

# *Asian and trans-Pacific dust: a multi-model and multi-remote sensing observation analysis*

Article

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1 Asian and trans-Pacific Dust: A multi-model and multi-remote  
2 sensing observation analysis  
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28 Key points:

- 29 • Dust and total aerosol over Asia and the North Pacific Ocean are evaluated using  
30 observations and models.  
31
- 32 • Satellites estimate that a 35-70 % decrease of DOD from the west Pacific to the  
33 east Pacific.  
34
- 35 • Diversity of DOD is mostly driven by the diversity of the dust source followed by  
36 residence time and mass extinction efficiency.  
37

38

39

40 Abstract

41 Dust is one of the dominant aerosol types over Asia and the North Pacific Ocean, but  
42 quantitative estimation of dust distribution and its contribution to the total regional  
43 aerosol load from observations is challenging due to the presence of significant  
44 anthropogenic and natural aerosols and the frequent influence of clouds over the region.  
45 This study presents the dust aerosol distributions over Asia and the North Pacific using  
46 simulations from five global models that participated in the AeroCom phase II model  
47 experiments, and from multiple satellite remote-sensing and ground-based measurements  
48 of total aerosol optical depth (AOD) and dust optical depth (DOD). We examine various  
49 aspects of aerosol and dust presence in our study domain: (1) the horizontal distribution,  
50 (2) the longitudinal gradient during trans-Pacific transport, (3) seasonal variations, (4)  
51 vertical profiles, and (5) model-simulated dust life cycles. This study reveals that the  
52 diversity of DOD is mostly driven by the diversity of the dust source followed by  
53 residence time and mass extinction efficiency.

54

55 1. Introduction

56 Dust aerosol can impact the Earth's weather, climate, and eco-systems by  
57 interacting with solar and terrestrial radiation, altering cloud amount and radiative  
58 properties, fertilizing land and ocean, and modulating carbon uptake (Haywood et al.,  
59 2003; Jickells et al., 2005; Forster et al., 2007; Evan et al., 2008; Kim et al., 2010; Maher  
60 et al., 2010; Creamean et al., 2013; Yu et al., 2015a; Song et al., 2018). The majority of  
61 global dust sources are from arid surfaces such as North Africa, the Middle East, and

62 parts of Asia, and to a lesser extent Australia and Patagonia (e.g., Tegan et al., 2002;  
63 Prospero et al., 2002; Huneus et al., 2011; Ginoux et al., 2012).

64         Although dust emission from Asia is estimated as only 25~35% of that from  
65 North Africa (Chin et al., 2007; Su and Toon, 2011; Ginoux et al., 2012), it is a dominant  
66 source of dust not only over the land areas of Asia. Asian dust is also significant over the  
67 North Pacific Ocean, western North America, and the Arctic (e.g., Chin et al., 2007) via  
68 long-range transport, playing a key role in the climate and eco-system in these regions  
69 (Uno et al., 2009; Shao et al., 2011; Yu et al., 2012). Observation-based estimates of dust  
70 amount based on multiple years of satellite AOD data from the Moderate Resolution  
71 Imaging Spectro-radiometer (MODIS) suggest that about 140 Tg (1 Tg =  $10^6$  tons) of  
72 dust are exported from East Asia; among which 56 Tg (40%) reach the west coast of  
73 North America, and the remaining 84 Tg are deposited in the North Pacific and/or are  
74 transported to the Arctic (Yu et al., 2012). Dust is more efficiently transported across the  
75 North Pacific Ocean (40%) than other continental aerosols (25%) (Yu et al., 2008) due to  
76 the higher elevation of dust layers (Yu et al., 2010, 2012). The satellite-based estimate of  
77 trans-Pacific dust transport and deposition differs significantly from those estimated from  
78 in-situ measurements and simulated by models, as summarized in Yu et al. (2013).

79         On the other hand, previous modeling studies of dust outflow from Asia and  
80 deposition to the North Pacific have shown different results. A study with the Northern  
81 Aerosol Regional Climate Model estimated that out of 120 Tg of dust (< 41  $\mu\text{m}$  in  
82 diameter) emitted from Asia in Springtime, 31 Tg (26%) is exported from Asia to the  
83 Pacific Ocean and only 4 Tg (13%) of the exported dust reaches North America (Zhao et  
84 al., 2006). An inter-model comparison study with eight regional dust emission/transport

85 models demonstrated that participating dust models differ by a wide range over Asia,  
86 from emission to surface concentration, horizontal distribution, and vertical profiles  
87 during long-range transport (Uno et al., 2006). They suggested that measurements of dust  
88 fluxes and accurate, up-to-date land-use information are crucial to achieve more realistic  
89 simulations over these regions. Dust simulated from global models have also been  
90 extensively compared in the past AeroCom studies (Kinne et al., 2006; Huneus et al.,  
91 2011; Koffi et al., 2012, 2016; Kim et al., 2014), but none of them specifically devoted to  
92 assessing model performance in the Asian-Pacific region, partially due to the lack of  
93 reliable data over this region. For example, Huneus et al. (2011) pointed out that a  
94 specific Asian dust data set is needed to evaluate the global dust models, and suggested  
95 that one way to assess the performance of global dust models over Asia would be to  
96 compare measurements of coarse-mode AOD against modeled ones. However, extracting  
97 dust data from satellite observations in the Asian-Pacific region is challenging because of  
98 the frequent cloud occurrence in the North Pacific and the large amount of pollution  
99 aerosol over the Asian continent. Wu et al. (2019) showed that different dust retrieval  
100 algorithms based on the CALIOP observations yield significant differences in the dust  
101 vertical distribution, which complicates the evaluation of model simulations.

102         With the recent development of methods to derive satellite-based dust vertical  
103 profiles and transport flux estimates based on the CALIOP and MODIS data (Ginoux et  
104 al., 2012; Yu et al., 2015a, b; Yu et al., 2019a, 2019b), we present in this paper an  
105 evaluation of multiple, global model dust simulations in the Asian-Pacific region from  
106 the AeroCom Phase II (AeroCom II) Hindcast model experiment with multiple satellite  
107 observations. We also examine several key physical and optical model parameters in

108 order to explain discrepancies between observations and models, and among the models.  
109 We use an approach similar to our previous study (Kim et al., 2014), that evaluated  
110 AeroCom II model-simulated dust with updated satellite observations in the African-  
111 North Atlantic region, and addressed the key processes causing model diversity and  
112 deficiency.

113 In section 2, we briefly describe the AeroCom II Hindcast model simulations and  
114 the satellite- and ground-based remote-sensing data. In section 3, we compare the  
115 observed and modeled total aerosol and dust aerosol optical depths, including their  
116 longitudinal gradients and vertical distributions. In section 4, we investigate details of the  
117 dust life cycle in the models, and we compare results from the present study with those of  
118 North Africa. Discussion is presented in section 5, followed by a summary in section 6.

119

## 120 2. Models and data

### 121 2.1 AeroCom models

122 AeroCom is an internationally coordinated effort to advance the understanding of  
123 atmospheric aerosols and to document and diagnose differences between models and  
124 between models and observations (<http://aerocom.met.no>). The AeroCom II Hindcast  
125 experiments produced multi-year simulations from 1980 to 2007, but models cover  
126 different simulation lengths. Following Kim et al. (2014), we use the five AeroCom  
127 models that provided dust simulations and diagnostics over the time period 2000-2005.  
128 The model setup and configurations are highly model-dependent, for example, with  
129 horizontal resolution from 1.1° in SPRINTARS to 2.8° in ECHAM5 (Table 1). Vertical  
130 coordinates range from 30 layers in GOCARTv4 (hereafter GOCART) to 56 in

131 SPRINTARS. The meteorology fields that drive dust emissions and transport are taken  
132 from three reanalysis products, namely NCEP (used by SPRINTARS and GISS-E2-  
133 OMA, formerly known as GISS-modelE and hereafter as GISS), ECMWF (used by  
134 HadGEM2 and ECHAM5-HAMMOZ, hereafter ECHAM5), and GEOS4 (used by  
135 GOCART). Some models use 10-m wind for dust mobilization parameterization  
136 (GOCART, GISS, and SPRINTARS), whereas others use friction velocity ( $u^*$ )  
137 (ECHAM5 and HadGEM2). Dust density values are similar among the models, ranging  
138 from 2.5 to 2.65 g cm<sup>-3</sup>. The range of dust size and the number of size groups are  
139 different among models (Table 1). GOCART and SPRINTARS has the same size range  
140 (0.1-10  $\mu\text{m}$  in radius) but different size bins (5 and 6, respectively), GISS includes more  
141 extended particle sizes (0.1-16  $\mu\text{m}$ ) with 5 size bins, and HadGEM2 covers a wider range  
142 of dust particle sizes (0.03-31.6  $\mu\text{m}$ ) in 6 size bins. By contrast, ECHAM5 includes only  
143 sub-micron particles, in 2 modes ranging from 0.05 to 0.5  $\mu\text{m}$ . The differences in size  
144 distribution affect total dust mass amount included in emission, transport, deposition  
145 fluxes, mass loading, and overall lifetime, as well as the average mass extinction  
146 efficiency that converts mass to light-extinction in different models.

147         Participating models commonly have two dry removal processes of 1)  
148 gravitational settling as a function of aerosol particle size and air viscosity (Fuchs, 1964)  
149 and 2) surface deposition as a function of surface type and meteorological conditions  
150 (Wesely 1989). Wet scavenging removal in each model is empirically parameterized with  
151 the precipitation rate and the scavenging coefficient; thus, a wide range of scavenging  
152 coefficients are found among the models. Both GOCART and GISS have similar wet  
153 scavenging parameterizations based on the previous work (Giorgi and Chameides 1986;

154 Balkanski et al., 1993), where Balkanski et al. (1993) adopted a 50% aerosol scavenging  
155 efficiency in shallow convection and a 100% scavenging efficiency in deep convection.  
156 SPRINTARS uses a size dependent collision efficiency with raindrops (Equation A6 in  
157 Takemura et al., 2000); HadGEM2 uses a particle-size-dependent scavenging coefficient  
158 ( $2 \times 10^{-5}$  for  $< 0.3 \mu\text{m}$   $\sim 4 \times 10^{-4}$  for  $> 3.16 \mu\text{m}$ ) (Table 1 in Woodward, 2001); ECHAM5 has  
159 a scavenging parameter in the range of 0.1~0.9, depending on cloud type (stratiform or  
160 convective cloud), or cloud status (liquid, mixed, or ice cloud), and mixing status (Table  
161 3 in Stier et al., 2005).

162 Overall, dry and wet deposition efficiencies are highly empirical, and depend on  
163 the vegetation type, surface conditions, atmospheric stability, particle sizes, and  
164 meteorological fields. The model diversity in deposition processes is found from the  
165 differences in the spatial distributions of LF and  $f_{\text{WET}}$  (Figure 10) between models. The  
166 differences in size range also affect model diversity in many dust-associated fields,  
167 including net emission amount, dry deposition, and DOD.

