



Dust aerosol optical depth at thermal infrared wavelength from an AeroCom/AeroSat study: Comparative analysis and perspectives

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ABSTRACT

Mineral dust interacts with Earth's radiation across a broad spectral range, from near UV to the
 thermal Infrared (TIR). While global distributions of dust optical depth at mid-visible



wavelength (at 0.55 μm , $\text{DOD}_{0.55}$) are well characterized by remote sensing and models, corresponding TIR products (at 10 μm , DOD_{10}) remain limited to a few satellite retrievals and are rarely simulated by models. This coordinated AeroCom–AeroSat study addresses these gaps by presenting the current state of DOD_{10} using four satellite TIR products, six AeroCom model simulations, a model-based, observation-constrained climatological database, and laboratory measurements of dust properties. The analysis reveals substantial differences in DOD_{10} across satellite products and models, sometimes exceeding a factor of ten. Discrepancies among satellite products may link to retrieval algorithms and assumptions, while model differences arise from dust emission, removal processes, and mass extinction efficiencies determined by dust optical properties and size distributions. Multi-model mean results indicate that coarse-mode dust (diameter $> 2.5 \mu\text{m}$) accounts for nearly 80% of dust mass loading and DOD_{10} but only about 40% for $\text{DOD}_{0.55}$. The absence of a reference dataset for DOD_{10} poses a major challenge, limiting validation to indirect comparisons with proxies such as AERONET coarse-mode $\text{AOD}_{0.55}$, which is informative but insufficient for DOD_{10} validation. Laboratory measurements of spectral-dependent optical properties highlight the potential of combining shortwave and longwave remote sensing to advance dust compositions analysis through their distinct spectral sensitivities.

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1. Introduction

Mineral dust is among the most abundant aerosol types in Earth’s atmosphere, emitted primarily from arid and semi-arid surfaces through aeolian processes such as saltation and aerodynamic lifting (Gillette et al. 1998; Marticorena and Bergametti, 1995; Marticorena et al., 1997; Shao et al., 2011). Dust plays a pivotal role in the climate system by interacting with radiation across a broad spectral range, altering atmospheric stability, and acting as cloud-condensation and ice-nucleating particles (Haywood et al., 2005; Forster et al., 2007; Evan et al., 2008; DeMott et al., 2010; Creamean et al., 2013; Colarco et al., 2014; Rosenfeld et al., 2014; Jordan et al., 2020). Both fine and coarse dust particles interact with solar and terrestrial radiation, resulting in an overall cooling radiative effect in the shortwave (SW) spectral range but a warming radiative effect in the longwave (LW) (Di Biagio et al., 2020; Kok et al., 2023, 2026; Wang et al., 2024).



63 Dust deposited on snow have profound impacts on the regional hydrological cycle and climate
64 system, by decreasing surface albedo and increasing snow and ice melting (Bullard et al. 2016).
65 Dust deposition to the land and ocean also affects the biogeochemical cycles and ecosystem
66 (e.g., Yu et al., 2015; Westberry et al., 2023).

67

68 Due to dust's short atmospheric lifetime and large spatial and temporal variability, high-quality
69 observations are essential for quantifying its distributions and environmental effects (Ginoux et
70 al., 2001; Kim et al., 2014; Ridley et al., 2016; Kok et al., 2017, 2023). The global distribution of
71 dust is commonly represented by dust optical depth (DOD) at mid-visible wavelength (typically
72 reported at 550nm or 0.55 μ m, referred here as DOD_{0.55}), derived from retrieved aerosol optical
73 depth (AOD_{0.55}) and particle properties related to dust size and shape (Kaufman et al., 2005;
74 Ginoux et al., 2012; Yu et al., 2015, 2019; Pu and Ginoux, 2016). DOD_{0.55} has been widely used
75 for model evaluations (e.g., Kim et al., 2014, 2019, 2021; Yu et al., 2020; Wu et al., 2020). In
76 contrast, DOD at thermal infrared (TIR) wavelength (typically at 10 μ m, DOD₁₀) is retrieved
77 from a limited number of satellite sensors, most notably the Infrared Atmospheric Sounding
78 Interferometer (IASI) on MetOP satellites (Capelle et al., 2018; Clarisse et al., 2019;
79 Vandenbussche et al., 2026) and, more recently, the Moderate Resolution Imaging
80 Spectroradiometer (MODIS) TIR retrievals (Zheng et al., 2022, 2023, 2024, 2026). Generally,
81 DOD_{0.55} is more sensitive to the fine-mode dust particles whereas DOD₁₀ is more sensitive to the
82 coarse-mode particles (e.g., Song et al., 2022; Li and Ginoux, 2025). Because coarse dust
83 dominates longwave radiative effects (Kok et al., 2026), DOD₁₀ provides critical information in
84 assessing the dust impacts on the Earth's energy budget.

85

86 Despite its importance, robust evaluation of DOD₁₀ data remains difficult due to the absence of
87 reliable reference observations in the TIR spectral region (Castellanos et al., 2024; Zheng et al.,
88 2024; Vandenbussche et al., 2026). Current validation approaches often convert DOD₁₀ to
89 DOD_{0.55}, either using simplified conversion factors based on assumed particle properties or
90 empirical values (Peyridieu et al., 2010, 2013; Capelle et al., 2018; Vandenbussche et al., 2026),
91 or by using retrieved dust effective size and related wavelength-dependent information (Zheng et
92 al., 2026), then compare the converted values with AERONET coarse-mode AOD_{0.55} over dust-
93 dominated regions. This indirect approach introduces substantial uncertainties, especially away



94 from dust sources, and remains inconclusive regarding the quality of DOD₁₀. To date, systematic
 95 efforts to examine the current state of DOD₁₀ products are lacking, leaving them poorly
 96 constrained, under-studied, and under-used, which hinders accurate estimation of dust effects on
 97 terrestrial radiation.

98
 99 To address these gaps, this study presents the first coordinated multi-model and multi-satellite
 100 assessment of DOD₁₀, under the auspices of the internationally coordinated AeroCom
 101 (<http://aerocom.met.no/>) and AeroSat (<https://aerosat.org/>) projects. We analyze four satellite
 102 DOD₁₀ products from IASI and MODIS, six global model simulations from the AeroCom Phase-
 103 III dust source attribution (DUSA) modeling experiment, and the Dust Constraint from joint
 104 Observational-Modelling-experiMental analysis (DustCOMM) global climatological dataset.
 105 Collectively, these datasets provide a comprehensive perspective on current observational and
 106 modeling capabilities for representing DOD in the TIR spectral regime.

107
 108 The objectives of this study are to (1) document and intercompare satellite-retrieved and model-
 109 simulated DOD₁₀, (2) quantify the diversity in dust optical properties across datasets, particularly
 110 the spectral dependence of DOD and mass extinction efficiency (MEE), and (3) estimate fine-
 111 and coarse-mode contributions to dust mass loading and optical depth using size-resolved model
 112 outputs. By synthesizing multiple complementary datasets, this work provides an assessment of
 113 the present state of dust representation in the TIR, highlighting key observational and modeling
 114 gaps that must be addressed to improve estimates of dust radiative forcing and climate impacts.

115

116 **2. Observational datasets and model simulations**

117

118 **2.1 AeroCom models and DustCOMM**

119

120 Six global models participated in AeroCom Phase-III DUSA experiment (Kim et al., 2024) have
 121 contributed simulations of dust emission, transport, deposition, and optical properties for this
 122 study. The models are CAM5-ATARS-AP3 (CAM5-ATRAs in short), CESM2.1.3 (CESM2),
 123 GEOS-GOCART (GEOS), GEOS-Chem, GFDL-AM4, and MIROC-SPRINTARS
 124 (SPRINTARS). Additionally, we include the same variables from DustCOMM, which is a global
 125 database that integrates an ensemble of model simulations, constrained by dust size distribution,



extinction efficiency, and regional AOD at visible wavelengths, and calculates DOD at TIR based on the constrained properties (Adebiyi et al., 2020; Kok et al., 2021a, b). Model configurations and key information are summarized in Table 1.

Table 1. Description of the participating models.

