text{TIR}}$ retrieval uncertainty caused by the pre-assumed dust properties. The $d_{\text{BT}}$ simulation also depends on the atmospheric states, the surface properties, and the dust vertical distribution. To evaluate that, we study the sensitivity of $d_{\text{BT}}$ at IIR 10.6 $\mu$m channel for two selected cases. One is collected over the sub-tropical Atlantic Ocean (Figure 8b), the other is observed at the coastal region near the Sahara Desert (Figure 8e). Table 3 lists the parameters of the two cases in the sensitivity studies.

<table>
<thead>
<tr>
<th>Time</th>
<th>Geolocation</th>
<th>Surface temperature</th>
<th>Surface emissivity at 10.6 $\mu$m</th>
<th>Integrated water vapor path</th>
<th>Simulated $B_{\text{clean}}$</th>
<th>Input DAOD$_{\text{TIR}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>2008-07-18</td>
<td>7.5N, 28.75W</td>
<td>301.462 K</td>
<td>0.984</td>
<td>5.510 g/cm$^2$</td>
<td>295.612 K</td>
<td>0.2</td>
</tr>
<tr>
<td>03:30:04 UTC</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2006-07-01</td>
<td>16.5N, 20.625W</td>
<td>296.672 K</td>
<td>0.984</td>
<td>2.722 g/cm$^2$</td>
<td>294.853 K</td>
<td>0.2</td>
</tr>
<tr>
<td>03:03:34 UTC</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In the first case, a long-term transport dust layer is observed between about 2.5 km and 6.25 km by CALIOP (Figure 8c), with a layer mean temperature around 270 K compared to the warm surface temperature at 301 K (Figure 8b). In the sensitivity test, we keep the DAOD$_{\text{TIR}}$ settled at
0.2 at the 10.6 µm and then use FASDOM to simulate the $BT_{\text{dust}}$ and the corresponding $dBT$ (i.e., $BT_{\text{dust}}$ minus $BT_{\text{clean}}$) with different combination of SSA from 0 and 1.0 and g-factor from 0 to 1.0. The $dBT$ result is shown as the color contour in Figure 8a. When SSA approaches zero, the scattering effect of dust diminishes, which explains the independence of $dBT$ on the g-factor, and in this case, the dust layer can be regarded as a purely absorbing gas layer. Because the dust layer is much colder than the surface, its absorption effect dominates, leading to a negative $dBT$ around -2K. When SSA attains to unity and g-factor approaches zero (i.e., lower right corner of Figure 8a), the backward scattering effect dominates, and dust emission diminishes. This condition yields the most negative $dBT$. When both SSA and g-factor approaches to unity (i.e., upper right corner of Figure 8a), although the scattering effect of dust is strong, the scattered direction is forward, which means the emission from the surface can "pass" through the dust layer despite the strong scattering. In this condition, the dust layer appears to be "transparent", and as a result, the $dBT$ is zero.

After understanding how $dBT$ varies with hypothetical SSA and g-factor in this case, we over-plot the "real" SSA and g-factor computed based on a different combination of dust PSDs and RIs (i.e., color lines with dot marker). Each of the eight color lines corresponds to one of the eight RI in the Sahara and Sahel deserts (see Figure 4) in the Di-Biagio database. Each dot marker in a line corresponds to a lognormal dust PSD with an effective radius ($re$) from 0.4 µm to 7.7 µm with one standard deviation of 0.6 µm. Furthermore, we use the black stars to indicate the scattering properties based on the AERONET PSD and blue stars for the Fennec PSD. When dust size is small, both SSA and g-factor are close to zero. As dust size increases, the SSA first increases faster than the g-factor. But after passing about the size of AERONET PSD, the SSA remains almost invariant for a given RI while the g-factor keeps increasing. For a given dust size, the variation of
RI mainly affects the SSA and has little influence on the g-factor, which is consistent with the discussion in Figure 5. Combining the behavior of line plots and background color contour, one can see that the dBT simulation at 10.6 \( \mu \)m is more sensitive to dust PSD than RI. It also becomes clear that with the same DAOD\text{\tiny TIR} input, the BT\text{\tiny dust} simulated based on the Fennec PSD is warmer than that on the AERONET PSD due to the contrast in g-factor. In other words, when retrieving DAOD\text{\tiny TIR} from the same observed dBT, the retrieved DAOD\text{\tiny TIR} based on the Fennec PSD is larger than that based on AERONET PSD, as shown in Figure 7d.