168 We compare several monthly mean fields from the model output with remote  
169 sensing data or observation-derived quantities, namely the total aerosol optical depth  
170 (AOD), dust aerosol optical depth (DOD), and the vertical extinction profiles of total and  
171 dust aerosols ( $\sigma_{\text{aer}}$  and  $\sigma_{\text{du}}$ , respectively, in  $\text{km}^{-1}$ ). Since the dust vertical extinction  
172 profiles from the models were not available in the AeroCom archive, they are constructed  
173 from the model-calculated dust mass concentrations and the mass extinction coefficient,  
174 assuming dust does not take up water vapor, such that DOD does not depend on the  
175 ambient relative humidity. The dust mass extinction coefficient is obtained by dividing  
176 model calculated DOD with dust mass loading. In addition, model-calculated dust mass

177 loading (LOAD), emission (EMI), dry deposition (DRY), wet deposition (WET), and  
178 total precipitation are used to assess possible causes of the inter-model diversity.

179         When comparing with satellite retrievals and AERONET observations that are  
180 available only under clear-sky conditions, it is desirable to use the modeled AOD for  
181 clear-sky as well. However, only the GISS model provides such output (other models just  
182 provide all-sky results). A previous study showed that clear-sky AOD from the GISS  
183 model is 30% lower than all-sky AOD over the North Africa-Northern Atlantic region  
184 (Kim et al., 2014). In another estimate based on the GEOS-Chem model, clear-sky AOD  
185 is 20% lower than all-sky AOD on global average (Yu et al., 2012). DOD is not sensitive  
186 to differences between clear-sky and all-sky conditions due to the hydrophobic nature of  
187 dust (Kim et al., 2014), although the different averaging times between all-sky and clear-  
188 sky conditions are also expected to produce different AOD values. DOD in ECHAM5 is  
189 approximated from the dust volume-weighted AOD of two internally mixed modes where  
190 dust is present (Stier et al., 2005). The internal mixing of dust has the potential to cause  
191 additional differences between ECHAM5 and other models in the inter-model  
192 comparison. Although some models do not consider the chemistry on dust surfaces,  
193 previous studies have estimated that the enhanced hygroscopicity of dust by  
194 heterogeneous mixing can reduce the global dust burden on 17%~28% in GISS (Bauer  
195 and Koch, 2005) and 5% in ECHAM5 (Pozzoli et al., 2008).

196

## 197 2.2 Remote sensing data

### 198 2.2.1. Vertical profiles

199           To evaluate the vertical distribution of dust, we use the aerosol and dust extinction  
200 profiles from CALIOP at 532 nm, following the method developed by Yu et al. (2015b).  
201 As CALIOP data are only available after June 2006, we use the monthly CALIOP data  
202 averaged from 2007 to 2011. The difference of time periods between CALIOP and model  
203 simulations may cause some vertical profile differences; however, its effect is not  
204 expected to be significant, as the climatological data is averaged over a large domain for  
205 a long time. Mean extinction profiles of total and dust aerosol are derived from version  
206 4.10 CALIOP Level 2 aerosol profile data with a nominal along-track resolution of 5 km  
207 and vertical resolution of 30 m.

208           The first step is to collect quality-assured aerosol extinction profile data. Here, we  
209 use cloud-free nighttime CALIOP data to minimize interference from clouds and sun, and  
210 select extinction profiles with good retrieval quality, i.e., QC flag of 0, 1, 16, or 18,  
211 following recommendations by Winker et al. (2013). We then separate aerosol from  
212 clouds according to the cloud-aerosol-discrimination (CAD) scores, for which the aerosol  
213 scores are typically in the range of -100 to -20 (Winker et al., 2013; Tackett et al., 2018).  
214 However, in this study we choose a more stringent CAD-score range of -100 to -70 when  
215 selecting aerosol data (Yu et al., 2019a), which provides greater confidence in excluding  
216 possible cloud contamination. Compared to the relatively relaxed criteria of CAD  
217 between -100 and -20, the total aerosol sampling is reduced by up to 15% with our  
218 stricter criteria (Figure S1).

219           The dust fraction for backscatter in each profile is calculated using the CALIOP  
220 observed particulate depolarization ratio ( $dp$ ), as coarse, non-spherical dust particles  
221 produce a depolarization signal. The maximum threshold value ( $dp > 0.2$ ) and the  $dp$  of

222 non-dust particles is assumed to be 0.02 (Hayasaka et al., 2007, Tesche et al., 2009, and  
223 Yu et al., 2012, 2015b, 2019a). A constant lidar ratio value of  $44 \text{ sr}^{-1}$  (Omar et al., 2010;  
224 Young et al., 2018) is used to convert dust backscatter to dust extinction at 532 nm. We  
225 calculate the average vertical extinction profile using all the individual profiles during a  
226 month within the  $2^\circ$  in latitude  $\times$   $5^\circ$  in longitude grid. All averaged total and dust aerosol  
227 profiles are at 60-m vertical resolution.

228         Aerosol extinction is retrieved only where aerosol is detected by the CALIOP  
229 feature finder. However, in reality aerosol is present virtually everywhere throughout the  
230 troposphere, although aerosol concentration can be very low in pristine oceanic regions.  
231 When the aerosol signal is weak, below CALIOP detection limit, no feature is detected in  
232 the level 2 atmospheric sounding, and the sample is classified as “clear-air.” Aerosol  
233 extinction is set to zero ( $\text{km}^{-1}$ ) in the level 3 algorithm, whereas several studies have  
234 sought to characterize the optical depth of aerosol layers undetected by CALIOP (Tackett  
235 et al. (2018) and references therein). For data identified as “clear-air” in the present  
236 comparison, we adopt the approach used in generating the standard level-3 product  
237 (Tackett et al., 2018). However, this could cause a low bias in the averaged data because  
238 aerosols at low concentrations are missing, especially over the Pacific Ocean. This may  
239 also introduce a difference in the shape of aerosol profile because CALIOP tends to  
240 detect “clear-air” more often in free troposphere than in the atmospheric boundary layer.  
241 In addition to the level 3 algorithm method, we further average the vertical profiles, but  
242 excluding “clear-air” data from the averages, which we could expect to represent an  
243 upper bound on the profile data. The results are discussed in section 5.

244

### 245 2.2.2. AOD and DOD

246 The observational datasets used to evaluate the model simulations are listed in  
247 Table 2. Seasonal and spatial distributions of AOD are taken from the Moderate  
248 Resolution Imaging Spectroradiometer (MODIS) at 550 nm and the Multiangle Imaging  
249 SpectroRadiometer (MISR, version V22) at 555 nm on board the EOS-Terra satellite.  
250 The merged MODIS dataset used here is the Collection 6 version with combined retrieval  
251 results from the Dark Target and Deep Blue algorithms (Levy et al., 2013). Whereas the  
252 Dark Target algorithm provides observations over ocean, the Deep Blue algorithm  
253 provides observations over bright land and desert scenes using the deep-blue wavelengths  
254 (i.e., 0.41 and 0.47  $\mu\text{m}$ ).

255 MODIS AOD over ocean and fine-mode fraction ( $f$ ) measurements have been  
256 used to empirically separate dust ( $\text{du}$ ) AOD from that of combustion aerosol ( $\text{co}$ ) and  
257 marine aerosol ( $\text{ma}$ ) in a self-consistent way (Kaufman et al., 2005; Yu et al., 2009,  
258 2019b). Given that  $\tau = \tau_{\text{ma}} + \tau_{\text{du}} + \tau_{\text{co}}$  and  $f = [f_{\text{ma}}\tau_{\text{ma}} + f_{\text{du}}\tau_{\text{du}} + f_{\text{co}}\tau_{\text{co}}]/\tau$ , dust optical depth ( $\tau_{\text{du}}$   
259 or DOD) is derived from the MODIS Collection 6 data using representative values for  
260  $f_{\text{ma}}$ ,  $f_{\text{du}}$ ,  $f_{\text{co}}$ , and  $\tau_{\text{ma}}$  (Yu et al., 2019b). Although large spatial and temporal variability of  
261  $f_{\text{ma}}$  is accounted for following a method in Yu et al. (2009), we assume constant values  
262 for  $f_{\text{du}}$  and  $f_{\text{co}}$  because of lack of observational constraints. In this study, marine AOD is  
263 parameterized as a function of surface wind speed derived from previous studies (Yu et  
264 al., 2019b). A detailed description of the method, including uncertainty estimates and  
265 assumptions, can be found in the literature (Yu et al., 2009 and 2019b). **DOD over land is**  
266 **also derived from MODIS Collection 6 data but with an approach different than ocean,**  
267 **because MODIS fine-mode fraction retrieval over land is less reliable. Over land, DOD is**

268 extracted from the MODIS Deep Blue (MDB) datasets, based on 1) the co-function of the  
269 continuous angstrom exponent values derived by Anderson et al. (2005), 2) single  
270 scattering albedo  $\omega$  at 412 nm less than 1, and 3) a positive difference of  $\omega$  between 412  
271 and 670 nm ( $\omega_{670} - \omega_{412} > 0$ ) (Ginoux et al., 2012; Pu and Ginoux, 2016).

272         Similar to our previous study of transatlantic dust (Kim et al., 2014; Guo et al.,  
273 2013), we use MISR AOD over land and ocean, and the non-spherical AOD over ocean,  
274 as a proxy for DOD (Kalashnikova and Kahn, 2006; Kahn et al., 2010). Non-spherical  
275 AOD is generally of higher quality over ocean for MISR, due to uncertainties in  
276 accounting for the brighter and more varying land surface (Kahn and Gaitley, 2015).  
277 However, the frequent interference by clouds, especially thin cirrus, contributes to the  
278 AOD and the non-spherical AOD uncertainties over the study region (Pierce et al., 2010).  
279 Note also that for both MODIS and MISR, sensitivity to the particle-property proxies  
280 used to identify the dust component diminishes when the total mid-visible AOD falls  
281 below about 0.15 or 0.2. The resulting uncertainty probably contributes significantly to  
282 the differences in MODIS and MISR DOD presented in the section 3 below, especially in  
283 the low-AOD areas over ocean.

284         CALIOP monthly AOD and DOD is calculated by vertically integrating the total  
285 and dust aerosol extinction coefficient profile at 532 nm, respectively, as described in the  
286 previous section.

287         We also use total AOD and coarse-mode AOD at 550 nm (Version 2, Level 1.5  
288 and 2) from ground-based AEROSOL ROBOTIC NETWORK (AERONET) (Holben et al.,  
289 1998) sites located within the study domain to evaluate both satellite measurements and  
290 model simulations, although not all coarse-mode aerosols are dust, and some dust is in

291 the fine-mode. Twenty-nine AERONET sites were chosen, to allow enough geographical  
292 coverage across the study region (see Table S1 for the latitude and longitude coordinates  
293 of these sites). However, AERONET data are rather limited over the ocean in our study  
294 domain and time period, as only two remote AERONET sites, in Midway and Hawaii,  
295 are available in the northern Pacific, and the AERONET-coordinated Maritime Aerosol  
296 Network (MAN, [http://aeronet.gsfc.nasa.gov/new\\_web/man\\_data.html](http://aeronet.gsfc.nasa.gov/new_web/man_data.html)) data are not  
297 available in the Pacific during the study period.