	CESM2	CAM5- ATRAS	GEOS	GEOS-Chem	GFDL-AM4	SPRINTARS	DustCOMM
lon°× lat°	1.25°×0.93°	2.5°×1.875°	0.5°×0.5°	2.5°×2.0°	1.25°×1.0°	0.56°×0.56°	2.5°×1.9°
#lev	32	30	72	47	33	40	48
Meteorology	ERA5 (Nudged)	MERRA-2 (Nudged)	MERRA-2 (Replay)	MERRA-2	NCEP (Nudged)	ERA5 (Nudged)	Multiple ³
Bounds of size bins (µm in diameter)	3 modes ¹ 0.02–0.2– 2.0–20.0	12 bins 0.001–0.003– 0.006–0.016– 0.039–0.078– 0.156–0.313– 0.625–1.25– 2.5–5.0–10.0	5 bins 0.2–2.0–3.6– 6.0–10.0– 20.0	7 bins ² 0.2–0.36– 0.6–1.2–2.0– 3.6–6.0–12.0	5 bins 0.2–2.0–3.6– 6.0–10.0– 20.0	6 bins 0.2–0.44– 0.92–2.0– 4.30–9.28– 20.0	6 bins 0.2–0.5–1.0– 2.5–5.0– 10.0–20.0
Dust emission scheme	Zender et al. (2003)	Zender et al. (2003)	Ginoux et al. (2001)	Zender et al. (2003)	Ginoux et al. (2001)	Gillett (1998)	Multiple ³
Refrac. index (0.55 µm)	1.56 + 0.00194i	1.513 + 0.002074i	1.53 + 0.0024i	1.53 + 0.0033i	1.526 + 0.006i	1.53 + 0.002i	1.53 + 0.003162i
Refrac. index (10 µm)	2.917 + 0.65i	2.533908 + 0.769727i	2.1 + 0.5i	2.57 + 0.5i	2.21 + 1.02i	1.74 + 0.04975i	1.70 + 0.398107i
Main Reference	Liu et al. (2012, 2016)	Matsui et al. (2014, 2017) Matsui and Mahowald (2017)	Colarco et al. (2010, 2014) Collow et al. (2023)	Bey et al. (2001)	Zhao et al. (2018)	Takemura et al. (2000, 2005)	Kok et al. (2021a, b)

¹Size in CESM2 is the modal diameter of each mode. CESM2 has four aerosol modes, but dust is only carried in three of them. ²Bins 1–4 (0.2–0.2 µm) in GEOS-Chem are grouped together for mass simulations (emission, deposition, transport) (Zhang et al., 2025). ³DustCOMM is constructed based on multi-model ensemble output without harmonizing the meteorological fields and dust emission schemes.

The models differ in horizontal spatial resolution (ranging from 0.5° longitude × 0.5° latitude to 2.5° × 2°), number of vertical levels (30–72), meteorological forcing, and dust size representation. Four models include dust particle size up to 20 µm in diameter (D), while the other two truncate at 10–12 µm. For consistency, DustCOMM variables are included for particle sizes up to 20 µm, although information for larger sizes is available in the database (Adebiyi et al., 2023). All models and DustCOMM report dust emission flux, deposition flux (including gravitational settling, aerodynamic dry deposition, in-cloud rainout, and below-cloud washout), atmospheric mass loading, and MEE and DOD at 0.55 µm and 10 µm wavelengths, separated



144 into fine ($D \leq 2.5 \mu\text{m}$) and coarse ($D > 2.5 \mu\text{m}$) modes. AeroCom models provide monthly
 145 output between 2009 and 2012 while DustCOMM offers seasonal climatological quantities.
 146

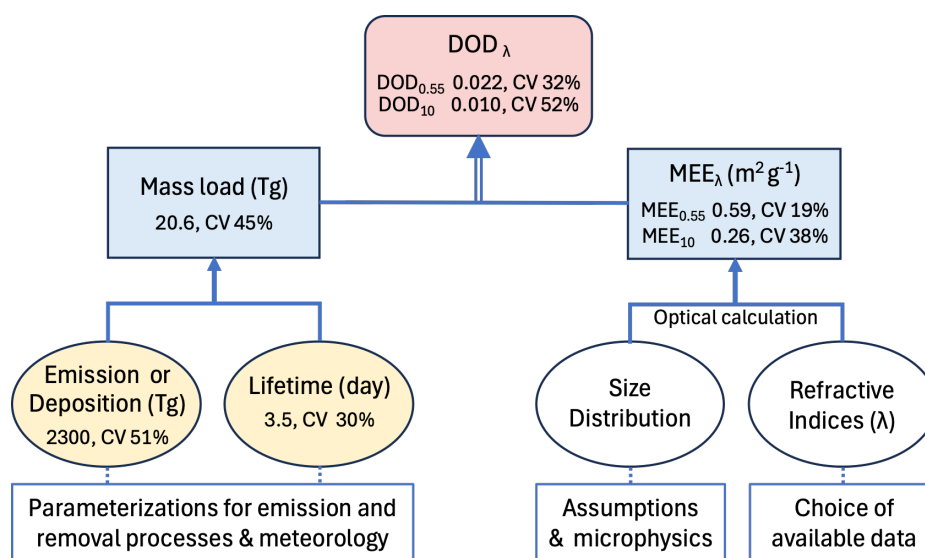


Figure 1. Simplified illustration of DOD calculated from the key bulk variables. The color-filled elements are discussed in the paper. The multi-model mean and inter-model coefficient of variation (CV), defined as standard deviation of model-calculated quantity divided by the multi-model ensemble mean, are listed under each variable and will be presented in Sect. 3 and 4. λ indicates wavelength-dependence. (In practice, DOD is integrated throughout the atmospheric column from the dust aerosol extinction profile, which is the product of vertically resolved dust mass concentrations and corresponding MEEs.)

147 Figure 1 illustrates the links of principal variables to calculate DOD in the models. On a global,
 148 annual scale, total dust emission should balance total deposition, and this balance, along with the
 149 lifetime determined by wet/dry removal frequencies, sets the atmospheric dust mass loading.
 150 Total DOD is the product of dust mass loading and MEE obtained from dust particle size
 151 distribution, complex refractive indices (CRI), and particle density. The variables highlighted in
 152 color are analyzed in this paper.

153

154 2.2. Remote sensing products

155

156 This study includes four satellite-based DOD_{10} datasets, three retrieved from IASI and one from
 157 MODIS. We use the Level-3 (L3) monthly composites with $1^{\circ} \times 1^{\circ}$ horizontal resolution with day



158 and night data (Copernicus Climate Change Service, Climate Data Store, 2019). Table 2

159 summarizes these products, with brief descriptions below.

160

161 Table 2. Summary of satellite DOD₁₀ data used in this study.

	IASI-LMD	IASI-MAPIR	IASI-ULB	MODIS-TIR
Primary approach for retrieving DOD ₁₀	Look-up table (LUT) approach: - Construction of TIR radiance LUTs for atmospheric/surface conditions and for dust - Retrieving DOD ₁₀ based on LUTs using proximity recognition	Optimal estimation method (OEM): - Retrieving vertical dust concentration profiles from TIR radiances - Obtaining DOD ₁₀ by integrating the dust concentration profiles $\times$ extinction cross-section	Artificial Neural Network (NN): - NN trained with vertical profiles of dust, temperature and humidity - DOD ₁₀ = $R \times CR$, where R = dust index from TIR radiance and CR = conversion ratio from NN	Synergistic and optimization approach: - 3-D dust <i>a priori</i> based on MODIS coarse AOD _{0.55} and CALIOP - RTMs calculation with optimization and minimized cost function for DOD ₁₀ and D _{eff} retrieval
Particle size ¹	Lognormal distribution (one mode): $R_{eff} = 2.3 \mu m$, $\sigma_g = 2.2$	Lognormal distribution (one mode): $R_g = 0.6 \mu m$, $\sigma_g = 2$, $R_{eff} = 2 \mu m$	Lognormal distribution in NN (one mode): $R_g = 0.5 \mu m$, $\sigma_g = 2$	D _{eff} retrieved dynamically together with DOD ₁₀
Refractive index	Two sets (Balkanski et al., 2007; Volz, 1973)	One set (Jacquinet-Husson et al., 2011)	One set (Volz, 1973)	19 source region-specific sets (Di Biagio et al., 2017)
L3 Output Products	DOD ₁₀ , mean layer altitude	DOD ₁₀ , mean layer altitude	DOD ₁₀	DOD ₁₀ , D _{eff}
DOD ₁₀ to DOD _{0.55} conversion	DOD ₁₀ = DOD _{0.55} $\times f$, where $f = Q_{10}/Q_{0.55} = 0.56-0.89$ varying with location ²	DOD ₁₀ = DOD _{0.55} $\times f$, where $f = Q_{10}/Q_{0.55} = 0.56$ globally ²	DOD ₁₀ = DOD _{0.55} $\times f$, where $f = 0.5$ (empirical)	DOD _{0.55} calculated with 19 source-specific refractive indices and retrieved D _{eff}
Main references	Capelle et al, 2018	Vandenbussche et al., 2026	Clarisse et al., 2019	Zheng et al., 2023, 2026

162 ¹R_{eff} = effective radius, R_g = geometric modal radius, σ_g = geometric standard deviation.

163 ²Q _{λ} = extinction efficiency from optical calculation with invariant size distribution and either one set of refractive
 164 index (IASI-MAPIR) or two sets (IASI-LMD).

165

166 IASI is a hyperspectral infrared sounder aboard the MetOP satellites, providing twice-daily
 167 global coverage (~ 9:30 AM and 9:30 PM local time) at ~12 km nadir resolution. The three IASI
 168 DOD₁₀ products are retrieved using different approaches and assumptions, each assuming a fixed
 169 particle size distribution with choices of dust CRI datasets.

- 170 • IASI-LMD (produced by Laboratoire de Météorologie Dynamique) uses physical Look-
 171 Up Tables (LUTs) of simulated IASI cloud-free radiance, constructed with extensive
 172 datasets of diverse atmospheric and surface conditions and dust characteristics. Using a
 173 proximity recognition, the first step determines the atmospheric state based on the



174 Atmospheric LUT and the second step retrieves DOD_{10} and mean dust aerosol altitude
 175 based on the Aerosol LUT (Capelle et al., 2018).