In the second case, a dust layer extends from about 6.0 km to 0.5 km but concentrates mostly near the surface. Moreover, there is a temperature inversion (TI) in the upper boundary layer between 0.5 km and 1.25km. Such TI was often observed over the coastal region near the Sahara Desert. It is believed to the result of the warmer Saharan Air Layer overlaying colder Atlantic Ocean surface (Dunion and Velden 2004; Gutleben et al. 2019; Wong et al. 2009). Both the lower altitude and the temperature inversion help enhance the emission effect of dust. As a result, the dependence of dBT on SSA and g-factor in the case (see Figure 8d) is quite different from that in the first case (Figure 8a). In particular, the dependence of dBT on the SSA and, therefore, the choice of RI is significantly stronger due to a more substantial emission effect. It implies that using a pre-assumed RI for DAOD\text{\tiny TIR} retrieval when the real RI has significant variability could induce larger uncertainty when the dust emission is strong. Fortunately, as discussed later in Section 5, TI is mainly found in the narrow coastal regions of North Africa and the Middle East (Clarisse et al. 2019).

Generally, for the transported dust with the sub-tropical atmospheric states (Figure 8a), the assumed dust PSD dominates the DAOD\text{\tiny TIR} retrieval uncertainty due to the a priori dust assumption.
The uncertainty due to dust RI assumption should be noticed if the dust emission effect is enhanced by TI, which would occur over the coastal region near dust sources.

Figure 8 (a) and (d) represent the contours of dBT between BT\textsubscript{clean} and BT\textsubscript{dust} from the FASDOM simulation at IIR Band 10.6 μm with perturbed g factor (y-axis) and SSA (x-axis) by the given DAOD\textsubscript{TIR} (value of 0.2) corresponding to the sub-tropical (b) and SAL (e) atmospheric profiles, respectively. (c) and (f) represent the corresponding vertical profiles of dust extinction coefficient with the atmospheric profiles of (b) and (e), respectively. The real and dash contour lines represent positive and negative values of dBT, respectively. The dot lines with color in (a) and (d) represent the g-factor and SSA calculated based on combinations of Di-Biagio RIs in Sahara/Sahel deserts and the perturbed PSDs. Each dot marker in a line corresponds to a lognormal dust PSD with an effective radius (re) from 0.4 μm to 7.7 μm with one standard deviation of 0.6 μm. Stars with dash lines in (a) and (d) represent the g-factor and SSA based on AERONET PSD (black) and Fennec PSD (blue) with corresponding dust RIs.

3.6 Uncertainty analysis and post-filtering
As we separate DAOD\textsubscript{TIR} retrieval into two sets based on two dust PSDs, the difference between the two retrievals is served as the estimation of uncertainty due to dust size. Apart from this, the uncertainty from observation, atmospheric assumption and a priori dust RI is further quantified for the global retrieval results.

As mentioned in section 2.2, the BT\textsubscript{clean} difference with a standard deviation, $S_d\textsubscript{BT}$, can be counted as the combined uncertainty in the instrument, ancillary data (e.g., MERRA-2 profiles), and radiative transfer simulation. For nighttime observations of the IIR 10.6 μm channel over ocean, we use $S_d\textsubscript{BT}=0.856$ K (as shown in Figure 2b). The influence of the uncertainty in dust RI is decomposed into two parts corresponding to the impacts of dust RI on SSA and g-factor, respectively. Based on these considerations, we propose to use the following equation to estimate the uncertainty in the retrieved DAOD:

$$ s_{DAOD} = \sqrt{\left(\frac{\partial DAOD}{\partial dBT}\right)^2 s_{dBT}^2 + \left(\frac{\partial DAOD}{\partial SSA}\right)^2 s_{SSA}^2 + \left(\frac{\partial DAOD}{\partial g}\right)^2 s_g^2} \quad (2) $$

where $s_{DAOD}$ is the absolute uncertainty on the retrieved DAOD, $s_{SSA}$ and $s_g$ are the standard deviation of SSA and g-factor, respectively, which are calculated based on each regional RIs in the corresponding RI regime. The perturbation of dB\textsubscript{T} is 20% of the observed IIR dB\textsubscript{T} (i.e., IIR BT\textsubscript{cdust} – FASDOM BT\textsubscript{clean}), while the perturbations of SSA and g-factor are the difference between the maximum and minimum values calculated from the regional RIs. The corresponding change of DAOD to the perturbation is then used to obtain $\frac{\partial DAOD}{\partial dBT}$, $\frac{\partial DAOD}{\partial SSA}$ and $\frac{\partial DAOD}{\partial g}$.