298 All the model-data comparisons are performed on a monthly, seasonal, or multi-  
299 year average basis. This approach may introduce some differences between satellite data  
300 and model results because of location and time mis-matches; however, given the large  
301 amount of data in our expansive domain over a six-year time span, it should not affect  
302 our statistics and conclusions, as shown in several previous evaluation studies (e.g., Chin  
303 et al., 2007, 2014; Colarco et al., 2010; Randles et al., 2017). Also, additional caution is  
304 needed when comparing remote-sensing-derived and modeled DOD and dust extinction  
305 profiles, as the dust data from remote sensing are either dust proxies, or are obtained with  
306 several assumptions, and are thus subject to large uncertainties.

307

### 308 3. Evaluation and comparisons of model simulations with observations

309 In this section, we evaluate the model results with satellite and ground-based  
310 remote sensing data by comparing (i) the mean AOD and DOD in the study domain; (ii)  
311 the longitudinal gradient of AOD and DOD from the dust source region in East Asia to  
312 the downwind areas in the Pacific; (iii) the seasonal variations of AOD and DOD; and  
313 (iv) the vertical profiles of aerosol and dust over land and ocean. The results are

314 summarized in Tables 3 and 4. A study domain (60°E~120°W; 10°N~70°N) was chosen  
315 to cover dust source regions in Asia and the trans-Pacific transport route. We divide the  
316 study area into land (60°E-140°E; 20°N-60°N) and ocean (140°E-140°W; 20°N-60°N)  
317 regions and define six sub-domains for vertical profile analysis. Detailed domain  
318 information is provided in Figure 1.

319

### 320 3.1 Mean AOD and DOD

321 Figure 2 shows a comparison between satellite observations and model  
322 simulations of the 6-year mean total AOD averaged from 2000 to 2005, with AERONET  
323 AODs at 29 sites superimposed using the same color scale. MODIS and MISR agree  
324 within 15 % over the study domain (average AOD = 0.226 and 0.194, respectively), with  
325 larger difference over land (0.274 and 0.209) than over ocean (0.177 and 0.179) (Table  
326 3). These results reflect the known behavior of the MISR and MODIS products (e.g.,  
327 Kahn et al., 2009). On the other hand, the CALIOP AOD is significantly lower than  
328 MODIS (47 % lower over ocean and 21 % lower over land compared to MODIS), which  
329 is also shown in previous studies (Redemann et al., 2012; Kim et al., 2013). There are a  
330 few known factors that contribute to the uncertainty of CALIOP AOD over the study  
331 domain, including the underestimation of aerosol extinction in the upper troposphere due  
332 to the detection limit (Winker et al., 2013), and the narrow lidar swath that may miss  
333 some episodic aerosol plumes (Yu et al., 2013).

334 The satellites and AERONET show high annual mean AOD (>0.4) over East  
335 China and the Indo-Gangetic Plain, which are known to be highly polluted regions.  
336 Models capture the geographical pattern of the AOD distribution from the satellites, i.e.,

337 the higher AOD over polluted regions, the decreasing gradient over ocean from west to  
338 east, and northward shifting of the AOD plume center toward the eastern Pacific. Satellite  
339 AOD better agrees with AERONET and gives better statistics, showing higher correlation  
340 and lower bias than the models (Figure S2). The multi-year domain-averaged AOD from  
341 the models differs within 50%, ranging from 0.16 (SPRINTARS) to 0.20 (GOCART)  
342 (20%) over the entire domain, 0.18 (ECHAM5) to 0.25 (GOCART) (24%) over land, and  
343 0.11 (SPRINTARS) to 0.19 (GISS) (42%) over ocean.

344 For dust, satellite-derived DOD is available from MODIS and CALIOP over both  
345 land and ocean and MISR only over ocean (Figure 3). Both MODIS and CALIOP  
346 products show substantial dust presence ( $DOD > 0.2$ ) over the land source regions of  
347 Taklimakan desert, Thar desert, Gobi desert, and Loess Plateau, and the areas  
348 immediately downwind. The MODIS and CALIOP DOD values (0.11 and 0.09,  
349 respectively) over land are supported by the coarse-mode AOD (proxy for DOD) from  
350 AERONET. Over ocean, all satellite data show transported DOD plumes over the  
351 northwestern Pacific (i.e., east of  $150^{\circ}\text{W}$ ;  $30^{\circ}\text{N}$ - $50^{\circ}\text{N}$ ), but the magnitude from CALIOP  
352 is much lower than MODIS and MISR. On average, DOD over ocean from CALIOP  
353 (0.027) is 54% and 50% lower than that from MODIS (0.059) and MISR (0.054),  
354 respectively. The average dust fractions of mid-visible AOD from MODIS and CALIOP  
355 are about 36 and 42 % over land and 30 and 29 % over ocean, respectively.

356 Compared to the relatively small difference ( $\sim 20\%$ ) of average AOD among  
357 models (AOD = 0.16-0.20), the difference in average DOD is much larger – a factor of  
358 10 in the domain-average (0.008-0.08). Over land, DOD from ECHAM5 (0.01) and  
359 HadGEM2 (0.02) are significantly lower than satellites (0.09-0.11) and other models

360 (0.05-0.11). The underestimation of DOD in ECHAM5 and HadGEM2 is attributed to  
361 lower emissions and more efficient loss frequency of dust, respectively, which is  
362 discussed in detail in the later sections. Over the ocean domain, the magnitude of  
363 GOCART DOD (0.05) is in between the MODIS-derived DOD (0.06) and CALIOP-  
364 derived DOD (0.03), whereas the other models obtain much smaller values (0.001-0.009).  
365 Compared with the coarse-mode AOD (proxy of DOD) from AERONET, most models  
366 (except GOCART) seem to significantly underestimate the dust transport from source  
367 regions across the North Pacific.

368         Satellites indicate that  $f_{\text{DOD}}$  values vary depending on sensor type and region  
369 ranging 0.27-0.36. The satellite mean  $f_{\text{DOD}}$  over land (0.39) is 0.11 greater than over  
370 ocean (0.28). Models show large range of  $f_{\text{DOD}}$  both over land (0.11-0.42) and ocean  
371 (0.007-0.29). The ensemble means of model AOD, DOD and  $f_{\text{DOD}}$  are 0.21, 0.05, 0.25  
372 over land and 0.16, 0.02, and 0.1 over ocean, respectively (Table 4). The comparison  
373 between satellite and model ensemble means again shows within 10 % differences in  
374 AOD over land and ocean, but a factor of two low bias in model is shown for DOD and  
375  $f_{\text{DOD}}$  over ocean.

376

### 377 3.2 Longitudinal gradient

378         We examine the longitudinal gradient with the mean AOD and DOD from  
379 satellites and models between 20°N and 60°N in 5° longitude intervals between 60°E-  
380 120°W (Figure 4a). MODIS shows the highest AOD (0.47) at 115°E-120°E, whereas  
381 MISR and CALIOP have the peaks in the same location but with lower values (0.29 and  
382 0.35, respectively). All satellite data show a gradually decreasing pattern eastward across

383 the Pacific Ocean (i.e., east of 140°E). The range of west-to-east AOD gradient between  
384 140°E-120°W in MODIS (from 0.23 to 0.11, a factor of 2.1) is larger than that in MISR  
385 (from 0.21 to 0.13, a factor of 1.6). The pattern of the CALIOP AOD gradient over ocean  
386 (from 0.11 to 0.06, a factor of 1.8) is similar to that of MODIS and MISR, but the  
387 magnitude of AOD is about half of other satellites. Differences in sampling and cloud-  
388 masking account for much of the diversity in the satellite-derived AOD gradients. All  
389 models capture the location of the maximum AOD over Eastern China, but some of them  
390 miss the peak over the Indo-Gangetic Plain and Taklimakan. Although the magnitudes of  
391 the decreasing longitudinal AOD gradients vary by model, all models show a decreasing  
392 longitudinal gradient of AOD.

393 Over land, MODIS and CALIOP DOD over the Taklimakan and Thar deserts  
394 (i.e., west of 85°E) are larger (0.19 and 0.14, respectively) than over the Gobi Desert and  
395 Loess Plateau (0.14 and 0.1, respectively). All the models except GOCART show lower  
396 DOD than CALIOP, especially ECHAM5 and HadGEM2, as the average DOD from  
397 these two models is only 0.01-0.05 over land. Over ocean, MODIS and MISR show  
398 similar decreasing DOD gradient from the west (0.10 and 0.07) to the eastern Pacific  
399 (0.03 and 0.04), respectively. The decreasing gradient of CALIOP DOD from west (0.05)  
400 to east Pacific (0.01) is only half the MODIS and MISR values. Overall, the satellites  
401 show a 40-60 % decrease of AOD and 35-70% decrease of DOD during the long-range  
402 transport from the Asian coast to the eastern North Pacific Ocean (i.e., 130°E-125°W).  
403 Although most models except GOCART have lower DOD than MODIS by a factor of 3-  
404 10 in the coastal region (i.e., 130°E), all models also show the decreasing DOD gradient,

405 which is clear when the data are normalized to their respective values at the Asian coast  
406 (130°E).

407 The CALIOP DOD fraction over land ( $f_{\text{DOD}}$ , bottom panel in Figure 4a) is highest  
408 (0.55) near 60°E; then it gradually decreases across the Pacific towards the east to 0.32 at  
409 125°W. MODIS also show similar  $f_{\text{DOD}}$  gradient between west and east (i.e., 0.65 to  
410 0.30). The satellite  $f_{\text{DOD}}$  values over ocean are close to each other, in the range of  
411 0.24~0.34, across the Pacific. The maximum  $f_{\text{DOD}}$  values from the models near 60°E are  
412 spread by a factor of two (0.28~0.57), and most models seem to show much faster  $f_{\text{DOD}}$   
413 decrease from west to east over land (a factor of 3-4 decrease) than the satellites and the  
414 GOCART model. Over ocean, the mean  $f_{\text{DOD}}$  values from the models show a large (factor  
415 of 30) difference, from 0.01 (ECHAM5) to 0.29 (GOCART), and the latter is the closest  
416 to the satellite data.

417 When normalized to the value at 130°E, satellites estimate a 38-59 % AOD  
418 decrease, and a decrease of 34-69 % for DOD, during trans-Pacific transport (Figure 4b).  
419 The increasing gradient of MISR  $f_{\text{DOD}}$  is due to the steeper gradient in DOD than AOD,  
420 although its physical explanation needs more investigation. In contrast, models show a  
421 wider range of decreasing longitudinal gradients: 42-69 % for AOD and 44-88 % for  
422 DOD. The normalized AOD gradient from the models is generally similar to that from  
423 satellites, although GISS and ECHAM5 show an increase of AOD in the middle of the  
424 Pacific Ocean (160°E-150°W). By contrast, the longitudinal gradients of normalized  
425 DOD and  $f_{\text{DOD}}$  are much more spread out in the satellite data and models, revealing large  
426 discrepancies (a fact or of 4) not only between the satellites over the North Pacific, where

427 AOD and DOD are relatively low, but also among models in dust transport and removal  
428 processes.

429 Overall, all satellites show a gradual decrease of AOD and DOD eastward during  
430 trans-Pacific transport. They show that 40-60% of AOD and 30-65% of DOD reach the  
431 eastern Pacific from the Asian coast. Models capture the decreasing gradient of the  
432 satellite AOD and DOD; however, most models except GOCART largely underestimate  
433 DOD and  $f_{\text{DOD}}$  over ocean.