- 176 • IASI-MAPIR (Mineral Aerosol Profiling from Infrared Radiances) employs a physical
 177 Optimal Estimation method to retrieve vertical dust concentration profiles from cloud-
 178 free TIR radiances. DOD_{10} is obtained by integrating the retrieved dust concentration
 179 vertical profiles, multiplied by the Mie-calculated extinction cross-section based on
 180 assumed size distribution and CRI (Vandenbussche et al., 2026).
- 181 • IASI-ULB (produced by the Université libre de Bruxelles) uses an Artificial Neural
 182 Network (NN) trained on synthetic spectra and dust vertical profile climatology from the
 183 Cloud-Aerosol Lidar with Orthogonal Polarization (CALIOP), along with IASI-retrieved
 184 temperature and humidity profiles. The NN computes a dust index from TIR radiances
 185 and calculates a conversion ratio, and the DOD_{10} is a product of the dust index and the
 186 conversion ratio (Clarisse et al., 2019).

187

188 The fourth satellite dataset, MODIS-TIR, retrieves DOD_{10} and the coarse-mode dust effective
 189 diameter (D_{eff}) simultaneously. Using dust vertical profiles from CALIOP, atmospheric states
 190 from ERA-5 reanalysis, MODIS brightness temperature at the TIR channels, and the initial guess
 191 of dust size distributions and optical properties at 10 μm wavelengths, the algorithm retrieves
 192 DOD_{10} and D_{eff} via radiative transfer modeling and optimization (Zheng et al., 2023, 2026).

193

194 All satellite datasets also include $DOD_{0.55}$ products converted from DOD_{10} , using dust size
 195 distributions and CRI consistent with DOD_{10} retrievals or empirical conversion factors (see
 196 Table 2). These converted $DOD_{0.55}$ products primarily represent the coarse-mode dust detected in
 197 the TIR. For reference, we also include a monthly $DOD_{0.55}$ product, derived separately over
 198 ocean (Yu et al., 2009, 2019, 2020; Kaufman et al., 2005) and land (Ginoux et al., 2012; Pu and
 199 Ginoux, 2016) based on MODIS total $AOD_{0.55}$, fine-mode fraction, and Ångström exponent,
 200 tailored to separate dust from other aerosol types with self-consistent methods. This dataset is
 201 referred to as MODIS-YG (after principal developers H. Yu and P. Ginoux).

202

203 2.3. Chamber study data

204



205 Laboratory measurements of dust microphysical and optical properties from the Experimental
 206 Multiphase Atmospheric Simulation Chamber (CESAM) (Di Biagio et al., 2017, 2019) are used
 207 to evaluate model-simulated MEE, a key parameter in converting dust mass to optical depth.
 208 Nineteen natural soil samples from major dust source regions worldwide, representing natural
 209 variability in dust mineral composition, were selected for chamber experiments. Samples were
 210 mechanically dispersed to generate realistic dust aerosols. Particle size distributions (D from 0.02
 211 μm to several tens of μm) were measured using mobility and optical particle counters. Spectral
 212 extinction coefficients over 0.37–15 μm wavelength range were derived from nephelometer,
 213 aethalometer, and Fourier Transform Infrared spectrometer (FTIR) measurements. The CRI was
 214 determined at solar and infrared wavelength from these measurements (Di Biagio et al., 2017,
 215 2019).

216
 217 Data from the CESAM chamber experiments were used to derive size-resolved estimates of dust
 218 MEE at the wavelengths of interest, MEE_{10} and $\text{MEE}_{0.55}$, along with their ratio. For each of the
 219 nineteen samples, MEE_{10} and $\text{MEE}_{0.55}$ were calculated using Mie theory with experimentally
 220 measured dust size distributions and the sample-specific CRI. The experimental size distribution
 221 corresponded to the particle effective diameter (D_{eff}) ranging from 1.4 μm to 8.3 μm . These
 222 CESAM-derived MEE estimates serve as an observation-based reference for evaluating the
 223 model-calculated MEE and their dependence on particle size.

224

225 **3. Comparisons of DOD between satellites and models**

226

227 **3.1. Comparisons of $\text{DOD}_{0.55}$ from satellites and models with AERONET products**

228

229 Due to the lack of reference datasets for DOD_{10} , evaluation of DOD_{10} products typically relies on
 230 the comparisons with AERONET coarse-mode $\text{AOD}_{0.55}$ as an indirect approach. To do so,
 231 satellite-retrieved DOD_{10} are converted to $\text{DOD}_{0.55}$ with assumptions of wavelength-dependent
 232 optical properties and particle size information (Capelle et al., 2018; Vandenbussche et al, 2026;
 233 Clarisse et al., 2019; Zheng et al., 2026), while $\text{DOD}_{0.55}$ from models are directly simulated. In
 234 this study, we use the AERONET coarse-mode $\text{AOD}_{0.55}$ retrieved with the SDA algorithm
 235 (Version 3, Level 2) (Holben et al., 1998; O'Neill et al. 2003) in regions with pronounced dust
 236 influences as the closest proxy of $\text{DOD}_{0.55}$ (Kim et al., 2019, 2024). A total of 55 AERONET



237 sites mostly located in the “dust belt” were selected, following Kim et al. (2024). Figure 2 shows
 238 comparisons of the AERONET mean $\text{DOD}_{0.55}$, averaged over the available months during 2009–
 239 2012, with corresponding mean $\text{DOD}_{0.55}$ values from five satellite-based products (four
 240 converted from DOD_{10} and MODIS-YG derived from MODIS $\text{AOD}_{0.55}$), six AeroCom models,
 241 and DustCOMM.
 242

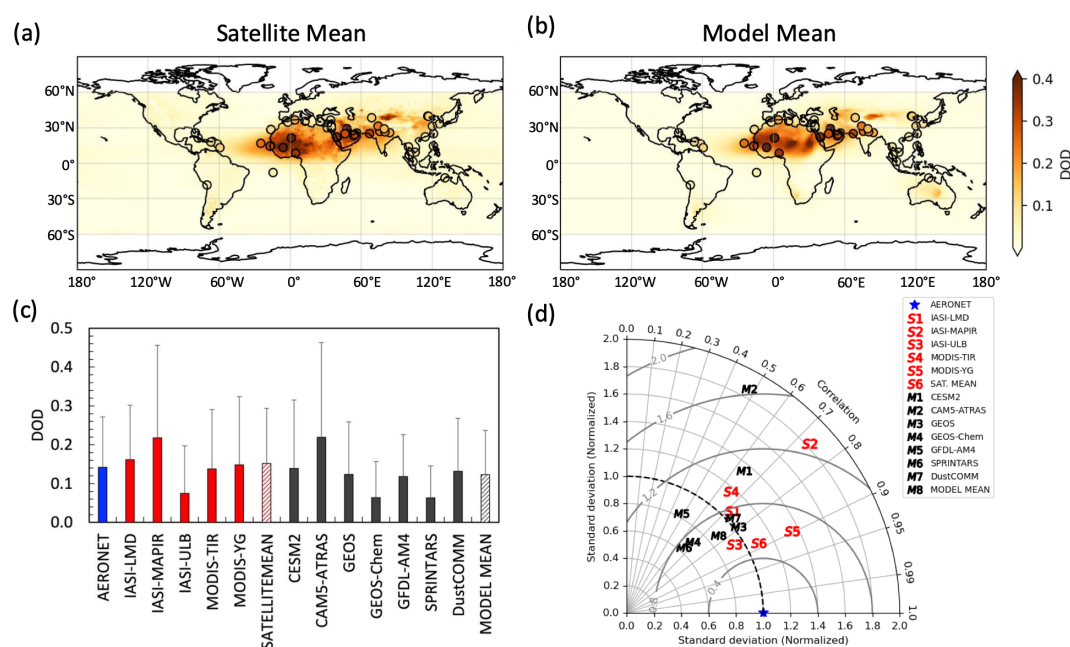


Figure 2. Horizontal distribution of $\text{DOD}_{0.55}$ averaged over 2009–2012 for (a) multi-satellite mean and (b) multi-model mean, superimposed with the AERONET $\text{DOD}_{0.55}$ (coarse mode $\text{AOD}_{0.55}$ in dust-dominant locations). (c) Mean and standard deviation of $\text{DOD}_{0.55}$ from AERONET, satellites, and models averaged over the 55 AERONET sites. (d) Taylor diagram of statistics of $\text{DOD}_{0.55}$ comparisons between individual dataset and AERONET.

243
 244 Both satellites and models broadly capture the magnitude and spatial variability of AERONET
 245 $\text{DOD}_{0.55}$ averaged over 2009–2012 (Fig. 2a–b). The AERONET mean $\text{DOD}_{0.55}$ over the 55 sites
 246 (0.14 ± 0.13) is comparable to the multi-satellite mean (0.15 ± 0.14) and the multi-model mean
 247 (0.12 ± 0.12), though individual datasets may differ by up to a factor of three (Fig. 2c). The
 248 Taylor diagram (Fig. 2d) shows the spatial correlation coefficients between individual datasets
 249 and AERONET ranging from 0.72 to 0.90 for satellites and from 0.48 to 0.79 for models, and



250 normalized standard deviations (relative to AERONET, with 1 indicating perfect match) vary
 251 from 0.93 to 1.82 for satellites and from 0.64 to 1.87 for models (Fig. 2d). Overall, multi-dataset
 252 means perform better than most individual datasets compared to AERONET, reflected in higher
 253 correlation coefficients and smaller differences in normalized standard deviation (Fig. 2d).
 254
 255 3.2. Global distributions of DOD_{10} and $DOD_{0.55}$ from satellite products and model simulations
 256
 257 Comparisons of global distributions of DOD are shown for the latitudinal range between 60°S –
 258 60°N , encompassing major dust source regions and transport pathways. Figures 3 and 4 compare
 259 spatial patterns of DOD_{10} and $DOD_{0.55}$, respectively, from satellites and models averaged over
 260 2009–2012, with mean values over the globe, land, and ocean (between 60°S – 60°N) from each
 261 product listed on the top of each panel.