The information content of dust with small DAOD or low layer height is generally lower than the uncertainties from the observation and the forward model simulation (Klüser et al. 2015). Hence, for CALIOP DAOD less than 0.05 at 532 nm, the retrieval of DAOD\textsubscript{TIR} is hardly achievable. These cases are set to be zero for reducing bias.
Figure 9a, and 9b show the mean retrieved DAOD\textsubscript{10.6\textmu m} and mean uncertainty for two-year data from 2013 to 2014. The retrieval uncertainty is as comparably large as the DAOD. Figure 9c shows the histogram of the three propagation terms of uncertainties in Eq. (4). Consistent with the discussion in section 3.5, dust RI contributes only ~10\% of in the DAOD uncertainty by the perturbation on SSA and g-factor. About 90\% of the uncertainty is from the term of dBT uncertainty, representing the uncertainty from instrumental noise, atmospheric assumptions, and radiative simulations.

Because of the relatively large uncertainties, we alternatively use the synergic CALIOP DAOD\textsubscript{532nm} to filter the unrealistic retrieval results. As mentioned in section 3.2, the DAOD\textsubscript{532nm} also contains uncertainties from the a priori dust DPR and LR, which are not evaluated in this study. Based on Figure 5b and precious studies (Song et al. 2018), the ratio of DAOD\textsubscript{10.6\textmu m} to DAOD\textsubscript{532nm} is most likely smaller than unity. Including the mean retrieval uncertainty, retrievals have a chance to get close to or exceed 100\% relative uncertainty. Therefore, as listed in Table 2, we assign post\_QA = 1 for results with a ratio DAOD\textsubscript{10.6\textmu m} / DAOD\textsubscript{532nm} > 2 as they are no longer physically meaningful. We also assign post\_QA = 2 for a few unretrievable cases (1.72\%) with the simulated BT\textsubscript{dust} warmer than BT\textsubscript{clean}. Although it is theoretically possible if a significant temperature contrast between the dust layer and the surface occurs, it also requires a strong dust absorption effect (see Figure 8d), which is hardly achieved by the a priori dust at 10.6 \textmu m. Therefore, we believe that these cases are due to the uncertainty in the observation and/or radiative transfer simulation. In the rest of the paper, the retrieval results are all applied QA flags with pre\_QA \leq 1 and post\_QA = 0.
4. Retrieval results

4.1 Spatial and temporal pattern of DAOD at 10.6μm
In this section, we present the climatological DAOD\textsubscript{10.6\textmu m} retrieval results from 2013 to 2017 from our algorithm as explained above. Figure 10 shows the seasonal variation of the retrieved DAOD\textsubscript{10.6\textmu m} based on the AERONET PSDs (left column, referred to as “AERONET DAOD\textsubscript{10.6\textmu m}” hereafter) and Fennec PSD (middle column, hereafter “Fennec DAOD\textsubscript{10.6\textmu m}”). We also plot the CALIOP DAOD\textsubscript{532nm} based on the method in Section 3.2 (right column) for comparison purposes.

As the retrieval uncertainties of DAOD\textsubscript{532nm} are not evaluated in this study, instead of focusing on the absolute value of DAOD\textsubscript{532nm}, we use the DAOD\textsubscript{532nm} as the reference for the seasonal variation patterns of the retrieved DAOD\textsubscript{10.6\textmu m} and the implication of the ratio between VIS (i.e., 532 nm) and TIR (i.e., 10.6 \textmu m). Table 4 shows the seasonal-averaged DAOD retrieved from IIR and CALIOP using AERONET and Fennec PSD. Note that the global average weighted by surface areas excludes the polar region where dust is rarely found. We also highlight regional mean DAODs over four active dust transport regions (i.e., North Atlantic (NA), Tropical Atlantic (TA), Indian Ocean (IO) and Northwest Pacific (NP)) with geolocation range in Figure 10 and Table 4.

Table 4 The seasonal and global/regional mean of all retrieved DAOD from 2013 to 2019