434

### 435 3.3 Seasonal cycle and inter-annual variability

436 The seasonal variation of multiyear mean AOD and DOD for land and ocean are  
437 shown in Figures 5 and 6, respectively. The seasonal variability of the three satellite  
438 AODs agree with each other over land (Figure 5), showing high AOD during April-July  
439 and low AOD between October and January. MODIS AOD (0.17-0.37) is higher than  
440 MISR and CALIOP by 0.06 to 0.07. The seasonal variation of MODIS and CALIOP  
441 DOD is similar to that of AOD with the peak in April (0.21 and 0.14, respectively). The  
442  $f_{\text{DOD}}$  is highest in March-April (0.46-0.50) for MODIS and CALIOP, and lowest in  
443 December-January (0.27-0.28) in MODIS and July-August (0.33) in CALIOP.

444 Models also show strong seasonal variability over land; however, only GOCART  
445 shows the AOD and DOD maxima in April, reproducing the seasonal cycles in the  
446 satellite data. The other models shift the seasonal maximum to the boreal summer  
447 months. The differences between the modeled AODs range from 0.06-0.07 in winter to  
448 0.18 in April. GOCART resembles closely the magnitude of MODIS, whereas the other  
449 models simulate AOD values similar to MISR and CALIOP. The maximum DOD in

450 GOCART, GISS and SPRINTARS ranges from 0.12-0.22, which is comparable to  
451 satellites (0.14-0.21). Interestingly, despite the large differences in seasonal variation  
452 among the models, they all consistently show a maximum  $f_{\text{DOD}}$  in April, even though the  
453 values differ by a factor of 2, from 0.3 in ECHAM5 to 0.6 in GOCART, which can be  
454 compared to the CALIOP  $f_{\text{DOD}}$  maximum of 0.5 in spring. Overall, the models capture  
455 the magnitude of the satellite AOD over land, but the seasonality differs; apparently,  
456 reproducing the magnitude of the observed DOD is more difficult.

457         Over ocean, there are clear discrepancies among the satellite data. Although the  
458 seasonal variability and magnitude of AOD from MODIS and MISR agree with each  
459 other (Figure 6) as both showing the highest AOD (0.28 and 0.26, respectively) in April-  
460 May, the CALIOP AOD is quite different not only in seasonal variation (maximum AOD  
461 from January through April and a minimum in August), but also in magnitude (about a  
462 factor of 2 lower). Discrepancies of similar magnitudes are found for satellite-derived  
463 DOD and  $f_{\text{DOD}}$  as well, with the largest difference appearing in the summer. Both MISR  
464 and CALIOP display DOD and  $f_{\text{DOD}}$  minima in July, a feature that is lacking in the  
465 MODIS data. As noted in Section 2, sensitivity to the proxies used to identify the DOD  
466 component in the satellite retrievals diminishes when the AOD is low.

467         Model simulations over the ocean also show large discrepancies. Although the  
468 AOD seasonal variation from GOCART (0.27) closely follows that from MODIS and  
469 MISR with a maximum AOD (0.26-0.28) in April-May, GISS and ECHAM5 indicate a  
470 maximum AOD in winter (0.21-0.25) and a minimum AOD (0.12) in summer, which is  
471 also out of phase with the seasonal cycle simulated by SPRINTARS and HadGEM2. The  
472 largest DOD and  $f_{\text{DOD}}$  differences over ocean among the models appear between

473 GOCART and ECHAM5: GOCART-simulated DOD ( $f_{\text{DOD}}$ ) over the North Pacific varies  
474 from 0.02 (0.2) in winter to 0.14 (0.48) in April, similar to the corresponding values from  
475 MODIS, whereas these fields from ECHAM5 are below 0.03 (Figure 6, right-bottom  
476 panel). Overall, the DOD and  $f_{\text{DOD}}$  diversity among the models is huge, with differences  
477 up to a factor of twenty. The same result is obtained when the analysis is conducted over  
478 the smaller domains (Figures S3-S5).

479 Overall, most models, except for GOCART, strongly underestimate the  
480 magnitude of DOD over ocean, relative to the satellite results. The absence of dust over  
481 ocean in these models produces large differences in ocean-AOD seasonality, with peaks  
482 in summer or winter that disagree with the MODIS and MISR AOD. In addition, the  
483 AOD and DOD differences between MODIS, MISR, and CALIOP over ocean highlight  
484 the challenge of DOD observation in the Northern Pacific region. We will discuss the  
485 differences presented by the CALIOP DOD further in later sections.

486

### 487 3.4 Vertical distribution of aerosol and dust

488 The vertical profiles of modeled aerosol and dust are compared with CALIOP  
489 profiles averaged over 2007-2011. Considering the spatial variability within the large  
490 domain, we chose six sub-domains (Figure 1); three domains include major dust source  
491 regions over the Thar desert (THAR, 70°E-75°E; 25°N-30°N), the Taklimakan desert  
492 (TAKL, 75°E-90°E; 35°N-45°N), and the Gobi desert (GOBI, 95°E-115°E; 40°N-45°N),  
493 and three sub-domains across the Pacific capture the trans-Pacific transport of aerosol and  
494 dust [NWP (135°E-140°E; 25°N-50°N), NCP (175°E-180°E; 30°N-55°N), and NEP  
495 (130°W-125°W; 35°N-60°N)].

496 The comparison includes the area-averaged vertical profiles of extinction  
497 coefficients for total aerosol ( $\sigma_{\text{aer}}$  in  $\text{km}^{-1}$ ) and dust ( $\sigma_{\text{du}}$  in  $\text{km}^{-1}$ ), and the ratio of dust  
498 extinction to total aerosol extinction from the surface up to 12 km (Figure 7-8). We also  
499 compare the height representing the center of aerosol extinction ( $Z_{\alpha}$ ) in each vertical  
500 column, following Koffi et al. (2012), such that  $Z_{\alpha} = \frac{\sum_{i=1}^k (b_{\text{ext},i} \cdot Z_i)}{\sum_{i=1}^k b_{\text{ext},i}}$ , where  $k$  is the total  
501 number of layers in each column and  $b_{\text{ext},i}$  is extinction coefficient for layer  $i$  within the  
502 column.

503 The sub-domain-averaged CALIOP vertical profiles calculated with both  
504 “including clear-air” (solid black line) and “excluding clear-air” (dashed black line) are  
505 plotted in Figures 7-8 together with the corresponding profiles from the models. The  
506 column-integrated AOD and DOD, and the extinction-weighted height, are listed on each  
507 panel. In the present section, we focus on the “including clear-air” case of the CALIOP  
508 averaged data (described in section 2.2.1); the results for the “excluding clear-air” case  
509 are covered subsequently, in the discussion section. We present the result for the spring  
510 season between March and May, as CALIOP and the models have stronger aerosol and  
511 dust signals during spring in five out of six sub-regions over the sources and the ocean,  
512 except for THAR, which has its peak during summer.

513 Over the dust source regions of THAR, TAKL, and GOBI, the CALIOP  
514 observations show a layer of total aerosol and dust extending from the surface to the  
515 middle troposphere (~6 km) during the spring season (Figure 7). The CALIOP profiles  
516 show different maximum extinction values among these regions, ranging 0.09-0.11  $\text{km}^{-1}$   
517 for total aerosol and 0.04-0.06  $\text{km}^{-1}$  for dust. The peak aerosol extinction appears near the  
518 surface in THAR, but is more elevated in TAKL and GOBI (i.e., 1.0-2.0 km). The

519 extinction-weighted average height of total aerosol ( $Z_{a,aer}$ ) from CALIOP (2.06-2.59 km)  
520 is about 0.1-0.4 km lower than that of dust aerosol ( $Z_{a,du}$ ) (2.17-2.97 km), suggesting that  
521 even near these source regions, dust tends to reside higher in the atmosphere than other  
522 aerosols. The column-integrated AOD and DOD vary with location, between 0.27-0.30  
523 and 0.13-0.18, respectively. In contrast, a clear and significant contribution of dust to  
524 total aerosol extinction ( $f_{DOD}>0.5$ ) appears at most altitudes over all sub-regions. The  
525 strong negative bias near the surface is due to a signal artifact that occurs when the level  
526 1B attenuated backscatter becomes strongly negative, preceding a strongly scattering  
527 target such as the surface (Winker et al. 2009, 2013; Tackett et al., 2018).

528         There is a large spread in model-simulated aerosol and dust extinction vertical  
529 distributions over the dust source regions in spring (Figures 7). Most models show a  
530 maximum value of total aerosol and dust extinction at or near the surface. The average  
531 aerosol height ( $0.86<Z_{a,aer}<2.01$ ) and the average dust height ( $0.75<Z_{a,du}<2.07$ ) from the  
532 models are about 1-2 km lower than CALIOP. Differences in AOD and DOD in the three  
533 dust source regions also appear among the models. GOCART has the highest AOD over  
534 TAKL (0.36), whereas other models have the highest AOD over THAR (0.21-0.35), and  
535 CALIOP reports highest AOD over GOBI (0.30). For DOD, the highest values appear  
536 over TAKL in GOCART (0.30), THAR in GISS (0.17), and GOBI in SPRINTARS  
537 (0.30) and HadGEM2 (0.07); CALIOP finds essentially equal springtime DOD peak  
538 values over TAKL and THAR (0.18). Figure 7 shows that HadGEM2 severely  
539 underestimates the dust amount in THAR and TAKL. The shape of  $f_{DOD}$  between  
540 CALIOP and models are very different, as CALIOP is consistent throughout the

541 atmosphere whereas the models show  $f_{DOD}$  decreasing with elevation. The magnitudes of  
542 the modeled  $f_{DOD}$  values are spread widely, showing large differences with CALIOP.

543 Over ocean (Figures 8), CALIOP displays a shallower aerosol and dust layer and  
544 lower extinction magnitudes compared to the features in the source regions. According to  
545 CALIOP, aerosol and dust are confined below 1 km in all ocean domains. Although the  
546 average aerosol height decreases by 0.5 km during long-range transport from NWP ( $Z_{a,aer}$   
547 =2.27 km) to NEP ( $Z_{a,aer}$  =1.77 km), that of dust maintains at about the same level ( $Z_{a,du}$  =  
548 2.49 km in NWP and 2.57 km in NEP). The CALIOP total-column AOD and DOD show  
549 strongly decreasing gradients from west to east (from 0.18 over NWP to 0.08 over NEP  
550 for AOD, from 0.07 over NWP to 0.03 over NEP for DOD). The  $f_{DOD}$  values (~0.5) over  
551 ocean are lower than over the land regions.

552 Large model diversity in aerosol and dust vertical profiles also appears over ocean  
553 (Figure 8). In general, total aerosol extinction peaks are located near the surface and  
554 decrease with altitude, except for GISS, which places a second aerosol layer around 2  
555 km. However, the models show that dust extinction reaches maximum values in layers  
556 aloft, centered around 3 km, and then decreases with altitude. Consequently the averaged  
557 dust height  $Z_{a,du}$  (2.56-4.22 km) is significantly higher than the average aerosol height  
558  $Z_{a,aer}$  (0.69-2.58 km). It is worth noting that  $Z_{a,du}$  of all models increases (from 2.56-3.38  
559 km to 3.57-4.22 km) between NWP and NEP, in contrast with the nearly constant height  
560 reported by CALIOP, and the modeled  $Z_{a,du}$  values are up to 1.5 km higher than CALIOP  
561 in the ocean domains.