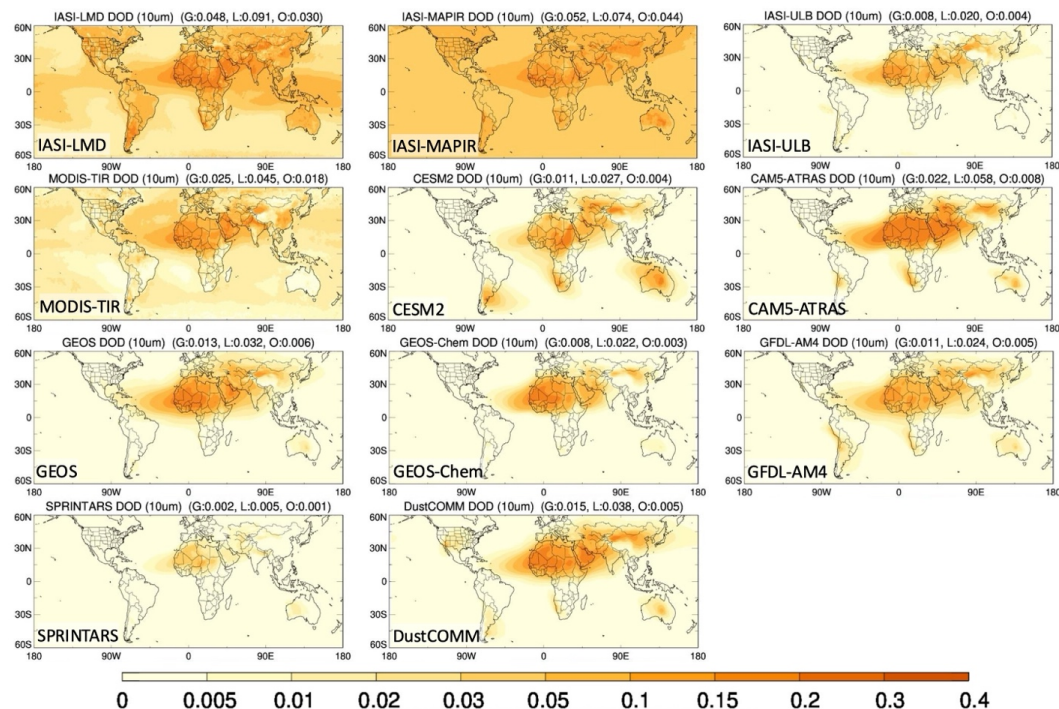


Figure 3. Horizontal distribution of DOD_{10} from four satellite retrievals, six model simulations averaged over 2009–2012, and climatological means from DustCOMM. The mean values over the globe (G), land (L), and ocean (O) between 60°S – 60°N from each product are listed on the top of individual panels.

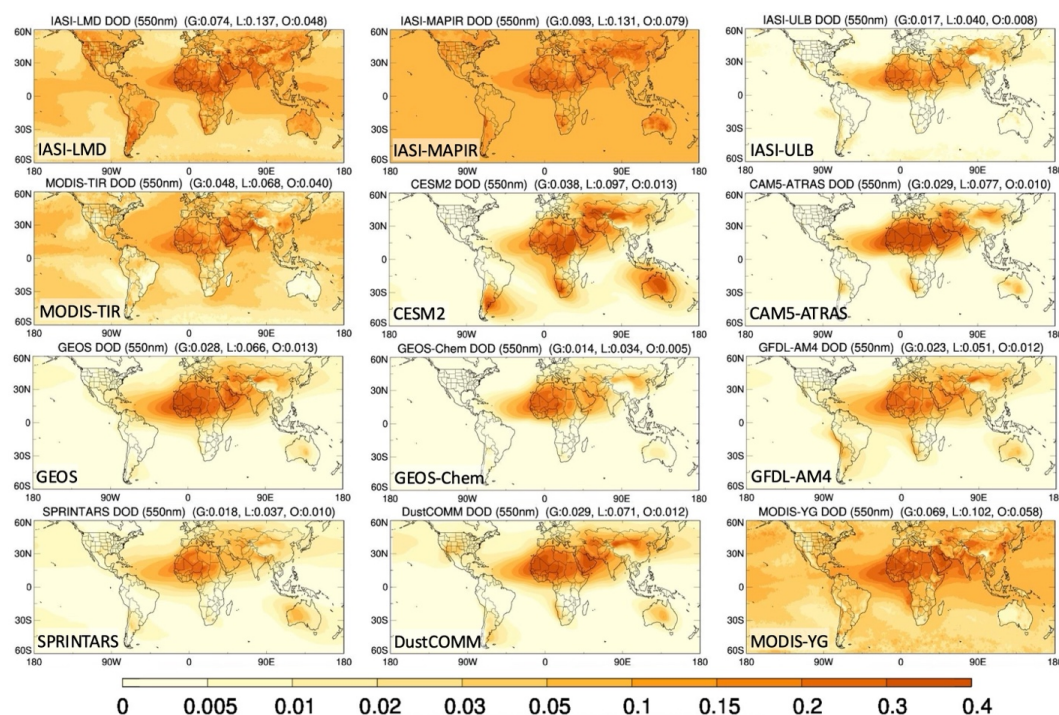


Figure 4. Same as Figure 3 but for $DOD_{0.55}$, plus MODIS-YG (last panel).

263
 264 All datasets reproduce major dust source regions and downwind transport pathways, but the
 265 magnitude and spatial extent vary significantly, including a factor of 10 difference in DOD_{10}
 266 over ocean (0.044 in IASI-MAPIR and 0.004 in IASI-ULB). Differences among satellite
 267 products are especially pronounced in Southern Hemispheric source regions and over oceans
 268 (Figure 3 and 4). For example, IASI-LMD and IASI-MAPIR show strong dust values over South
 269 America, southern Africa, and Australia ($DOD_{10} > 0.1$, $DOD_{0.55} > 0.2$), features absent in other
 270 satellite datasets, while IASI-ULB retrieves much lower dust amount outside of major source
 271 regions. Among models, CESM2 is the only one that simulates high DOD values over the
 272 Southern Hemispheric source regions ($DOD_{10} > 0.05$, $DOD_{0.55} > 0.2$); others show much lower
 273 values. Over Asia, most satellites and models capture Taklamakan, Gobi, and Thar desert
 274 sources, though some models (GEOS-Chem and SPRINTARS) exhibit weaker signatures.
 275 Quantitatively, global, land, and ocean means differ by up to an order of magnitude across
 276 datasets, with satellite spread comparable to model spread.



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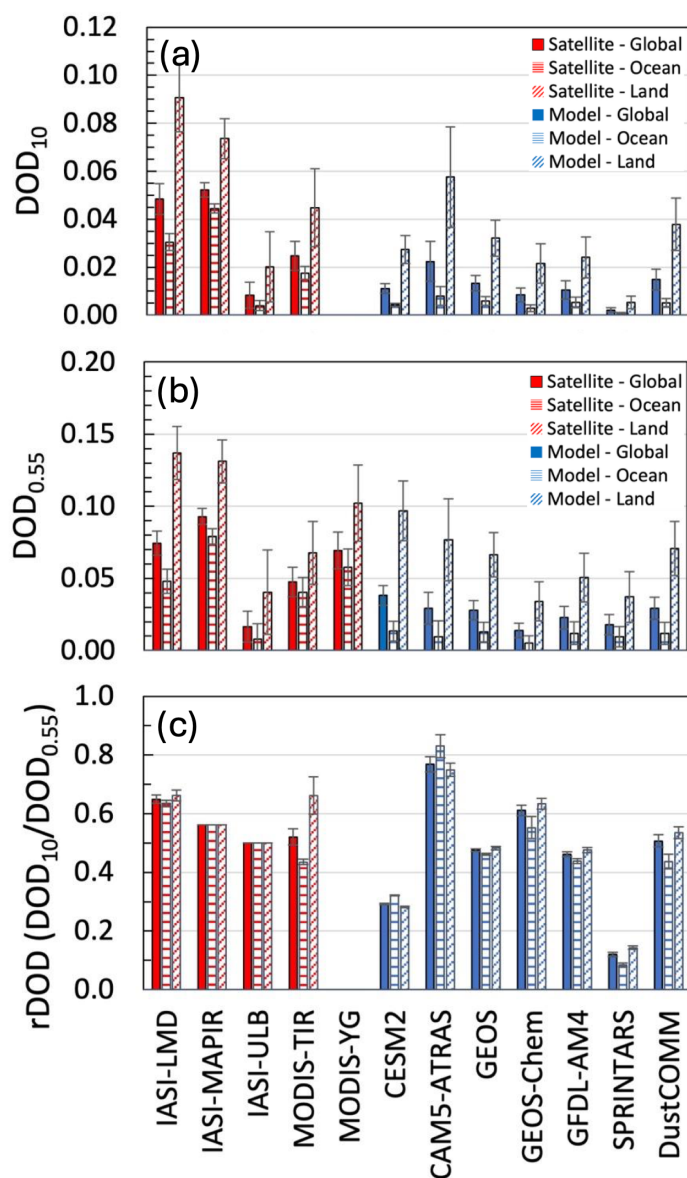


Figure 5. Global (solid), ocean (horizontal pattern), and land (gradient pattern) means of (a) DOD_{10} , (b) $DOD_{0.55}$, and (c) $rDOD$ from satellites (red) and models (blue) averaged over 60°S – 60°N for 2009–2012. Error bar is the standard deviation of monthly mean values.