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<tr>
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<tbody>
<tr>
<td>IIR</td>
<td>Spring</td>
<td>0.007</td>
<td>0.020</td>
<td>0.025</td>
<td>0.045</td>
<td>0.013</td>
</tr>
<tr>
<td></td>
<td>Summer</td>
<td>0.008</td>
<td>0.036</td>
<td>0.007</td>
<td>0.069</td>
<td>0.002</td>
</tr>
<tr>
<td>AERONET</td>
<td>Autumn</td>
<td>0.005</td>
<td>0.015</td>
<td>0.007</td>
<td>0.032</td>
<td>0.003</td>
</tr>
<tr>
<td>DAOD\textsubscript{10.6\textmu m}</td>
<td>Winter</td>
<td>0.004</td>
<td>0.012</td>
<td>0.032</td>
<td>0.017</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>Annual</td>
<td>0.006</td>
<td>0.021</td>
<td>0.018</td>
<td>0.040</td>
<td>0.006</td>
</tr>
</tbody>
</table>
In spring, the outflow of Asian dust to NP is seen from DAOD\textsubscript{532nm}. Both AERONET and Fennec DAOD\textsubscript{10.6\textmu m} capture this pattern. However, the DAOD\textsubscript{10.6\textmu m} decreases fast eastward of 180°W while the CALIOP DAOD is still noticeable even around the west coast of the U.S. A possible reason is that the large dust particles deposit to the ocean during transport, leading to a reduction of both dust size and total AOD, and therefore a reduced signal for the TIR retrieval. In summer, the DAOD\textsubscript{10.6\textmu m} captures the outbreaks of dust transport from Sahara and Sahel to NA,
with averaged values ranging from 0.03 to 0.06. Meantime, dust over IO is transported from the Middle East and/or Sahara source regions, which has an average DAOD from 0.07 to 0.12. In autumn, the dust transport over NA, IO, and NP is weakened compared to summer. In winter, the south-shifted trade wind in the northern hemisphere drives more dust transport to TA than NA. We find the highest DAOD$_{532\text{nm}}$ (~0.1) and DAOD$_{10.6\mu\text{m}}$ (0.03 ~ 0.04) over TA in winter compared with other seasons. Meanwhile, dust has more chance to mix with smoke and biomass burning aerosols emitted from Tropical Africa. The mean DAOD$_{532\text{nm}}$ in winter over TA shares a similar average value (~0.1) with that in summer over NA, while the mean DAOD$_{10.6\mu\text{m}}$ in winter over TA is lower than that (0.04 ~ 0.05) in summer over NA, implying a reduced TIR signal due to the lower fraction of dust in the mixture during the transport to TA.

Figure 10 The global distribution of seasonal averaged DAOD$_{10.6\mu\text{m}}$ based on AERONET PSD (left columns) and Fennec PSD (middle columns) and CALIOP DAOD$_{532\text{nm}}$ (right columns) from 2013 to 2019 over oceans at nighttime. From up to down represents seasons from spring to winter.
As mentioned in section 3.5, the assumption of dust PSD impacts the DAOD\textsubscript{TIR} retrieval. In Figure 10, the difference between AERONET and Fennec DAOD\textsubscript{10.6\textmu m} represents the retrieved DAOD\textsubscript{TIR} uncertainty due to dust PSD assumptions in the TIR observation. However, without the TIR observation, to obtain DAOD\textsubscript{TIR}, we must extend the CALIOP DAOD\textsubscript{532nm} to the TIR region. How would the extended results be compared to the retrieved DAOD\textsubscript{10.6\textmu m}? With this question, we performed the following investigations.

First, we convert the 7-year averaged CALIOP DAOD\textsubscript{532nm} in summer to be DAOD at 10.6 \textmu m (referred to as “CALIOP DAOD\textsubscript{10.6\textmu m}”) based on the equation \( \text{DAOD}_{10.6\textmu m} = \text{DAOD}_{532nm} \cdot \frac{Q_{\text{ext},10.6\textmu m}}{Q_{\text{ext},532nm}} \), where the \( \frac{Q_{\text{ext},10.6\textmu m}}{Q_{\text{ext},532nm}} \) is introduced in section 3.3 as TIR/VIS ratio. As shown in Figure 5b, Fennec PSDs’ TIR/VIS ratio is from 0.35 to 0.5 at 10.6 \textmu m, which can be 4 to 6 times larger than that of AERONET PSD (from 0.05 to 0.14). Consequently, the CALIOP DAOD\textsubscript{10.6\textmu m} based on AERONET PSD is substantially smaller than that based on Fennec PSD (see Figures 11a and 11c), leading to a significant difference (~0.125) between the two CALIOP DAOD\textsubscript{10.6\textmu m} as shown in Figure 11e. Next, we retrieve the corresponding 7-year averaged AERONET DAOD\textsubscript{10.6\textmu m} and Fennec DAOD\textsubscript{10.6\textmu m} as shown in Figures 11b and 11d.