562 The comparison of vertical profiles showed that (1) CALIOP derives thick dust  
563 layers reaching up to 6 km over that dust source regions, and a shallower, weaker aerosol

564 and dust layer over ocean, whereas the models show a large spread in the vertical  
565 distribution of dust over both land and ocean; (2) the average height of dust in the models  
566 underestimates CALIOP over land, but they overestimate CALIOP over ocean; (3)  $Z_{\alpha,du}$   
567 of all models increases during long-range transport over ocean, whereas  $Z_{\alpha,du}$  barely  
568 changes according to CALIOP; and (4) CALIOP shows large dust fraction throughout the  
569 domains, whereas there are wide differences (factors of a few or more) in dust fraction  
570 among models.

571

572 4. Diversity of dust emission, removal, and optical parameters among models

573 4.1 Model emissions and physical/optical parameters

574 In this section, we examine the model simulations of the dust budget and several  
575 internal parameters in the study domain to help diagnose the large diversity among  
576 models, including emission, dry and wet depositions, dust mass loading, loss frequency  
577 (LF, which is the removal rate divided by the dust mass loading), optical depth, and the  
578 mass extinction efficiency (MEE, which converts dust mass to extinction at 550 nm). The  
579 results are summarized in Table 4 and some are shown in Figures 9 and 10. For dust  
580 emissions, Figure 9 indicates that all models produce similar “hot spots”, such as the  
581 Taklimakan desert, Gobi desert, Inner Mongolia, Thar desert, and the deserts in Central  
582 Asia. However, there are clear differences in locations and amounts of emission fluxes.  
583 GOCART and SPRINTARS show similar areas and emission rates in confined source  
584 locations in China, but they differ considerably for locations in India and central Asia.  
585 Dust emissions in other models are more spatially spread out but the emission rates are  
586 much lower than GOCART and SPRINTARS. Note that differences in dust emission

587 between models are determined not only by the emission parameterization scheme and  
588 meteorology, but also by the particle size distribution and the size range. However, the  
589 AeroCom database only contains total dust emissions without size-segregated  
590 information. The lowest mass emission is in ECHAM5 (77.4 Tg yr<sup>-1</sup>), which considers  
591 smaller size particles in its modal approach (0.05-0.5 μm in radius). SPRINTARS and  
592 GOCART have the same maximum size of 10 μm (radius), but SPRINTARS emission  
593 (825.9 Tg yr<sup>-1</sup>) is 21% larger than GOCART (680.5 Tg yr<sup>-1</sup>). GISS (200.4 Tg yr<sup>-1</sup>) and  
594 HadGEM2 (488.8 Tg yr<sup>-1</sup>) have maximum size larger than 10 μm (radius), but their  
595 emissions are lower than GOCART and SPRINTARS (see Table 4). Overall, the domain  
596 dust emission among models differs by more than a factor of 10, from 77.4 Tg yr<sup>-1</sup> in  
597 ECHAM5 to 825.9 Tg yr<sup>-1</sup> in SPRINTARS. The comparison here suggests that the  
598 differences in dust size-range alone cannot explain the diversity in dust emissions  
599 between the models. Rather, the dust uplifting mechanisms and/or meteorological  
600 conditions (e.g., winds, soil wetness) might also play a role in the dust emission  
601 differences among the models.

602 We compare three physical and optical parameters from the models in our study  
603 domain: loss frequency (LF in day<sup>-1</sup>), which is the total dust deposition rate (sum of wet  
604 and dry deposition rates) divided by the dust mass loading;  $f_{\text{wet}}$ , which is the dust wet  
605 deposition fraction of total deposition, and the dust mass extinction efficiency (MEE in  
606 m<sup>2</sup>g<sup>-1</sup>), which is the ratio of DOD to dust mass loading (Figure 10). The mean values of  
607 these parameters for each region per model are summarized in Table 4.

608 During long-range transport, aerosol loading and consequently LF are affected by  
609 advection and deposition as well as by particle size distribution. The range of the annual

610 mean LF values over the land and ocean domains among the models range between 0.20-  
611 0.53 and 0.09-0.21 day<sup>-1</sup>, respectively (Table 4 and Figure 10a). SPRINTARS and  
612 HadGEM2 show higher LF (> 0.9 day<sup>-1</sup>) in and around their respective source locations,  
613 indicating that dust aerosols are quickly removed before transport far from the source  
614 region occurs, due to the effective settling of large particles. GOCART and GISS show  
615 relatively lower LF (< 0.7 day<sup>-1</sup>) over source regions. ECHAM5, which allows dust to  
616 mix with other aerosols internally, shows low LF (< 0.5 day<sup>-1</sup>) in and near source regions,  
617 but it has high LF (> 0.9 day<sup>-1</sup>) outside the deserts over land. The highest LF (>0.9 day<sup>-1</sup>)  
618 in the Tibetan Plateau in ECHAM5 is explained by stronger wet-removal than other  
619 models. ECHAM5 has the highest LF, which explains why the steepest decreasing DOD  
620 gradient shown in Figure 4b corresponds to that model. All models show lower LF (<0.4  
621 day<sup>-1</sup>) in 20°N-60°N over ocean than near-source (over land).

622 Dust from the Taklimakan and Gobi Deserts is frequently to be transported  
623 toward the North Pacific. The highest emission from these regions is in GOCART (462.3  
624 Tg year<sup>-1</sup>), followed by SPRINTARS (374.6 Tg year<sup>-1</sup>), HadGEM2 (134.7 Tg year<sup>-1</sup>),  
625 GISS (81.6 Tg year<sup>-1</sup>), and ECHAM5 (26.1 Tg year<sup>-1</sup>) (Table S2). The contribution from  
626 these regions to the total domain emission is higher in GOCART (68 %) than other  
627 models (28 % in HadGEM2 ~ 45 % in SPRINTARS). Dust emission from the  
628 Taklimakan is factor of a few higher in GOCART (252.9 Tg year<sup>-1</sup>) and SPRINTARS  
629 (208.6 Tg year<sup>-1</sup>) than other models (0.1~31.2 Tg year<sup>-1</sup>). Similarly, GOCART and  
630 SPRINTARS DOD better agrees with MDB DOD over the Taklimakan Desert, whereas  
631 other models are understated (Figure S6). The result indicates that the higher DOD (0.08)  
632 in GOCART over the Northern Pacific is attributed by the combined effects of lower loss

633 frequency ( $0.15 \text{ day}^{-1}$ ) and higher emission. In contrast, dust emission in SPRINTARS is  
634 higher than GOCART but its mean DOD (0.05) is 33.5 % lower than GOCART, mainly  
635 due to the high loss frequency ( $0.26 \text{ day}^{-1}$ ) in SPRINTARS. Other models have much  
636 lower emissions than GOCART and SPRINTARS.

637         The models in the present study include two major deposition processes to  
638 remove dust aerosols from the atmosphere: dry (including gravitational settling and  
639 aerodynamic deposition) and wet (including convective scavenging and large-scale  
640 rainout/washout), and their efficiencies are highly model-dependent. The distributions of  
641 wet deposition fraction over total deposition,  $f_{\text{wet}}$  between models are compared in Figure  
642 10b. For major dust source regions over land, all models give consistently low  $f_{\text{wet}}$  values  
643 of less than 0.1, since total dust removal is dominated by gravitational settling of larger  
644 particles near the source. The  $f_{\text{wet}}$  increases away from the source over land ( $>0.9$  in  
645 GISS, ECHAM5, and HadGEM2, and 0.5~0.6 in the other models). Over the Pacific  
646 Ocean, the models show substantially higher  $f_{\text{wet}}$ , with the highest  $f_{\text{wet}}$  (0.92) in  
647 HadGEM2 and the lowest in GOCART (0.62), resulting in a 48 % relative difference  
648 between the two. The annual mean precipitation over the North Pacific Ocean ranges  
649 from  $2.86 \text{ (mm day}^{-1}\text{)}$  in SPRINTARS to  $3.49 \text{ (mm day}^{-1}\text{)}$  in GISS, and the precipitation  
650 field has a peak in summer in all models (Figure S7). The order of  $f_{\text{wet}}$  between models is  
651 not consistent with the order of precipitation, due to differences in the modeled wet and  
652 dry removal processes. Overall, GOCART LF along the dust transport route over ocean is  
653 also the lowest, resulting in the highest DOD among models, and it actually agrees best  
654 with the satellite data.

655           Although MEE is the extinction efficiency per unit mass, it is also affected by  
656 both particle size distribution and the optical properties adopted by the models (e.g., mass  
657 extinction coefficient is higher for fine-mode particles than coarse-mode particles). All  
658 models show that dust MEE is lower over source regions (0.3-0.8) than downwind  
659 towards the eastern Pacific Ocean, consistent with the notion that dust particle size is  
660 larger near the source, and that large particles are more efficiently removed than the fine  
661 particles. The mean MEE ( $\text{m}^2\text{g}^{-1}$ ) among models ranges from 0.57 (GOCART) to 1.01  
662 (SPRINTARS) over land, and from 0.61 (GOCART) to 1.12 (SPRINTARS) over ocean  
663 (Table 4). Overall, the spatial distribution of dust MEE is particle-size dependent, ranging  
664 from 0.3-0.7 in GOCART to 0.7-1.3 in SPRINTARS, with SPRINTARS' dust MEE  
665 overall about 80% larger than GOCART.

666           We estimate the model diversity (Table 4), which is defined as the ratio of the  
667 standard deviation of the model results to the multi-model mean (Textor et al., 2006).  
668 Over the full domain, diversity for the mass-related parameters (*i.e.*, emission, mass  
669 loading, dry deposition, and wet deposition) is in the range of 39-100 %. Diversity for the  
670 optical parameters of AOD and DOD is 10 and 84 %, respectively, indicating models  
671 experience more uncertainty in representing dust mass and DOD than AOD.

672           Inter-model comparison in this section allows us to explain the large diversity of  
673 DOD (*i.e.*, 84%); dust mass loading and mass extinction efficiency are the determining  
674 factors for DOD estimation. The diversity of LOAD (100%) is among the largest in the  
675 analyzed parameters, mainly due to the combined effects of EMI (69%), DRY (72%), and  
676 WET (39%). In comparison, the diversity of MEE is much smaller (23%), suggesting that  
677 the diversity of DOD is determined mainly by the diversity of LOAD. For EMI, each

678 model uses its own parameterization scheme, input surface condition, and surface wind  
679 speed, generating large differences among models. Each model uses a different  
680 parameterization scheme for DRY and WET processes, resulting in 31% diversity in LF.  
681 Differences in meteorological fields between models such as wind, precipitation, and  
682 circulation also contribute to the diversity of dust lifetime. Further, different optical tables  
683 and size distributions among models is an important factor for dust removal process and  
684 optical property calculation.