278



Table 3. Global, land, and ocean mean values of (a) DOD₁₀, (b) DOD_{0.55}, and (c) rDOD between 60°S–60°N from satellite retrievals and model simulations.

	(a) DOD ₁₀			(b) DOD _{0.55} ¹			(c) rDOD		
Satellite:	Global	Land	Ocean	Global	Land	Ocean	Global	Land	Ocean
IASI-LMD	0.048	0.091	0.030	0.074	0.137	0.048	0.649	0.662	0.635
IASI-MAPIR	0.052	0.074	0.044	0.093	0.131	0.079	0.562	0.562	0.562
IASI-ULB	0.008	0.020	0.004	0.017	0.040	0.008	0.500	0.500	0.500
MODIS-TIR	0.025	0.045	0.018	0.048	0.068	0.040	0.521	0.661	0.435
Mean	0.033	0.058	0.024	0.058	0.094	0.044	0.558	0.596	0.533
CV (%)	62.0	54.6	71.0	56.9	50.7	66.7	11.8	13.3	16.0
Rmax/min	6.50	4.55	11.00	5.47	3.43	9.88	1.30	1.32	1.46
Model:	Global	Land	Ocean	Global	Land	Ocean	Global	Land	Ocean
CESM2	0.011	0.027	0.004	0.038	0.097	0.013	0.292	0.282	0.322
CAM5-ATRAS	0.022	0.058	0.008	0.029	0.077	0.010	0.768	0.750	0.830
GEOS	0.013	0.032	0.006	0.028	0.066	0.013	0.476	0.483	0.462
GEOS-Chem	0.008	0.022	0.003	0.014	0.034	0.005	0.612	0.634	0.552
GFDL-AM4	0.011	0.024	0.005	0.023	0.051	0.012	0.462	0.476	0.439
SPRINTARS	0.002	0.005	0.001	0.018	0.037	0.010	0.120	0.143	0.084
DustCOMM	0.015	0.038	0.005	0.029	0.071	0.012	0.507	0.535	0.436
Mean	0.012	0.029	0.005	0.026	0.062	0.011	0.462	0.472	0.446
CV (%)	52.6	55.2	48.7	31.2	36.6	26.2	45.4	43.4	50.5
Rmax/min	11.00	11.60	8.00	2.71	2.85	2.60	6.40	5.24	9.88

¹MODIS-YG DOD_{0.55} data is not included in the statistics. For reference, its global, land, and ocean mean DOD_{0.55} values are 0.069, 0.102, and 0.058, respectively.

Figure 5 and Table 3 summarize mean values and dataset diversity, measured by the maximum-to-minimum ratio ($R_{\max/\min}$) and Coefficient of Variation (CV) defined as the ratio of multi-dataset standard deviation to the mean, expressed as percentage. Satellite-retrieved DOD₁₀ spans a factor of 6.5 globally (0.008–0.052) and 11 over ocean (0.004–0.044), with IASI-ULB systematically showing lower values than other satellite products (Fig. 5a and Table 3a). The CV for inter-satellite difference of DOD₁₀ is 55% over land and 71% over ocean. Even greater spread is found across the models: model-simulated DOD₁₀ varies by a factor of 11 globally (0.002–0.022, CV = 53%), with poorer agreement over land (0.005–0.058, CV = 55%) than over ocean (0.001–0.008, CV = 49%). Among the models, CAM5-ATRAS and SPRINTARS consistently exhibit the highest and lowest DOD₁₀ values, respectively, over both land and ocean.

For DOD_{0.55} (Fig. 5b and Table 3b), satellite spread remains large, with similar inter-satellite statistics as for DOD₁₀. IASI-ULB again produces lower DOD_{0.55} values over both land and ocean than other satellite products. In contrast, models agree more closely with each other for



298 DOD_{0.55} (within a factor < 3 , CV $\approx 30\%$). CESM2 and GEOS-Chem produce the highest and
 299 lowest DOD_{0.55}, respectively.

300

301 Several features emerge when comparing satellite products and model results. First, the model-
 302 simulated DOD values are generally lower than the satellite products, especially over ocean. The
 303 multi-model mean values over land and ocean are respectively only 51% and 19% of the
 304 corresponding multi-satellite mean for DOD₁₀, and 66% and 25% for DOD_{0.55}. Second, the land-
 305 ocean contrast of DOD from the models (mean land-to-ocean ratio = 6) is twice that indicated by
 306 satellite data (mean ratio = 3), consistent with longstanding issues indicating too rapid dust
 307 removal during transport in many global models (e.g., Kim et al., 2014; Yu et al., 2019). Third,
 308 the multi-model means are generally closer to MODIS-TIR over land but closer to IASI-ULB
 309 over ocean; agreement is worse with other satellite-retrieved quantities. The multi-model mean
 310 of land-to-ocean DOD ratio (6.3) also agrees better with that from IASI-ULB (5.0) than with
 311 other satellites (1.7–3.0).

312

313 3.3. Ratio of DOD₁₀ to DOD_{0.55}

314

315 The ratio of DOD₁₀ to DOD_{0.55} (rDOD) characterizes the dust extinction efficiency in the TIR
 316 relative to mid-visible wavelength. Prior studies estimated rDOD ≈ 0.3 –0.65, depending on CRI
 317 and dust particle size distributions (Pierangelo et al. 2004; Callewaert et al., 2019; Yu et al.,
 318 2019). This ratio is expected to be larger over source regions that are more dominated by coarse
 319 dust (Fig. S1).

320

321 Results of rDOD are summarized in Fig. 5c and Table 3c. Satellite-derived rDOD values reflect
 322 differences in both retrieval methodology for DOD₁₀ and conversion to DOD_{0.55} (Table 2). In the
 323 three IASI algorithms, dust particle D_{eff} and composition are fixed globally, such that the rDOD
 324 is either empirically assumed to be 0.5 in IASI-ULB or calculated based on the CRI used in
 325 IASI-LMD and IASI-MAPIR retrievals, resulting in rDOD = 0.56 from the single set of CRI in
 326 IASI-MAPIR but varies geographically in IASI-LMD from the mixture of the two CRI datasets,
 327 resulting in higher rDOD (> 0.7) in the dust belt than in more remote areas (Fig. S1). On the
 328 other hand, MODIS-TIR considers particle size and source region dependence, yielding higher
 329 rDOD over land (0.66) than over ocean (0.44). Across satellites, mean rDOD values fall within



330 30–40% with each other, with multi-satellite mean of 0.60 over land and 0.53 over ocean (Table
 331 3c).

332

333 Models show greater diversity in rDOD, with global mean value ranging from 0.12
 334 (SPRINTARS) to 0.77 (CAM5-ATRAS). Generally, rDOD is higher over land than over ocean
 335 in most models but the opposite in CAM5-ATRAS and CESM2 (also see Fig. S1), likely to be
 336 associated with the dust microphysical and optical properties not fully diagnosed here. On
 337 average, the model-calculated rDOD is 0.47 over land and 0.45 over ocean, lower than satellite
 338 means by ~ 0.1 . As illustrated in Fig. 1, DOD is the product of dust mass loading and MEE
 339 calculated in models. Since the dust loading does not change with wavelength, the inter-model
 340 differences of rDOD should reflect directly the ratio of MEE at 10 μm to that at 0.55 μm
 341 wavelengths (rMEE), calculated from dust particle size distributions and CRI. Inter-modal
 342 diversity of rDOD will be further examined next in the context of MEE.

343

344 3.4. Comparison of spectral MEE from models with CESAM chamber measurements

345

346 Four AeroCom models and DustCOMM provide dust particle size-resolved (size bins in Table 1)
 347 MEE at 10 and 0.55 μm wavelengths for dust particle diameter range from 0.2 to 20 μm , which
 348 are compared in Fig. 6 with CESAM chamber measurements available in the D_{eff} range of 1.4–
 349 8.3 μm . This section presents the results from the comparisons with further discussion provided
 350 in Section 5.

351

352 At 10 μm wavelength, both chamber data and most models show increasing MEE_{10} with dust
 353 particle size up to $\sim 2\text{--}4\text{ }\mu\text{m}$, followed by decreasing values for larger particles (Fig. 6a). The
 354 chamber data also exhibit a considerable spread in MEE_{10} values (up to $0.2\text{ m}^2\text{ g}^{-1}$ apart) at a
 355 given D_{eff} , primarily associated with variations in clay minerals and quartz proportions among
 356 the samples, which strongly affect the CRI and extinction at 10 μm (Di Biagio et al., 2017). Most
 357 models overestimate MEE_{10} relative to the chamber data for $D > 2\text{ }\mu\text{m}$, except SPRINTARS,
 358 which shifts the peak to larger particle sizes and produces notably much lower MEE_{10} at $D = 2\text{--}4$
 359 μm range than the chamber data and other models. MEE_{10} from SPRINTARS is about ten times
 360 lower than that from all other models at 0.2–1 μm diameter range and shows the largest variation
 361 of MEE_{10} with particle size.