In Figures 11e and 11f, the difference of retrieved DAOD\textsubscript{10.6\textmu m} due to the change of dust PSD is remarkably reduced by ~70% compared with converted CALIOP DAOD\textsubscript{10.6\textmu m}. The possible reason is discussed as follows. Firstly, the converted DAOD\textsubscript{10.6\textmu m} linearly depends on the TIR/VIS ratio, which is highly varied with dust PSD as shown in Figure 5 and previous studies (Figure 7 in Song et al. 2018). Secondly, as the observed dBT provides information on dust extinction, including absorption and scattering, changing the dust PSD assumption varies the dust SSA and g-factor in the retrieval. With the unchanged dust RI, the dependency of g-factor on dust
PSD eventually determines \( \text{dBT} \) and further the retrieved DAOD10.6\( \mu \text{m} \), as discussed in section 3.5 (see Figures 8a and 8d). Therefore, with the TIR observation, the change of TIR/VIS ratio by dust PSD no longer has an impact on DAOD10.6\( \mu \text{m} \). Instead, the change of dust scattering properties, in this case, the \( g \)-factor, by dust PSD determines the difference in the retrieved DAOD10.6\( \mu \text{m} \) (see Figures 11f). The moderate variation of \( \text{dBT} \) based on the change of dust PSD in the retrieval could be the reason leading to a less varied retrieved DAOD10.6\( \mu \text{m} \) than the converted DAOD10.6\( \mu \text{m} \). However, we should keep in mind that this result is neither guaranteed in using other TIR wavelengths nor in other combinations of a priori dust assumptions. A more dedicated study is needed for future research.

Moreover, by comparing the CALIOP DAOD\( 10.6\mu \text{m} \) with the retrieved DAOD\( 10.6\mu \text{m} \) based on the same dust PSD in Figure 11, we found that the converted DAOD\( 10.6\mu \text{m} \) using Fennec PSD is more consistent with the TIR observation than using AERONET PSD. This accordance means using the Fennec PSD is more suitable for representing the dust extinction spectrum in both VIS and TIR as Song et al. (2018) suggested at the point of view in dust DRE. It opens an exciting perspective for utilizing the synergic VIS and TIR observation to constraint the DAOD\( \text{TIR} \), the dust PSD and further the global dust cycle and DRE\( \text{LW} \) simulation (Song et al. 2018; Wu et al. 2020).
Figure 11 The global distribution of a) the mean converted CALIOP DAOD$_{10.6\mu m}$ based on Fennec PSD and c) AERONET PSD, and b) the mean retrieved DAOD$_{10.6\mu m}$ based on Fennec PSD and d) AERONET PSD, in summer (JJA) of 7-years IIR-CALIOP observation from 2013 to 2019. e) The difference of the mean converted CALIOP DAOD$_{10.6\mu m}$ between two PSD assumptions. f) The difference of the mean retrieved DAOD$_{10.6\mu m}$ between two PSD assumptions.

Although dust RI has a limited impact on the DAOD$_{TIR}$ retrieval in this study, it is also helpful to see if the TIR observation could constrain the uncertainty due to the dust RI assumptions. In this time, we calculate two CALIOP DAOD$_{10.6\mu m}$ based on the maximum and minimum TIR/VIS ratios corresponding to the variation of regional RIs and the unchanged Fennec PSD (Figures 12a and 12c). Then, the maximum and minimum ones among the retrieved Fennec DAOD$_{10.6\mu m}$ based on the regional RIs are shown in Figures 12b and 12d, respectively. Figure 12e shows that the difference of the two CALIOP DAOD$_{10.6\mu m}$ is substantial over the North Atlantic Ocean, with a mean value of around 0.019. With TIR observation, in Figure 12f, the difference of retrieved
DAOD$_{10.6\mu m}$ under different RI assumptions is reduced by about 26%, except the Sahara Desert's coastal region. The main reason causing this larger change is the alter of dust radiative signal due to the temperature inversion discussed in section 3.5 (see Figures 8d,8e,8f). It is restricted as the impact of temperature inversion is limited in the coastal region near the Saharan Desert. In addition, the absolute DAOD differences caused by RI are only ~37% of that caused by dust PSD. Consequently, the TIR observation also constrains the DAOD$_{\text{TIR}}$ uncertainty due to dust RI assumptions if conditions apply, that the TIR channel is less sensitive to dust RI and the atmosphere does not contain strong TI.

Figure 12 Same as Figure 11, except that the dust PSD is fixed (Fennec PSD) and the difference of assumptions are the regional dust RI with the maximum $Q_{\text{ext}}$ ratio and the minimum $Q_{\text{ext}}$ ratio.