685 A critical question in this study is which factor among emission, removal, and  
686 optical property is more responsible for contributing to the diversity of the AeroCom  
687 model simulated DOD? To answer the question, we have calculated a partial sensitivity  
688 of DOD to the above model parameters, based on the method in Schulz et al. (2006).  
689 Since DOD is determined by the dust load (LOAD) and mass extinction efficiency  
690 (MEE), and the LOAD is determined by the source (SRC) and the deposition removal  
691 rate (expressed as residence time RES, which is reciprocal of LF), the domain averaged  
692 DOD can be expressed as:  $DOD = SRC \text{ (g m}^{-2} \text{ s}^{-1}) \times RES \text{ (s)} \times MEE \text{ (m}^2 \text{ g}^{-1})$ .  
693 Because of the study domain is not global such that the dust emission is not necessarily  
694 balanced by the deposition term averaged over the study time period (several years) and  
695 domain, the net SRC is thus expressed as  $SRC = EMI + (EMI-DEP)$ . For each model  $n$ ,  
696 the DOD sensitivity with respect to factor  $x$  is defined as:  $DOD_{x,n} = x_n / \langle x \rangle \times \langle DOD \rangle$ ,  
697 where  $\langle x \rangle$  is the multi-model mean of  $x$  and  $\langle DOD \rangle$  is the multi-model mean DOD.  
698 Figure 11 shows the partial sensitivity of DOD to the net SRC, RES, and MEE for the  
699 five AeroCom models, with the last two points showing the DOD from each model and  
700 satellite. For reference, the partial sensitivity of DOD to EMI within the domain is shown

701 as “x” symbol for each model; the difference between the SRC and EMI is the net dust  
702 imported to the domain if  $SRC > EMI$  or export from the domain if  $SRC < EMI$ .

703 Comparing GOCART and SPRINTARS, the shorter residence time (i.e. the  
704 higher loss frequency) in SPRINTARS is likely to be responsible for the lower simulated  
705 DOD in SPRINTARS, despite higher dust source and higher MEE in SPRINTARS. The  
706 low DOD in GISS and ECHEM is most likely driven by the low dust source (low  
707 emission rates and net export). It is interesting that HadGEM2 shows much higher dust  
708 source ( $EMI + \text{net import}$ ) than GISS but comparable residence time (or loss frequency)  
709 and MEE with GISS, but its simulated DOD is significantly lower than GISS, which is  
710 difficult to explain without more detailed information, such as size-segregated emission  
711 and optical properties. Overall, the result in Figure 11 shows that the diversity of DOD is  
712 mostly driven by the diversity of the dust source followed by that of the residence time,  
713 and to a less extent by the differences in MEE.

714 Among the five models, GOCART agrees with the satellite data the best in terms  
715 of DOD over land and ocean, transpacific DOD gradient, and seasonal cycle. However,  
716 there is still a lack of observational data to validate or constrain the emission, dry and wet  
717 removal (the slowest among models), and MEE (the lowest among models) in GOCART.  
718 We can only say that the combination of these factors allows GOCART to simulate the  
719 DOD magnitude, horizontal distributions, and seasonal variations that are the closest to  
720 the satellite observations.

721

722 4.2 Comparison with North African dust

723 To address how model-simulated dust over the Asia-Pacific Ocean compares with  
724 North Africa-Atlantic Ocean, we compare AOD and five dust physical and optical  
725 parameters (DOD,  $f_{\text{DOD}}$ ,  $f_{\text{wet}}$ , LF, and MEE) from the current study with our previous  
726 study over North Africa and the Atlantic Ocean (i.e., Kim et al., 2014) (Figure 12 and  
727 Table 5). In the comparison, each parameter from the models is averaged over land and  
728 ocean to simplify the discussion.

729 Due to the differences in dust size and meteorology in the source regions, dust  
730 emission and DOD over North Africa (1048 Tg yr<sup>-1</sup> and 0.18, respectively) is 2~3 times  
731 larger than over Asia (454 Tg yr<sup>-1</sup> and 0.05). The models show a factor of two difference  
732 in  $f_{\text{DOD}}$  between North Africa (0.52) and Asia (0.25), indicating that other pollutants play  
733 a more important role over Asia. Dust LF is comparable between the two continents  
734 (about 10%), with that over North Africa (0.39 day<sup>-1</sup>) slightly larger than over Asia (0.36  
735 day<sup>-1</sup>). Considering the spectral dependency of dust particle size, the lower dust MEE  
736 between North Africa (0.65 m<sup>2</sup>g<sup>-1</sup>) and Asia (0.73 m<sup>2</sup>g<sup>-1</sup>) suggests larger dust particle size  
737 over North Africa than Asia. The higher  $f_{\text{wet}}$  over Asia (0.55) than over North Africa  
738 (0.32) reflects more frequent and abundant precipitation over Asia than North Africa. The  
739 comparison between the Atlantic and Pacific Oceans shows a similar pattern as in North  
740 Africa and Asia (Figure 12b). Furthermore, the longitudinal gradient of the trans-Pacific  
741 dust is about one-half of the trans-Atlantic dust, due to higher dust elevation and  
742 differences in precipitation.

743 AeroCom models use the same anthropogenic emissions, but dust emission is  
744 calculated by each model. As a result, the diversity of model AOD over the more polluted  
745 Asia region (13%) is much smaller than that for North Africa (50%). However, the

746 diversity of DOD (66-75%) is larger for Asia and North Africa than diversity of AOD.  
747 Over ocean, the AOD diversity for the Pacific Ocean (21%) is smaller than for the  
748 Atlantic Ocean (34%), but the diversity of DOD for the Pacific Ocean (121%) is three  
749 times as large as for the Atlantic Ocean (45%), due to the differences in meteorological  
750 fields and removal processes. Diversities of other physical and optical parameters  
751 between North Africa and Asia are low and comparable, with differences generally less  
752 than 10%.

753

## 754 5. Discussion

755       The present inter-model dust comparison has shown that there are large  
756 differences among models, among the satellite observations, and between models and  
757 satellite observations. Among the five participating AeroCom models, most of them  
758 except GOCART significantly underestimate DOD relative to the satellite-derived values  
759 over Asia and the Pacific Ocean, whereas GOCART emits more dust (i.e., 2<sup>nd</sup> most dust  
760 emission after SPRINTARS) and shows longer dust lifetime during transit. The  
761 participating models have different size range and thus they have different size  
762 distributions as reflected in Table 1. Recent studies have shown that the wide spread in  
763 size-distribution between models, and in addition models generally simulate too much  
764 fine dust compared to observations (Kok et al., 2017). The differences in emission, size  
765 distribution and dry deposition efficiency (i.e., the ratio of DRY to EMI in Table 4)  
766 between models contribute to the large diversity in DRY between models. The aerosol  
767 size distribution is a subject of future inter-model comparison studies.

768 In summary, the analysis of model diversity for various physical/optical  
769 parameters raises the following points: (1) Among the mass-related parameters (emission,  
770 load, dry and wet deposition), the greatest diversity appears in the dust mass loading,  
771 especially over ocean. (2) The diversity of dry deposition is about twice larger than that  
772 of wet deposition. (3) There is a sharp contrast between the diversity of AOD and that of  
773 DOD, i.e., the diversity of AOD is only 12-17% of the diversity of DOD. (4) The  
774 diversity of almost all parameters over ocean is larger than the corresponding quantities  
775 over land. (5) The diversity of DOD is mostly driven by the diversity of the dust source  
776 followed by that of the residence time, and to a less extent by the differences in MEE.

777 As presented in section 3, we assigned CALIOP aerosol extinction in “clear-air”  
778 a value of  $0 \text{ km}^{-1}$  following the method described in section 2.2.1. CALIOP data using  
779 this method agrees with MODIS and MISR for AOD, and MODIS for DOD over land.  
780 However, this causes a low bias in averaged aerosol vertical profiles and thus  
781 underestimates AOD and DOD relative to MODIS and MISR, especially over ocean. As  
782 constraining aerosol extinction below the detection limit is highly uncertain, we also  
783 provide an upper bound on the extinction profiles by excluding the “clear-air” data in the  
784 average. If we exclude the clear-air data in the average, it removes much of the sampling,  
785 approximately 70 % over dust source regions and 90 % over remote ocean (Figure S1f).  
786 The “excluding clear-air” case does not alter the AOD and DOD horizontal patterns and  
787 their longitudinal gradients much. However, the AOD and DOD magnitudes are 70-80 %  
788 larger than the “including clear-air” case over land and ocean (Figure 13, left panel and  
789 Table 6). Actually, in the “excluding clear-air” case, the CALIOP longitudinal gradients  
790 agree better with the other satellites over ocean, but the resulting CALIOP AOD and

791 DOD over land is larger than the other satellites (Figure 13, right panel). Overall, the  
792 effects of how “clear-air” is represented produces large differences in AOD and DOD  
793 over land and ocean, yet the change to  $f_{DOD}$  is less than 10%.

794         The impact of how “clear-air” is represented on the shape and magnitude of the  
795 CALIOP vertical profiles is large (solid and dashed lines in black in Figures 7-8). Over  
796 the land domains, the aerosol and dust extinctions of the “excluding clear-air” case are  
797 about twice as large as the “including clear-air” case at all altitudes. Also, the average  
798 heights ( $Z_a$ ) increase by 0.4-0.9 km for total aerosol and 0.6-1.0 km for dust. Over the  
799 ocean domains, aerosol extinctions for the “excluding clear-air” case are about 3-5 times  
800 larger and  $Z_{a,aer}$  is about 1.2-1.8 km higher than the “including clear-air” case. Dust  
801 extinction for the “excluding clear-air” case is 2-5 times larger, and  $Z_{a,du}$  is about 1.4-1.8  
802 km higher, than the “including clear-air” case. These results suggest that the low  
803 detection limit of CALIOP may miss large amount of background aerosol and dust signal,  
804 which is consistent with a previous study (Watson-Parris et al., 2018). Given the  
805 limitations and uncertainties in the CALIOP vertical profiles over ocean, where the  
806 aerosol amount is low, it is difficult to use the CALIOP data to meaningfully evaluate the  
807 model-simulated vertical profiles.

808         Finally, our study shows that satellite remote sensing is crucial to better  
809 understand the large-scale distribution and variation of dust. Although the three satellite  
810 data sets considered show general agreement of AOD and DOD patterns, they also leave  
811 large uncertainties in estimating aerosol and dust over Asia and especially over Pacific  
812 Ocean due to 1) the presence of sea-spray aerosol and clouds, 2) mixing of dust with other  
813 continental aerosol, and 3) data sampling biases and instrument sensitivity limitations.

814 Our study emphasizes that better aerosol and dust detection over the Pacific Ocean is  
815 essential to reduce the uncertainty inherent in the present study.

816

## 817 6. Summary

818 We evaluated dust and total aerosol over Asia and the North Pacific Ocean for  
819 five AeroCom II global models by comparing the model-simulated spatial and temporal  
820 distributions with a suite of satellite remote-sensing data and with AERONET sun  
821 photometer measurements. Our evaluation targeted four areas: (1) spatial distributions of  
822 AOD and DOD over Asia and the North Pacific Ocean, (2) longitudinal gradient of AOD  
823 and DOD during trans-Pacific transport, (3) seasonal variations of AOD and DOD, and  
824 (4) vertical extinction profiles of total aerosol and dust. To understand the inter-model  
825 differences in the dust simulations, we also compared several key model parameters,  
826 including dust emission, dry and wet deposition, loss frequency, and dust mass extinction  
827 efficiency.