362

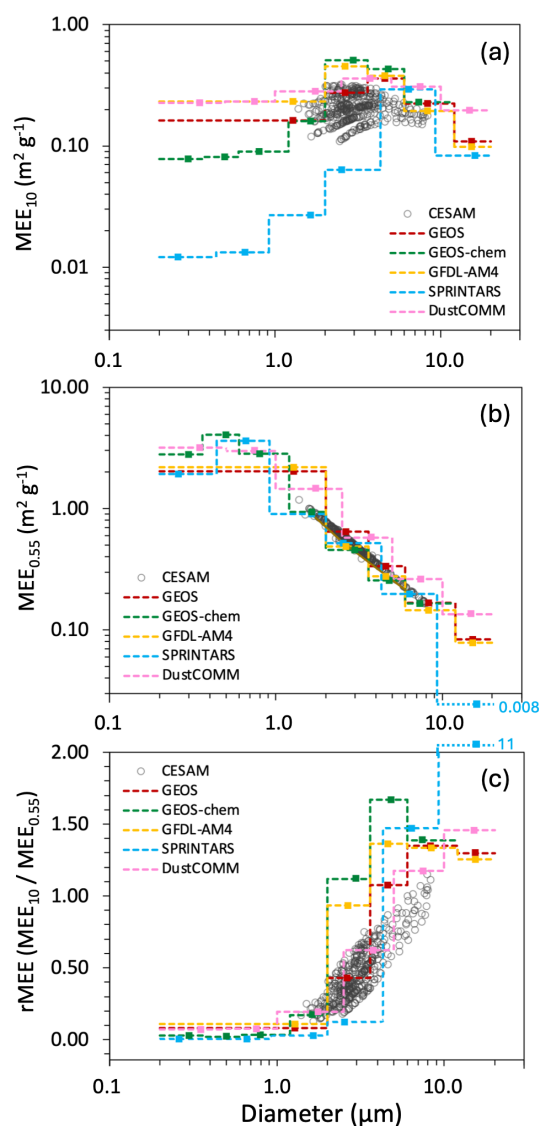


Figure 6. Comparisons of dust particle size-dependent MEE available from four of the participating models and DustCOMM (colored lines and symbols) with the CESAM laboratory measurements (grey circles). (a) MEE at 10 μm wavelength. (b) MEE at 0.55 μm wavelengths. and (c) ratio of MEE at 10 μm to that at 0.55 μm wavelengths (rMEE). Dashed color lines represent the model calculated MEE values for each size bins (diameter bounds in Table 2) and the colored symbols are the D_{eff} for the corresponding size bins. Values of the largest dust size bin in SPRINTARS in panels (b) and (c) are beyond the y-axis ranges and are indicated by the off-scale light blue dotted-lines together with actual values.

363



At 0.55 μm wavelength, chamber data and models both show an exponential decrease of $\text{MEE}_{0.55}$ with the increase of particle size (Fig. 6b), and the modeled $\text{MEE}_{0.55}$ values generally agree with the chamber data within $\sim 30\%$ in their overlapping particle size range (DustCOMM is higher than other models). However, inter-model differences are more substantial outside the chamber size range, with SPRINTARS $\text{MEE}_{0.55}$ at 10–20 μm diameter as a clear outlier for its two orders of magnitude lower value than other models. Unlike MEE_{10} (Fig. 6a), chamber $\text{MEE}_{0.55}$ data from different soil samples are essentially identical, independent of mineral composition.

Figure 6c shows the ratio of MEE_{10} to $\text{MEE}_{0.55}$ (rMEE) as a function of dust particle diameter. The ratio increases with particle size in the chamber data driven mostly by the magnitude of $\text{MEE}_{0.55}$ decrease with particle size (Fig. 6b), because the change of MEE_{10} with size is much weaker (Fig. 6a). DustCOMM seems to better represent the range of the rMEE from the chamber data compared to other models, though its MEE_{10} and $\text{MEE}_{0.55}$ are generally higher. Other models display model-specific behaviors, with SPRINTARS showing a steep monotonic increase in the entire particle size range ($D = 0.2\text{--}20\ \mu\text{m}$), with the lowest rMEE at $D < 4.5\ \mu\text{m}$ because of its low MEE_{10} (Fig. 6a) but extremely high rMEE at $D > 9\ \mu\text{m}$ due to its very low $\text{MEE}_{0.55}$ (Fig. 6b).

4. Differences in dust physical and optical properties represented in models

In this section, we analyze inter-model differences in simulated dust quantities, including mass budget, optical properties at 0.55 μm and 10 μm wavelengths, and the respective contributions of fine ($D \leq 2.5\ \mu\text{m}$) and coarse ($D > 2.5\ \mu\text{m}$) mode dust. The results are summarized in Fig. 7, with detailed values provided in Tables S1–S3, where model simulations are averaged globally ($90^\circ\text{S--}90^\circ\text{N}$).

4.1. Model differences in dust mass budget and optical properties in determining DOD

Figure 7 presents the global annual mean dust mass and optical property variables from the AeroCom models and DustCOMM, supplemented by Table S1. Across models, global total dust emission (Fig. 7a) and the column mass loading (Fig. 7b) vary widely, with a multi-model mean of $2300 \pm 1178\ \text{Tg yr}^{-1}$ for emission ($\text{CV} = 51\%$) and $20.6 \pm 9.2\ \text{Tg}$ for loading ($\text{CV} = 45\%$).



396 CAM5-ATRAS produces the highest emission (4031 Tg yr⁻¹) and largest mass loading (33 Tg),
 397 despite having the smallest coarse-mode size range (up to 10 μm in diameter, Table 1) among the
 398 models. In contrast, GEOS-Chem, with similar coarse-mode size range (up to 12 μm), shows the
 399 lowest emission (1131 Tg yr⁻¹) and nearly the lowest mass loading (11 Tg). Notably, differences
 400 in mass loading do not scale directly with emission, as dust lifetimes also vary considerably
 401 across models (2–5 days; CV = 30%). For example, GEOS produces ~20% lower emission than
 402 SPRINTARS but ~2 times higher loading, due to a longer dust lifetime (5.3 vs. 2.3 days).
 403

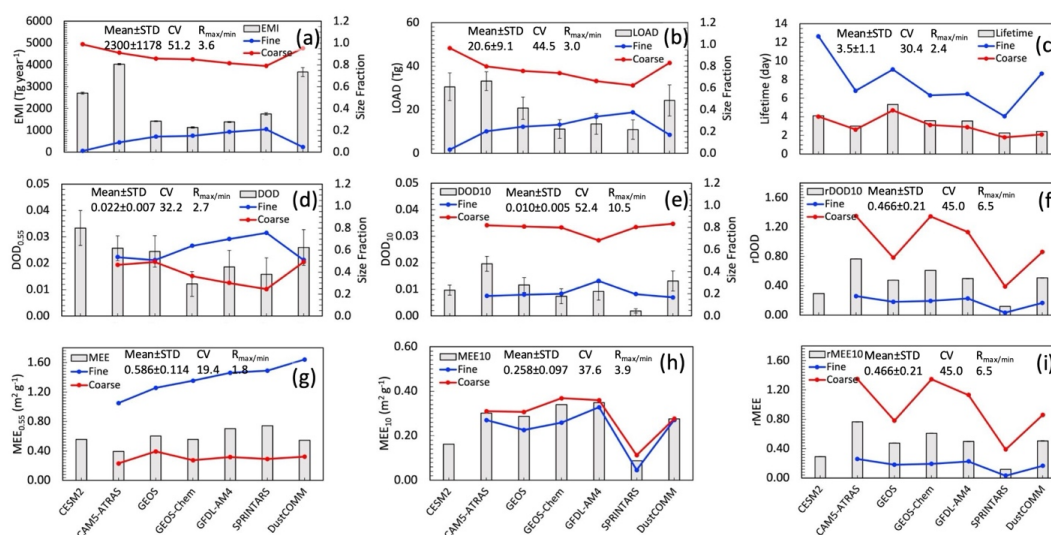


Figure 7. Global means of (a) emission, (b) column loading, (c) lifetime, (d) DOD_{0.55}, (e) DOD₁₀, (f) rDOD, (g) MEE_{0.55}, (h) MEE₁₀, and (i) rMEE from the models, averaged over 2009–2012. Blue and red lines represent fine- and coarse-mode dust, respectively, fractions in panels a, b, d, and e but actual values in other panels. Numbers on top of each panel are multi-model mean, standard deviation, Coefficient of Variation (CV), and the ratio of maximum to minimum values across models. (The numbers on each panel are slightly different from Table 2 which shows the means over 60°S–60°N for proper comparisons to satellite data.)

404
 405 Model-simulated DOD reflects differences in both total mass loading and bulk MEE. DOD_{0.55}
 406 varies by a factor of 2.7 with CV = 32% (Fig. 7d), which is less than the spread in mass loading
 407 (CV = 45%, Fig. 7b) but more than that in MEE_{0.55} (19%, Fig. 7g). Models may produce similar
 408 DOD_{0.55} by compensating high (low) mass loading with low (high) MEE_{0.55}. For example, the
 409 loading from CAM5-ATRAS is ~37% higher than DustCOMM whereas the MEE_{0.55} from
 410 DustCOMM is ~38% higher than CAM5-ATRAS, resulting in identical DOD_{0.55} values (0.026).