### 4.2 Climatology Comparison with IASI-retrieved DAOD
As suggested in the previous section, the Fennec DAOD$_{10.6\mu m}$ makes a better agreement with the theoretically converted CALIOP DAOD$_{10.6\mu m}$. Therefore, to evaluate the IIR-CALIOP retrieval, we compare the Fennec DAOD$_{10.6\mu m}$ with two independent IASI-based DAOD at 10 μm (DAOD$_{10\mu m}$) products developed by different teams. The first one is derived by the group at Laboratoire de Météorologie Dynamique (LMD) (referred to as “IASI-LMD”) and the other by the group at Université libre de Bruxelles (ULB) (referred to as “IASI-ULB”). The IASI-LMD algorithm has a long history. It was initiated by Pierangelo et al. (2004) for AIRS and further developed as a decadal dataset for IASI by several follow-up studies (Capelle et al. 2018; Capelle et al. 2014; Peyridieu et al. 2013). It uses a LUT-based retrieval method to retrieve both DAOD at 10 μm and the mean dust layer altitude based on the selected channels of IASI. Instead of using LUTs, the IASI-ULB algorithm utilizes a neural network method to learn the dust spectral characteristics represented by the dust index R based on the observed outgoing longwave spectral radiance (Clarisse et al. 2019). The retrieved DAOD is then obtained by multiplying the observed R with the NN-predicted conversion ratio CR. The NN training process is based on the given atmospheric conditions, dust properties, the monthly mean CALIOP dust altitude and the given IASI observation. As the observed R contains the independent random instrumental noise with a mean of 0, it allows the retrieved DAOD to be negative for reducing bias.

The different spatiotemporal resolution between IASI and CALIPSO prevents enough reliable collocations for the pixel-by-pixel comparison. Here, we only compare the grid-level (i.e., latitude-longitude grid) climatology between Fennec DAOD$_{10.6\mu m}$ and DAOD$_{10\mu m}$ from the IASI products. Note that the IIR-CALIOP retrieval is implemented over oceans at nighttime only, while the current IASI grid-level products include data in the daytime and over lands. To alleviate the sampling difference, we first apply the following filtering procedures for the IASI level-2 (i.e.,
pixel-level) products in 7 years from 2013 to 2019 and then aggregate them to the corresponding grid-level climatological results ($2^\circ \times 2^\circ$ grids):

1) Only the nighttime samples over oceans are selected from both IASI products using their surface masks and day/night flags.

2) Only the filtered results after applying the required QA flags in three products are considered. For IIR/CALIOP retrieval, $\text{pre}_{-}\text{QA} \leq 1$ and $\text{post}_{-}\text{QA} = 0$ are applied. Quality control processes of IASI retrievals are detailed in Capelle et al. (2018) and Clarisse et al. (2019).

It is necessary to point out that both IASI products do DAOD$_{\text{TIR}}$ retrievals on the detected cloud-free pixels with ad hoc dust detection based on the dust TIR spectral patterns. Their cloud masking and dust detection are different from those of the Lidar-based method in the IIR-CALIOP retrieval, leading to the difference in the cloud-free dust sampling. Thus, it should be carried when comparing the 7-year averaged seasonal retrieved DAOD among three products, as shown in Figure 13. Note that there also is a spectral difference of DAOD at 10.0 $\mu$m and 10.6 $\mu$m, which depends on the assumptions of dust PSD, RI and shape. Therefore, a perfect match of the retrieved DAOD is not expected in the comparison. Rather than that, all three products have a good agreement on the seasonal variations of dust transport over NP (in spring), NA and IO (in summer) and TA (in winter), with containable discrepancies of the mean DAOD value, which is listed in Table 4.

In Figure 13, the most apparent discrepancy among DAOD$_{10.6\mu m}$ (left column), IASI-ULB and IASI-LMD DAOD$_{10\mu m}$ (middle and right columns) are over the "background" region with low DAOD (Fennec DAOD$_{10.6\mu m} < 0.01$) as the non-dust aerosol dominates. The IASI-LMD
DAOD$_{10\mu m}$ over the "background" region has a significantly larger value (~0.06) than DAOD$_{10.6\mu m}$ ($\leq 0.01$), especially over the West Pacific "warm pool" and ITCZ, which has high occurrence frequency of cirrus cloud (Prabhakara et al. 1993; Sassen et al. 2008). It implies that the IASI-LMD retrieval technique might overestimate the DAOD$_{10\mu m}$ due to false detected dust radiative signal induced by the sub-pixel cirrus cloud over the "background" region.

Figure 13 The seasonal averaged global distribution of Fennec DAOD$_{10.6\mu m}$ (left columns), IASI-ULB DAOD$_{10\mu m}$ (middle columns) and IASI-LMD DAOD$_{10\mu m}$ (right columns). From up to down represents seasons from spring to winter.