828 The satellites agree that high AOD exists over major pollution regions, and  
829 gradually decreases downwind from the source regions. They show a peak in spring and a  
830 minimum in winter. Over land, satellite observations of DOD are derived from MODIS  
831 (0.11) and CALIOP (0.09), which shows a large dust contribution over land, accounting  
832 for 36% and 42% of the total AOD, respectively. Over ocean, satellite observations show  
833 that the average AOD is more than half (62%) the value over land, and DOD derived  
834 from MODIS, MISR, and CALIOP accounts for 27-30% of AOD. It is worth noting that  
835 AOD and DOD of MODIS and MISR are close each other, but CALIOP is much lower

836 than the other satellites over the ocean domain. Overall, satellites show a 35-70 %  
837 decrease of DOD from the west Pacific to the east Pacific.

838         Large differences among models and between models and observations were  
839 found in all categories (column AOD/DOD, longitudinal gradient, seasonal variations,  
840 and vertical profiles) in this analysis. The mean AODs from models are within 20 % of  
841 the satellites; however, the inter-model differences over both land and ocean are  
842 comparable to the inter-satellite instrument differences. On the other hand, most models  
843 except GOCART underestimate DOD (0.00-0.05) compared to the satellite-derived  
844 products (0.03-0.06). The models show a wide range of decreasing longitudinal gradients  
845 for AOD (42-69 %) and DOD (45-88 %) across the Pacific Ocean, although the range is  
846 comparable to the differences between satellite products (35-70%). The models show  
847 large seasonal variations of AOD over land and ocean with a peak in spring or summer  
848 (0.2-0.35) and a minimum in winter (0.1-0.2) over land and ocean. The DOD and  $f_{DOD}$   
849 differences among the models are very large, as high as a factor of 20. The models also  
850 show peak DOD in spring and summer (0.05-0.24) and winter minima (<0.07).

851         The vertical profiles of CALIOP show thick dust layers up to 6 km over dust  
852 source regions, and a shallower and weaker aerosol and dust layer over ocean. The  
853 models display a large spread in dust vertical distributions over land and ocean; they  
854 underestimate average height of CALIOP over land, but they overestimate over ocean.  
855  $Z_{\alpha,du}$  according to CALIOP barely changes during long-range transport; in contrast, the  
856 modeled  $Z_{\alpha,du}$  increases during transport. Large dust fraction is detected from CALIOP  
857 throughout the domain, whereas dust fraction between models vary widely, showing  
858 factors of a few differences.

859           The differences in dust emissions among models are larger than a factor of 10  
860 (77.4-825.9 Tg yr<sup>-1</sup>) due to differences in source area size, dust size range, and  
861 meteorology, with a diversity value of 69%. The inter-model comparison also shows  
862 large diversity for mass-related parameters (*i.e.*, LOAD, DRY, and WET; 39-100 %),  
863 which explains the large diversity of DOD (84%). The diversity for dry deposition is  
864 about twice larger than that for wet deposition. The comparisons show that the AOD  
865 diversity is only 12-17% of the DOD diversity. Overall, for most parameters, the  
866 diversity over ocean is larger than over land.

867           While GOCART agrees with the satellite data the best in terms of DOD, there is  
868 still a lack of observational data to validate the emission, dry and wet removal rates (the  
869 slowest among models), and MEE (the lowest among models) in GOCART. For the same  
870 reason, it is difficult to point out specific causes for other models' underestimate the  
871 DOD in our study domain. Observation-based estimates on these quantities are needed  
872 for future progress in modeling dust aerosols in the atmosphere.

873

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889

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1163

1164 Table 1. Description of the participating models and their physical characteristics of dust.  
 1165 Adopted from Kim et al. (2014).

	GOCART (GO)	GISS-E2- OMA (GI)	SPRINTARS (SP)	ECHAM5- HAMMOZ* (EC)	HadGEM2 (HG)
Resolution	2.5°×2°	2.5°×2°	1.125°×1.125°	2.8°×2.8°	1.875°×1.25°
Vertical Layers	30	40	56	31	38
Meteorology	GEOS-4 DAS	Horizontal winds nudged to NCEP Reanalysis	NCEP Reanalysis	ECMWF Reanalysis	ECMWF Reanalysis
Winds for emissions	$U_{10m}^3$	$U_{10m}^3$	$U_{10m}^3$	$U_*^3$	$U_*^3$
Size distribution ( $\mu m$ )	5 bins 0.1-1.0-1.8- 3.0-6.0-10.0	5 bins 0.1-1-2-4- 8-16	6 bins 0.1-0.22-0.46- 1.0-2.15-4.64- 10.0	2 modes (acc. And coarse) $0.05 < r_m < 0.5$ $0.5 < r_m$	6 bins 0.0316-0.1- 0.316-1.0- 3.16-10-31.6
Density ( $g\ cm^{-3}$ )	2.5	2.5 for clay 2.65 for silt	2.6	2.5-2.6	2.65
Dust-related key references	Chin et al. (2002,2009) Ginoux et al. (2001)	Miller et al., (2006); Bauer and Koch (2005)	Takemura et al. (2000, 2005)	Pozzoli et al. (2008, 2011)	Bellouin et al. (2011) (Appendix A)

1166 \* Dust particles are emitted in the insoluble accumulation and coarse modes with mass  
 1167 median radii of 0.37  $\mu m$  and 1.75  $\mu m$ , respectively. Once emitted dust particles can be  
 1168 mixed with other aerosols, and dust is distributed in two additional modes, internally  
 1169 mixed soluble accumulation and coarse modes.  
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1172 Table 2: Remote sensing data used in this study. Adopted from Kim et al. (2014).

Sensor/platform	Data products	Major references
MODIS	AOD (combined dark target and deep blue) DOD derived from AOD and aerosol fine-mode fraction over ocean DOD derived from deep blue retrievals over land	Levy et al. (2013); Hsu et al. (2004) Kaufman et al. (2005); Yu et al. (2009, 2019b) Ginoux et al. (2012); Pu and Ginoux (2016)
CALIOP	Aerosol and dust extinction profiles	Winker et al. (2009); Young et al. (2018); Yu et al. (2012, 2015b, 2019a)
MISR	AOD, non-spherical AOD	Kalashnikova and Kahn (2006); Kahn et al. (2010)
AERONET	AOD, coarse-mode AOD	Holben et al. (1998); Dubovik et al. (2000)

1173

1174 Table 3. Mean of optical properties of satellite over land and ocean domains.  $f_{DOD}$  is the  
 1175 ratio of DOD to AOD. Data is not available over land for some sensors. <sup>1</sup>Mean of  
 1176 satellites.  
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	Name	Unit	MODIS	MISR	CALIOP	Mean <sup>1</sup>
Domain (60°E-140°W, 20°N-60°N)	AOD	Unitless	0.226	0.194	0.152	0.191
	DOD	Unitless	0.085	-	0.061	0.073
	$f_{DOD}$	Fraction	0.329	-	0.352	0.341
Land (60°E-140°E, 20°N-60°N)	AOD	Unitless	0.274	0.209	0.217	0.233
	DOD	Unitless	0.111	-	0.094	0.103
	$f_{DOD}$	Fraction	0.362	-	0.416	0.389
Ocean (140°E-140°W, 20°N-60°N)	AOD	Unitless	0.177	0.179	0.084	0.147
	DOD	Unitless	0.059	0.054	0.027	0.047
	$f_{DOD}$	Fraction	0.296	0.268	0.285	0.283

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1180 Table 4. Budget analysis and optical properties of dust over different domains. Listed  
 1181 parameters are emission (EMI), dry deposition (DRY), wet deposition (WET), column  
 1182 mass loading (LOAD), aerosol optical depth (AOD), dust optical depth (DOD), DOD  
 1183 fraction to AOD ( $f_{\text{DOD}}$ ), WET fraction to total deposition ( $f_{\text{WET}}$ ), loss frequency (LF),  
 1184 mass extinction efficiency (MEE). Diversity of model parameters (%) is defined as the  
 1185 ratio of standard deviation to the mean of a parameter following Textor et al. (2006).  
 1186 Clear-sky AOD is listed for GISS.  
 1187

	Name	Unit	GOCART	GISS	SPRINTARS	ECHAM5	HadGEM2	Model mean	Diversity (%)
Domain (60°E- 140°W, 20°N- 60°N)	EMI	Tg yr <sup>-1</sup>	680.5	200.4	825.9	77.4	488.8	454.6	69.3
	DRY	Tg yr <sup>-1</sup>	518.8	123.4	468.0	35.1	323.5	293.8	71.8
	WET	Tg yr <sup>-1</sup>	164.4	105.8	150.8	70.0	73.2	112.8	38.5
	LOAD	Tg	9.12	2.35	3.06	0.75	1.45	3.34	100.0
	AOD	Unitless	0.202	0.191	0.157	0.182	0.166	0.180	10.2
	DOD	Unitless	0.080	0.028	0.045	0.008	0.013	0.035	83.6
	$f_{\text{DOD}}$	Fraction	0.352	0.138	0.234	0.058	0.101	0.177	66.6
	$f_{\text{WET}}$	Fraction	0.50	0.76	0.62	0.66	0.79	0.66	17.4
	LF	day <sup>-1</sup>	0.15	0.23	0.26	0.37	0.25	0.25	31.0
	MEE	m <sup>2</sup> g <sup>-1</sup>	0.59	0.79	1.06	0.67	0.77	0.78	23.0
Land (60°E- 140°E, 20°N- 60°N)	DRY	Tg yr <sup>-1</sup>	495.1	121.5	464.6	33.8	323.0	287.60	71.2
	WET	Tg yr <sup>-1</sup>	123.2	89.1	134.9	64.3	66.0	95.50	33.9
	LOAD	Tg	6.60	2.05	2.67	0.69	1.22	2.64	88.4
	AOD	Unitless	0.249	0.193	0.202	0.182	0.197	0.205	12.7
	DOD	Unitless	0.111	0.048	0.075	0.014	0.020	0.054	75.1
	$f_{\text{DOD}}$	Fraction	0.416	0.226	0.345	0.110	0.153	0.250	51.4
	$f_{\text{WET}}$	Fraction	0.38	0.62	0.51	0.57	0.67	0.55	20.0
	LF	day <sup>-1</sup>	0.20	0.28	0.39	0.53	0.41	0.36	35.3
	MEE	m <sup>2</sup> g <sup>-1</sup>	0.57	0.71	1.01	0.66	0.68	0.73	23.0
	Ocean (140°E- 140°W, 20°N- 60°N)	DRY	Tg yr <sup>-1</sup>	25.0	1.9	3.4	1.3	0.5	6.4
WET		Tg yr <sup>-1</sup>	43.3	16.7	15.9	5.7	7.2	17.8	85.1
LOAD		Tg	2.62	0.30	0.39	0.06	0.23	0.72	148.4
AOD		Unitless	0.155	0.189	0.111	0.182	0.136	0.155	20.9
DOD		Unitless	0.049	0.009	0.014	0.001	0.006	0.016	121.2
$f_{\text{DOD}}$		Fraction	0.286	0.049	0.122	0.007	0.048	0.102	108.1
$f_{\text{WET}}$		Fraction	0.62	0.89	0.73	0.74	0.92	0.78	15.8
LF		day <sup>-1</sup>	0.10	0.18	0.13	0.21	0.09	0.14	34.5
MEE		m <sup>2</sup> g <sup>-1</sup>	0.61	0.86	1.12	0.68	0.86	0.83	23.8