411
 412 In contrast, DOD_{10} (Fig. 7e) exhibits much larger inter-model variability ($R_{\text{max/min}} = 11$; $\text{CV} =$
 413 52%), inherited from the combined spread in mass loading and MEE_{10} ($\text{CV} = 38\%$, Fig. 7h).
 414 SPRINTARS produces the smallest bulk MEE_{10} , consistent with its size-resolved MEE_{10} (Fig.
 415 6a), likely attributable to a very low imaginary part of the CRI at $10\ \mu\text{m}$, which is 10–20 times
 416 lower than other models (Table 1). This low MEE_{10} , combined with its low mass loading, yields
 417 the lowest DOD_{10} in SPRINTARS, amplifying the overall model spread.
 418
 419 The ratio $\text{DOD}_{10}/\text{DOD}_{0.55}$ (rDOD ; Fig. 7f) is equivalent to rMEE (Fig. 7i) and varies by a factor
 420 of 6.5 across models (0.12–0.76). The multi-model mean rDOD (and rMEE) is 0.47 ± 0.21 (CV
 421 $= 45\%$), indicating substantial disparities in how models represent spectral dust optical
 422 properties.
 423
 424 In summary, large differences in dust emission and lifetime drive significant inter-model
 425 variability in dust mass loading. These differences are amplified at $10\ \mu\text{m}$ wavelength, due to
 426 greater divergence in MEE_{10} compared to $\text{MEE}_{0.55}$, resulting in the largest spread in DOD_{10}
 427 among all modeled variables (CV values for the key variables are summarized in Fig. 1).
 428
 429 4.2. Fine- and coarse-mode dust contributions to total dust
 430
 431 We use fine-mode ($D \leq 2.5\ \mu\text{m}$) and coarse-mode ($D > 2.5\ \mu\text{m}$) partitioning from five AeroCom
 432 models and DustCOMM to quantify their contributions to global dust emission, loading, and
 433 DOD . The global mean values are presented in Fig. 7 (colored lines, right y-axis) with
 434 supplementary information in Tables S2–S3 and Figures S2–S3).
 435
 436 All models show that the coarse dust dominates emission and mass loading, contributing on
 437 average 88% for emissions ($79\text{--}99\%$) and 77% for loading ($62\text{--}97\%$) (Fig. 7a–b). Lower
 438 coarse-mode fractions in loading relative to emissions reflect shorter lifetime of coarse particles
 439 (2–5 days) compared with fine particles (4–13 days) (Fig. 7c). Among individual models, coarse-
 440 mode contribution to emission and loading is lowest in SPRINTARS and highest in CESM2.
 441 Notably, the inter-model differences in emitted fine- and coarse-mode fractions seem to be
 442 predominantly determined by the diverse emission parameterizations rather than the size range;



for example, CAM5-ATRAS has the smallest coarse-mode dust size upper bound at 10 μm diameter but a higher coarse particle fraction in emission than models with extended coarse-mode particle size at 20 μm .

For $\text{DOD}_{0.55}$ (Fig. 7d), models fall into two groups: CAM5-ATRAS, GEOS, and DustCOMM report roughly equal fine/coarse contributions (51–54%; fine slightly higher) while GEOS-Chem, GFDL-AM4, and SPRINTARS show fine-mode dominance (64–76%). These differences reflect combined effects of size-dependent MEE and mass loading. Although all models show much higher $\text{MEE}_{0.55}$ for fine-mode ($1.0\text{--}1.6\text{ m}^2\text{ g}^{-1}$) than for coarse-mode ($0.2\text{--}0.4\text{ m}^2\text{ g}^{-1}$) (Fig. 7g), the fine-mode mass fractions in the second model group are larger than those in the first group, resulting in greater fine-mode contribution to $\text{DOD}_{0.55}$.

In contrast, estimated contributions of fine- and coarse-mode particles to DOD_{10} are much more consistent across models (Fig. 7e): most models indicate ~80% coarse-mode contributions (except 68% in GFDL-AM4) despite very similar MEE_{10} values between fine- and coarse-mode (Fig. 7h). Here, the larger coarse-mode fractions in dust mass loading (mean 77%; Fig. 7b) determine the comparable contributions of coarse-mode dust to DOD_{10} (mean 79%; Fig. 7e), indicating that DOD_{10} closely represents coarse-mode dust loading in the atmosphere.

This analysis also highlights the strong spectral-dependence of fine-mode dust MEE. It decreases by a factor of 6 from $1.37\text{ m}^2\text{ g}^{-1}$ at $0.55\text{ }\mu\text{m}$ wavelength to $0.23\text{ m}^2\text{ g}^{-1}$ at $10\text{ }\mu\text{m}$ (Table S2). In sharp contrast, coarse-mode MEE shows little variation between mid-visible and TIR, with $\text{MEE}_{0.55}$ only 5% higher than MEE_{10} on average ($0.30\text{ m}^2\text{ g}^{-1}$ vs. $0.29\text{ m}^2\text{ g}^{-1}$, Table S3).

Results from this study are broadly consistent with earlier modeling and observational studies. In a global study, Di Biagio et al. (2020) estimated that fine-mode dust ($D_{\text{eff}} \leq 2\text{ }\mu\text{m}$) contributes about 13% to dust mass loading and 54% to $\text{DOD}_{0.55}$, values within the ranges seen across models here, though multi-model means are somewhat higher (fine dust contributing 23% to mass loading and 61% to $\text{DOD}_{0.55}$, Table S2).

Field measurements in past 50 years synthesized by Formenti and Di Biagio (2024) showed that dust particles become increasingly smaller with transport time: fine-mode mass fractions



increase from 11% near sources to 22% after 1–4 days of transport and 53% after more than 4 days away from the source. This feature is qualitatively consistent with model simulated spatial gradient in this study, with fine-mode fractions lower over source regions and higher over remote oceans (Fig. S2), although model diversity remains large. Compared to other models, GEOS shows much smaller spatial contrasts for fine- and coarse-mode fractions (Figs. S2–S3). This is due to a modified dust settling velocity (per Maring et al., 2003) that much more effectively reduced sedimentation removal for particles with $D < 6 \mu\text{m}$ than for larger particles. Such modification resulted in reduced spatial inhomogeneity for fine and coarse mode fractions.

5. Discussion

5.1 Differences in DOD_{10} across satellite products

The results presented in previous sections reveal a substantial spread in satellite-retrieved DOD_{10} values, with a CV of 62% for the global mean (Table 3). Even with identical IASI top-of-atmosphere radiance measurements, the three IASI-based DOD_{10} retrievals exhibit considerable variability by a factor of six over land and ten over ocean (Table 3). Similar discrepancies among IASI DOD_{10} products have been documented in case studies, such as the Central Asia dust storm analyzed by Xi et al. (2025). These pronounced differences reflect variations in retrieval algorithms, assumptions about dust physical and optical properties, auxiliary data inputs, and handling of noise and interference. TIR retrievals are particularly sensitive to dust altitudes, composition (particularly the imaginary part of the CRI), surface emissivity, temperature contrast between the surface and dust layer, and cloud-clearing method. The uncertainties and differences in DOD_{10} among IASI products are amplified in regions outside primary dust sources and main transport pathways, where signal-to-noise ratios are higher. In contrast, DOD_{10} from MODIS-TIR, retrieved using a more sophisticated approach that accounts for dust mineral composition and particle size variations, fall within the range of IASI products.

The spectral ratio rDOD (DOD_{10} to $\text{DOD}_{0.55}$ ratio) further highlights differences in satellite approach. IASI products display constant or small variability in rDOD due to their invariant particle size distributions and lack of dust composition consideration. MODIS-TIR, however, incorporates retrieved particle sizes and a range of CRI values, reflecting the diversity of dust



507 composition associated with different source regions (see Table 2 and listed references),
 508 resulting in greater spatial variability in rDOD.

509

510 While the present study cannot fully quantify the individual factors contributing to discrepancies
 511 among satellite DOD₁₀ products, chamber measurements from CESAM (Fig. 6a) suggest that
 512 variations in MEE₁₀ across dust from different locations alone could cause a two- to threefold
 513 difference in DOD₁₀. This is primarily due to differences in dust composition, which are
 514 especially influential in the TIR wavelengths but are not considered in the IASI retrieval
 515 algorithms.

516

517 5.2. Differences in DOD₁₀ across model simulations

518

519 Our study also finds substantial differences across model-simulated DOD₁₀ with a spread (CV =
 520 52%) comparable in magnitude to the spread across satellite products. Notably, inter-model
 521 differences are more pronounced over land (more than a factor of 11) than that over ocean (a
 522 factor of 8). These discrepancies arise from both the variability in dust mass loading (CV =
 523 44%), which reflects differences in the treatment of dust emission and removal processes, and
 524 the difference in MEE₁₀ (CV = 38%), determined by dust CRI and size distributions (see Fig. 1).

525

526 For mass-related terms (dust emissions, mass loading, lifetime), the inter-model spread observed
 527 here is consistent with earlier AeroCom studies (Textor et al., 2006; Huneus et al., 2011),
 528 indicating limited convergence despite decades of model development. This persistent
 529 divergence is largely due to the lack of observational constraints for these quantities. Attribution
 530 of the large differences is challenging with available information; for example, three out of six
 531 AeroCom models employ the same dust emission scheme from Zender et al. (2003) (Table 1),
 532 yet emission amounts differ by a factor of three even with the same particle size range, as
 533 discussed in Section 3. More detailed examination of relevant meteorological fields, adjustment
 534 factors, particle size distributions, and emission parameterization is needed in future studies. This
 535 also applies to diagnosing removal processes, including settling velocity, dry and wet removal
 536 parameterizations, and associated meteorological fields.