To better compare the retrieved DAOD grid-by-grid over the four active dust transport regions, all the grid-level seasonal mean DAODs from three retrieval products over each region are plotted in Figure 14 with linear regression values (i.e., slope, intercept, correlation coefficient (r-value and p-value). The comparison between DAOD$_{10.6\mu m}$ and DAOD$_{10\mu m}$ Over NA (Figure 14a, 14e) and TA (Figure 14b, 14f) shows well-agreed variation as the r-values are higher than 0.8. However, the corresponding slopes deviate from unity, indicating a systematic difference of the absolute value of DAOD, which is also reflected in the mean value comparison in Table 4. Over IO, in
Figures 14c and 14g, DAOD$_{10.6\mu m}$ is still well-agreed with IASI-ULB DAOD$_{10\mu m}$ ($r = 0.832$), while it has a lower r-value (0.774) with IASI-LMD DAOD$_{10\mu m}$. In Figures 14d and 14h, dust over NP has an overall smaller DAOD ($< 0.15$) and would also have smaller dust particle size due to the deposition of the coarser particles during the long-term transport from Asia. As a result, the dust radiative signal is harder to be seen in TIR by IASI, leading to higher retrieval uncertainties and, therefore, the lowest r-values ($r=0.648$ and 0.226) of DAOD$_{10.6\mu m}$ with IASI-ULB and IASI-LMD DAOD$_{10\mu m}$. However, the CALIOP DPR-based dust detection approach can better estimate them based on their non-sphericity but not on their size. Therefore, shown in Figure 13 for over NP in spring and winter, there is a more evident DAOD$_{10.6\mu m}$ trend of dust transport westward than both IASI DAOD$_{10\mu m}$ at around 30°N. It implies that the collocated IIR-CALIOP has a better dust detection performance than that of IASI-only for dust transported from Asia.

Figure 14 The scatter plot of Fennec DAOD$_{10.6\mu m}$ versus IASI-ULB and IASI-LMD DAOD$_{10\mu m}$ over NA (a,e), TA (b,f), IO (c,g) and NP (d,h). Red lines with orange shadow represent the linear regression and its standard error. The k, c, r and p at the upper right of each panel represent the slope, intercept, correlation coefficient and p-value of the linear regression.
In summary, despite the discrepancies over the low DAOD areas, the IIR-CALIOP retrieval is well-agreed with two IASI retrievals on the seasonal variation of dust transport over NA, TA, and IO with confident correlations. In NP, the IIR-CALIOP retrieval reveals a more apparent trend of dust transport than both IASI retrievals at around 30°N. Regarding DAOD value, which is deviated among the three retrievals, further comparison of DAOD_{10.6\mu m} with the well-trusted ground-based AERONET measurement is necessary.

4.3 Seasonal and Interannual Comparison with AERONET Coarse-mode AOD

Most DAOD_{TIR} retrieval studies estimate the results through the collocated comparison with the AERONET coarse-mode AOD in VIS (500 nm; refer to as “AOD_{500nm}”) at the dust-dominated sites (Capelle et al. 2018; Capelle et al. 2014; Clarisse et al. 2019; Klüser et al. 2011 (Peyridieu et al. 2013)). However, the simultaneously collocated comparison of CALIPSO with AERONET needs to be within 40 km with a time window of ±30 mins of the overpass time to have a rigorous comparison (Omar et al. 2013; Schuster et al. 2012). In addition, the quantitative comparison with AOD_{500nm} requires the TIR/VIS ratio. With the limited information of dust properties, the assumed TIR/VIS ratio could significantly error the comparison results (Capelle et al. 2018), even if the AOD_{500nm} from dust-dominated sites. Alternatively, in this section, we make the seasonal and interannual comparison of the collocated 1° × 1° monthly mean grid-level DAOD_{10.6\mu m} with AOD_{500nm}. This approach aims to evaluate the consistency between DAOD_{10.6\mu m} and AOD_{500nm}, which has been used to evaluate CALIOP DAOD_{532nm} and AOD_{500nm} (Yu et al. 2015). Without considering the TIR/VIS ratio, it is unnecessary to guarantee the AOD_{500nm} contributed purely by dust. Therefore, we select 97 AERONET sites within the defined dust-concentrated area (see
Figure 1a) over oceans from 2013 to 2019, as shown in Figure 15a. Meanwhile, as a reference, the two monthly mean IASI-retrieved DAOD$_{10\mu m}$ are derived from the IASI-ULB and IASI-LMD level-2 products.

![Figure 1a) The geolocation of 97 selected AERONET sites. b) The seasonal interannual variation of AOD from IIR-CALIOP DAOD$_{10.6\mu m}$ (blue dot), IASI-ULB DAOD$_{10\mu m}$ (red triangle), IASI-LMD DAOD$_{10\mu m}$ (green star) and AERONET AOD$_{500nm}$ paired with IIR-CALIOP (pink square) and IASI (yellow diamond).]