537



Regarding dust optical property MEE, model results shown in Fig. 7 and Table S1 represent bulk quantities for the entire dust size range, derived from the ratio of DOD and mass loading per unit area. Comparisons of size-segregated MEE from models with CESAM chamber data (Fig. 6) indicate that the agreement of $MEE_{0.55}$ between models and chamber data is generally within 30% at 0.55 μm wavelength in their common dust size range (Fig. 6b). This is because dust extinction at 0.55 μm is governed by the real part of the CRI, which is nearly identical between models (1.53 ± 0.01 , Table 1) and CESAM chamber measurements (1.52 ± 0.02 from 19 soil samples, Di Biagio et al., 2019), resulting in similar $MEE_{0.55}$ with variation dictated by the change of particle size (Fig. 6b). In contrast, MEE_{10} values are much more widely spread among models as well as in the CESAM measurements (Fig. 6a), as dust extinction at 10 μm is largely determined by the imaginary part of the CRI, which varies significantly among models (0.55 ± 0.30 , Table 1) and also distinguishable among the soil samples (0.33 ± 0.15) measured by CESAM, reflecting mineral composition variability (Di Biagio et al., 2017). Notably, the substantially lower MEE_{10} in SPRINTARS is likely attributable to its 10–20 times lower imaginary refractive index at 10 μm compared to all other models (Table 1).

5.3. Challenges and recommendations

A major challenge in evaluating the DOD_{10} products from both satellite retrievals and model simulations is the lack of reference datasets for DOD_{10} . As a result, assessments must rely on indirect comparisons of $DOD_{0.55}$, either converted from satellite DOD_{10} using simple $rDOD$ values or simulated directly by the models, with the AERONET $DOD_{0.55}$ proxy (AERONET retrieved coarse-mode $AOD_{0.55}$ in dust dominated areas; see Sect. 3.1 and Fig. 2). While these comparisons show reasonable spatial correlations ($R = 0.72\text{--}0.90$ for satellites; $0.48\text{--}0.79$ for models), persistent discrepancies of a factor of 3–4 remain. Moreover, evaluations are limited to dusty continental and near-coastal sites, with no dust-specific reference observations are available over open ocean where DOD_{10} disagreement among satellite TIR products and between satellites and models is greatest. Thus, comparisons with AERONET $DOD_{0.55}$ proxy are informative but insufficient for validating DOD_{10} .

To advance understanding, more coordinated efforts are needed to address differences in DOD_{10} products across satellite retrievals and model simulations. For models, comparisons should go



beyond the present study to include emission schemes/parameterizations and associated meteorological fields, settling velocity and wet removal parameterizations, particle shape and size distributions, CRI and its wavelength dependence, optical calculation methods, and size-resolved mass and optical property outputs. For satellites, it may start with sensitivity tests using consistent external or prescribed information, such as emissivity, dust layer height, particle size distribution, and CRI. Collaboration between AeroCom and AeroSat communities is essential to define activities and establish ways forward to enhance the quality and confidence in DOD₁₀ products.

This study highlights not only the current state of DOD₁₀ from satellites and models, but also the potentials for remote-sensing and modeling studies of dust composition. The source-location dependent CESAM MEE₁₀ and MEE_{0.55} data used in this study, along with CRI and mineral information (Di Biagio et al., 2017, 2019), suggest the advantage of TIR remote sensing for dust composition analysis. Combining shortwave and TIR dust aerosol optical measurements offers the potential to map dust aerosol mineral composition with distinct spectral sensitivities. With the recent advances in soil mineral content observations from NASA's Earth Surface Mineral Dust Source Investigation (EMIT) satellite mission (Green et al., 2023; Thompson et al., 2024) and ongoing modeling development to incorporate atmospheric dust composition (e.g., Song et al., 2024; Li et al., 2026), it is a critical time for modeling and satellite communities to collaborate and address dust environmental effects from a composition perspective through the lenses of SW and LW spectral domains.

6. Conclusions

This AeroCom-AeroSat study presents the first comprehensive comparison of dust optical depth at 10 μm (DOD₁₀), synthesizing results from four satellite retrievals, six global model simulations, DustCOMM climatology, and laboratory measurements of dust properties. The main findings are as follows:

- *Substantial variability in DOD₁₀ products:* Both satellite-retrieve and model-simulated DOD₁₀ exhibit large spread across them. On average values over 2009-2012, satellite products differ by a factor of 4.6 over land and 11 over ocean, with coefficient of



601 variation (CV) at 62% for global mean values. Models differ by a factor of ~12 over land
 602 and 8 over ocean, with CV at 53% for global mean values.

- 603 • *Sources of discrepancy*: Differences among satellite DOD₁₀ products arise from
 604 algorithmic design, retrieval assumptions (including dust size distributions, optical
 605 properties, dust layer height, meteorological inputs), and auxiliary data sources, while the
 606 model DOD₁₀ differences are attributable to the diversities in dust emission.
 607 parameterizations, removal processes, and mass extinction efficiencies (MEE), which are
 608 determined by dust complex refractive indices (CRI) and size distributions.
- 609 • *Spectral ratios*: Spectral ratios of DOD₁₀/DOD_{0.55} (rDOD) from satellites fall within a
 610 relatively narrow range (differing within 40%), largely due to simplified assumptions
 611 regarding the spectral dependence of dust optical properties and size distributions. In
 612 contrast, model rDOD vary by more than a factor of 6–8, reflecting significant disparities
 613 in model TIR optical properties.
- 614 • *Mass extinction efficiency (MEE)*: Disagreement in MEE at 10 μm (MEE₁₀) is a major
 615 source of model discrepancy in DOD₁₀. Bulk MEE₁₀ from models differ by a factor of 4,
 616 which is twice the differences at 0.55 μm (MEE_{0.55}). Comparisons with laboratory
 617 chamber measurements highlight substantial spread in modeled size-dependent MEE₁₀,
 618 stemming from the discrepancies in CRI at 10 μm wavelength.
- 619 • *Fine vs. coarse dust contributions*: The multi-model mean indicates that fine-mode dust
 620 (diameter ≤ 2.5 μm) contributes approximately 60% to DOD_{0.55}, while coarse-mode dust
 621 (diameter > 2.5 μm) accounts for about 80% of DOD₁₀.

622

623 Collectively, these results demonstrate that the representation of coarse-mode dust, including its
 624 atmospheric abundance, size distribution, optical properties, and lifetime, remains a major source
 625 of uncertainty for both shortwave and longwave radiative effects (Adebisi et al., 2023). Progress
 626 in this area will require a) observational constraints on TIR dust optical properties, b) expanded
 627 laboratory measurements of size-resolved CRI and extinction efficiency to a wider particle size
 628 range, c) improved retrieval accuracy and sensitivity especially over dust transport pathways, and
 629 d) continued model developments to better represent coarse dust emissions, transport, removal,
 630 size distribution, and optical properties.

631



632 A reliable reference dataset for DOD₁₀ would substantially strengthen future satellite and model
 633 evaluations. Until such data becomes available, coordinated efforts between modeling and
 634 remote sensing communities on multi-platform comparisons, sensitivity analyses, and integration
 635 of new observational data, are essential. Advancing collaboration, especially in light of recent
 636 developments in dust composition measurements and modeling, will be crucial for enhancing the
 637 reliability and scientific value of DOD₁₀ products and for guiding improvements in the
 638 representation of dust in the Earth system.

639

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664

665 **Data availability**

666

667 The model simulation outputs from the AeroCom Phase III Dust Source Attribution (DUSA)
668 experiment used in this study are archived in the AeroCom repository hosted by the Norwegian
669 Institute of Meteorology. They can be accessed following the procedure described
670 at https://aerocom.met.no/FAQ/data_access/retrieve_data/ (last access: 27 April 2026).
671 DustCOMM data is available from <https://dustcomm.atmos.ucla.edu> (last accessed 7 Oct, 2024).
672 All IASI data product is available from the Copernicus Climate Change Service (C3S) Climate
673 Data Store (CDS) (DOI: 10.24381/cds.239d815c, last access: 29 August 2024). The MODIS-TIR
674 dust optical depth and effective diameter product is available in Zheng et al. (2026). The
675 CESAM data used in this study are available from the Database of Atmospheric Simulation
676 Chamber Studies (DASCS) and the Library of Advanced Data Products (LADP) of the
677 EUROCHAMP data center (<https://data.eurochamp.org/data-access/chamber-experiments/>) also
678 available via the ACTRIS data portal (<https://data.actris.eu/>).

679

680 **Author contributions**

681

682 DK and MC conceived this project, conducted analysis, and wrote the manuscript. All other
683 authors participated in the revising process and interpretation of the results. HY and PRC provided
684 detailed editing and intellectual contribution on the manuscript. DK, TT, PT, PG, XL, YS, and
685 HM conducted AeroCom model experiments. ZZ, JZ, SV, LC, SW, and VC produced satellite data
686 and contributed data analysis. JFK provided DustCOMM data. CDB and PF provided the CESAM
687 dataset and interpretation of these datasets. MS helped with organizing AeroCom model
688 experiments and provided infrastructure of logistics.



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