In Figure 15b, the correlation coefficient between DAOD$_{10.6\mu m}$ and AOD$_{500nm}$ is 0.754, suggesting that the IIR-CALIOP retrieval agrees reasonably well with AERONET coarse-mode AOD on the seasonal and interannual variations. Because of the higher sampling rate of IASI retrieval than IIR-CALIOP, the IASI-AERONET comparison pairs are 50% more than IIR-AERONET. As a result, we found better correlations in IASI-AERONET comparisons. In addition, the IIR-matched AOD$_{500nm}$ is 17% higher and more fluctuated than IASI-matched AOD$_{500nm}$.

Bearing the +17% difference in the number of pairs, we still found that the interannual mean...
DAOD_{10.6\mu m} is 50% larger than IASI-ULB DAOD_{10\mu m} and 50% less than that of DAOD_{10.6\mu m}. It implies that the IIR-CALIOP retrieved DAOD_{10.6\mu m} is agrees better with IASI-ULB DAOD_{10\mu m}.

5. Summary and Conclusions

This paper introduces a novel way to retrieve DAOD_{TIR} using the integrated CALIOP and IIR observations with a priori dust assumptions based on the state-of-art databases. The retrieval method is based on the BT contrast between the observed BT at the IIR 10.6 \mu m channel of the cloud-free dust scenario and the simulated cloud-free clean BT with corresponding assumed atmospheric and surface conditions. Thanks to the derived dust vertical distribution from CALIOP, the straightforward LUT depends on DAOD only, which can be built simultaneously with the cloud-free dust detection process. In addition, the 1-km resolution of IIR observation maximally reduces the sub-pixel cloud contamination on the dust radiative signal. Thus, we evaluated the retrieval uncertainties from the instrumental noise, ancillary data, radiative simulation and the a priori dust assumptions and produced climatological retrieval results (i.e., DAOD_{10.6\mu m}).

According to the non-spherical dust scattering properties calculation based on the spheroid shape distribution and the Di-Biagio RI database, the dust PSD assumption is the main contribution to the variation of TIR/VIS ratio in TIR atmospheric window bands, which would produce significantly different DAOD_{TIR} even with identical DAOD_{VIS}. However, with the TIR observation, the difference of retrieved DAOD_{TIR} caused by dust PSD assumptions is remarkably reduced. Combing with the synergic VIS observation offers an exciting prospect on constraining the DAOD_{TIR}, the dust particle size and further the DRE_{LW} uncertainty.
The comparison between DAOD\textsubscript{10.6\textmu m} and IASI-retrieved DAOD\textsubscript{10\textmu m} developed by the LMD and ULB groups is performed on a 7-year climatological scale with the assurance of sampling procedures. In general, DAOD\textsubscript{10.6\textmu m} shows good agreements of seasonal variations of dust transport with both IASI DAOD\textsubscript{10\textmu m} over the active dust transport regions but with deviations on the mean DAOD. Discrepancies over the low DAOD areas are possibly due to the difference in sampling approach (i.e., cloud masking and dust detection), retrieval methods and the 10.0\textmu m-to-10.6\textmu m spectral difference. Despite that, the consistency of the retrieved DAOD\textsubscript{10.6\textmu m} with AERONET observation is presented through the seasonal and interannual comparison with AERONET coarse-mode AOD over 97 selected sites over oceans.

The study presented here has several limitations. First of all, the limited spatial coverage of CALIOP and the nighttime-only retrieval leads to a relatively low DAOD\textsubscript{TIR} sampling rate. Secondly, as the highly varied surface emissivity and skin temperature over land would have significant uncertainties, the retrieval is operated over oceans only. Thirdly, the single-band retrieval approach subjects to massive uncertainties from the atmospheric gas absorptions, the instrumental noise, and the radiative transfer simulation. Moreover, it has insufficient information content for retrieving other dust properties such as dust PSD and RI. The retrieval can be improved by adding more information from other channels/instruments and better a priori assumptions. Therefore, the future developments on the current retrieval method to address the remaining challenges are listed below:

1) Propagate the retrieval to the 60-km IIR swath by assuming the vertical distribution of dust from CALIOP within a reasonable scale.
2) Seeking more helpful information from other IIR channels and/or collocated instruments in the A-Train (e.g., MODIS and AIRS) for constraining the retrieval uncertainties, exploring more retrievable properties, and expanding the spatial coverage of the retrieval.

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