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1193 Table 5. Multi-model mean and diversity over land and ocean domains for North Africa  
 1194 and Asia. The values of North Africa are adopted from Kim et al. (2014). Numbers in  
 1195 parenthesis are the diversity of model parameters (%), which is defined as the ratio of  
 1196 standard deviation to the mean of a parameter following Textor et al. (2006).  
 1197

Name	Unit	Land		Ocean	
		North Africa (17°W-30°E, 0°N-35°N)	Asia (60°E-140°E, 20°N-60°N)	North Africa (90°W-17°W, 0°N-35°N)	Asia (140°E-140°W, 20°N-60°N)
EMI	Tg yr <sup>-1</sup>	1047.8 (57.1)	454.6 (69.3)	-	-
LOAD	Tg yr <sup>-1</sup>	5.78 (74.8)	2.64 (88.4)	2.46 (56.5)	0.72 (148.4)
AOD	Unitless	0.29 (50.3)	0.21 (12.7)	0.17 (33.6)	0.16 (20.9)
DOD	Unitless	0.18 (65.8)	0.05 (75.1)	0.06 (44.8)	0.02 (121.2)
f <sub>DOD</sub>	Fraction	0.52 (31.1)	0.25 (51.4)	0.23 (50.2)	0.10 (108.1)
f <sub>WET</sub>	Fraction	0.32 (15.3)	0.55 (20.0)	0.62 (23.4)	0.78 (15.8)
LF	day <sup>-1</sup>	0.39 (44.0)	0.36 (35.3)	0.29 (37.1)	0.14 (34.5)
MEE	m <sup>2</sup> g <sup>-1</sup>	0.65 (26.9)	0.73 (23.0)	0.76 (29.3)	0.83 (23.8)

1198  
 1199

1200 Table 6. Mean of AOD, DOD and  $f_{DOD}$  of CALIOP satellite over land and ocean domains  
 1201 with different integration options of CAD score and clear-sky.  
 1202

Cases	Land			Ocean		
	AOD	DOD	$f_{DOD}$	AOD	DOD	$f_{DOD}$
-100<CAD<-20, exclude clear-air	0.416	0.197	0.429	0.205	0.079	0.305
-100<CAD<-20, include clear-air	0.223	0.109	0.425	0.117	0.040	0.291
-100<CAD<-70, exclude clear-air	0.388	0.169	0.410	0.178	0.058	0.286
-100<CAD<-70, include clear-air	0.211	0.095	0.409	0.104	0.032	0.274

1203  
 1204  
 1205  
 1206

1207 **Figure Captions**

1208

1209 Figure 1. Name and location of the sub-domains for (1) climatology (black dash-boxes)  
1210 and (2) CALIOP (red boxes) analysis. Color map is the annual mean of CALIOP DOD.  
1211 Color circles superimposed on the map are the AERONET retrieved coarse mode AOD.  
1212 The domains for climatological analysis are LAND [60°E-140°E; 20°N-60°N] and  
1213 OCEAN [140°E-140°W; 20°N-60°N]. The domain for CALIOP analysis are THAR  
1214 [70°E-75°E; 25°N-30°N], TAKL [75°E-90°E; 35°N-45°N], GOBI [95°E-115°E; 40°N-  
1215 45°N], NWP [135°E-140°E; 25°N-50°N], NCP [175°E-180°E; 30°N-55°N], and NEP  
1216 [130°W-125°W; 35°N-60°N].

1217

1218 Figure 2. Spatial distribution of mean AOD from satellites (MODIS, MISR, and  
1219 CALIOP) and models (GOCART, GISS, SPRINTARS, ECHAM5, and HadGEM2)  
1220 averaged over 2000-2005. CALIOP including clear-air samples is averaged for 2007-  
1221 2011. Color circles superimposed on the map represent AERONET observed AOD.

1222

1223 Figure 3. Spatial distribution of mean dust optical depth (DOD) from satellites (MODIS,  
1224 MISR, and CALIOP) and models (GOCART, GISS, SPRINTARS, ECHAM5, and  
1225 HadGEM2) averaged over 2000-2005. CALIOP including clear-air samples and is  
1226 averaged for 2007-2011. Color circles superimposed on the map are the AERONET  
1227 retrieved coarse mode AOD.

1228

1229 Figure 4. (a) Meridional mean of AOD, DOD, and  $f_{DOD}$  averaged from 20°N to 60°N.  
1230 Thick lines are satellite retrievals from MODIS (MD), MISR (MI), and CALIOP (CA),  
1231 and thin lines are model simulations. No DOD is available over land in MISR products.  
1232 Asia and North America is shaded in gray. (b) Same as (a), except for normalized to  
1233 values of each variable at the Asian coast of 130°E.

1234

1235 Figure 5. Monthly mean of (top) AOD, (middle) DOD, (bottom)  $f_{DOD}$  for land [60°E-  
1236 140°E; 20°N-60°N]. Left- and right-columns are from satellites and model, respectively.  
1237 All model plots are averaged from 2000 to 2005. Vertical bars are the standard deviation  
1238 of monthly mean values.

1239

1240 Figure 6. Monthly mean of (top) AOD, (middle) DOD, (bottom)  $f_{DOD}$  for ocean [140°E-  
1241 140°W; 20°N-60°N]. Left- and right-columns are from satellites and model, respectively.  
1242 All model plots are averaged from 2000 to 2005. Vertical bars are the standard deviation  
1243 of monthly mean values.

1244

1245 Figure 7. Mean spring season vertical profile of extinction coefficient of total aerosol  
1246 ( $\sigma_{aer}$  in  $\text{km}^{-1}$ ), extinction coefficient of dust ( $\sigma_{du}$  in  $\text{km}^{-1}$ ), and  $f_{\sigma_{du}}$ , the ratio of  $\sigma_{du}$  to  $\sigma_{aer}$   
1247 for THAR (Thar desert), TAKL (Taklimakan desert), and GOBI (Gobi desert) domains.  
1248 Model simulations are for 2006. CALIOP data is averaged from 2007 to 2011. Black  
1249 solid and dashed-lines are the means of CALIOP data including clear-air samples and  
1250 excluding clear-air samples, respectively, representing the lower and upper limits for the  
1251 CALIOP data (range shaded in grey). Numbers in parenthesis are CALIOP data  
1252 excluding clear-air samples.

1253

1254 Figure 8. Same as Figure 7 except for (left) north-west Pacific domain, (middle) north-  
1255 center Pacific, (right) north-east Pacific domains.

1256

1257 Figure 9. Mean dust emissions from models averaged from 2000 to 2005. Color contour  
1258 unit is in  $\text{gkm}^{-2}\text{s}^{-1}$ .

1259

1260 Figure 10. Map of loss frequency,  $f_{\text{WET}}$ , and MEE for dust from models averaged from  
1261 2000 to 2005. (a) Loss frequency is the ratio of total removal rate to LOAD ( $\text{day}^{-1}$ ), (b)  
1262  $f_{\text{WET}}$  is the fraction of wet removal to the total removal, and (c) MEE is dust mass  
1263 extinction efficiency at 550 nm ( $\text{m}^2\text{g}^{-1}$ ).

1264

1265 Figure 11. The partial sensitivity of DOD to various determining factors of Source (SRC  
1266 = EMI + mass imbalance), residence time (RES), and mass extinction efficiency (MEE).  
1267 Model values (GOCART, SPRINTARS, ECHAM5, HadGEM2, and GISS) are averaged  
1268 for 2000-2005 over the domain ( $60^\circ\text{E}$ - $140^\circ\text{W}$ ,  $20^\circ\text{N}$ - $60^\circ\text{N}$ ). “x” symbol of each model is  
1269 the partial sensitivity of DOD to EMI within the domain. MO and CA are the mean DOD  
1270 from MODIS and CALIOP averaged over the same time and domain, respectively.

1271

1272 Figure 12. Multi-model mean of optical and physical parameters over (a) Asia and North  
1273 Africa and (b) Pacific ocean and Atlantic ocean. Models (GOCART, SPRINTARS,  
1274 ECHAM5, HadGEM2, and GISS) are averaged from 2000 to 2005. Error bars are the  
1275 standard deviation of model values.

1276

1277 Figure 13. (left) Spatial distribution of mean AOD, DOD, and  $f_{\text{DOD}}$  from CALIOP  
1278 averaged for 2007-2011, where, CALIOP excludes clear-air samples. Color circles  
1279 superimposed on the map represent AERONET data. (right) same as Figure 4a except for  
1280 CALIOP excludes clear-air samples.

1281

1282

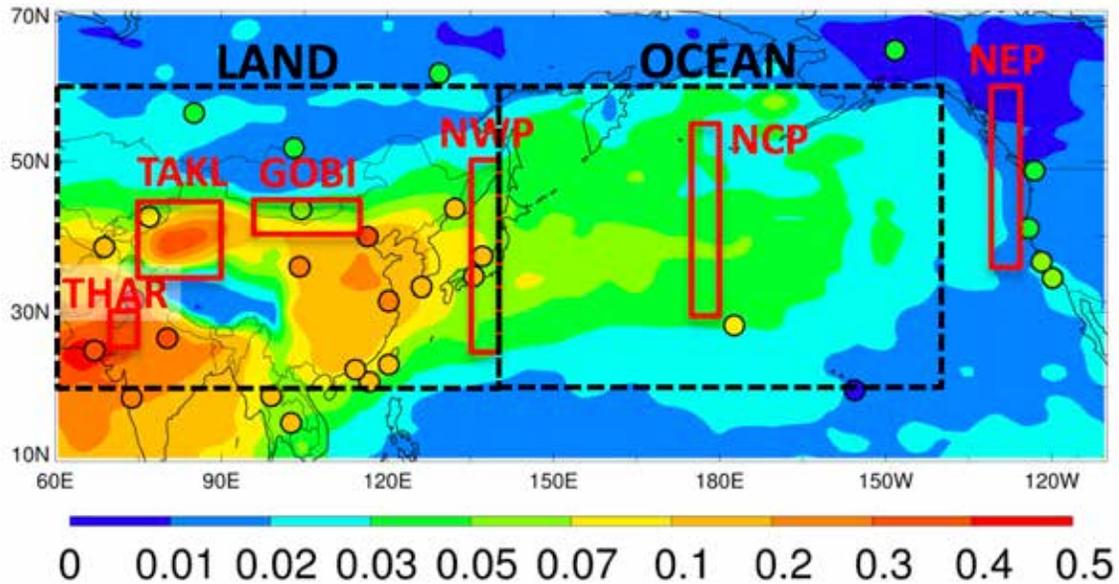


Figure 1. Name and location of the sub-domains for (1) climatology (black dash-boxes) and (2) CALIOP (red boxes) analysis. Color map is the annual mean of CALIOP DOD. Color circles superimposed on the map are the AERONET retrieved coarse mode AOD. The domain for climatological analysis are LAND [60°E-140°E; 20°N-60°N] and OCEAN [140°E-140°W; 20°N-60°N]. The domain for CALIOP analysis are THAR [70°E-75°E; 25°N-30°N], TAKL [75°E-90°E; 35°N-45°N], GOBI [95°E-115°E; 40°N-45°N], NWP [135°E-140°E; 25°N-50°N], NCP [175°E-180°E; 30°N-55°N], and NEP [130°W-125°W; 35°N-60°N].

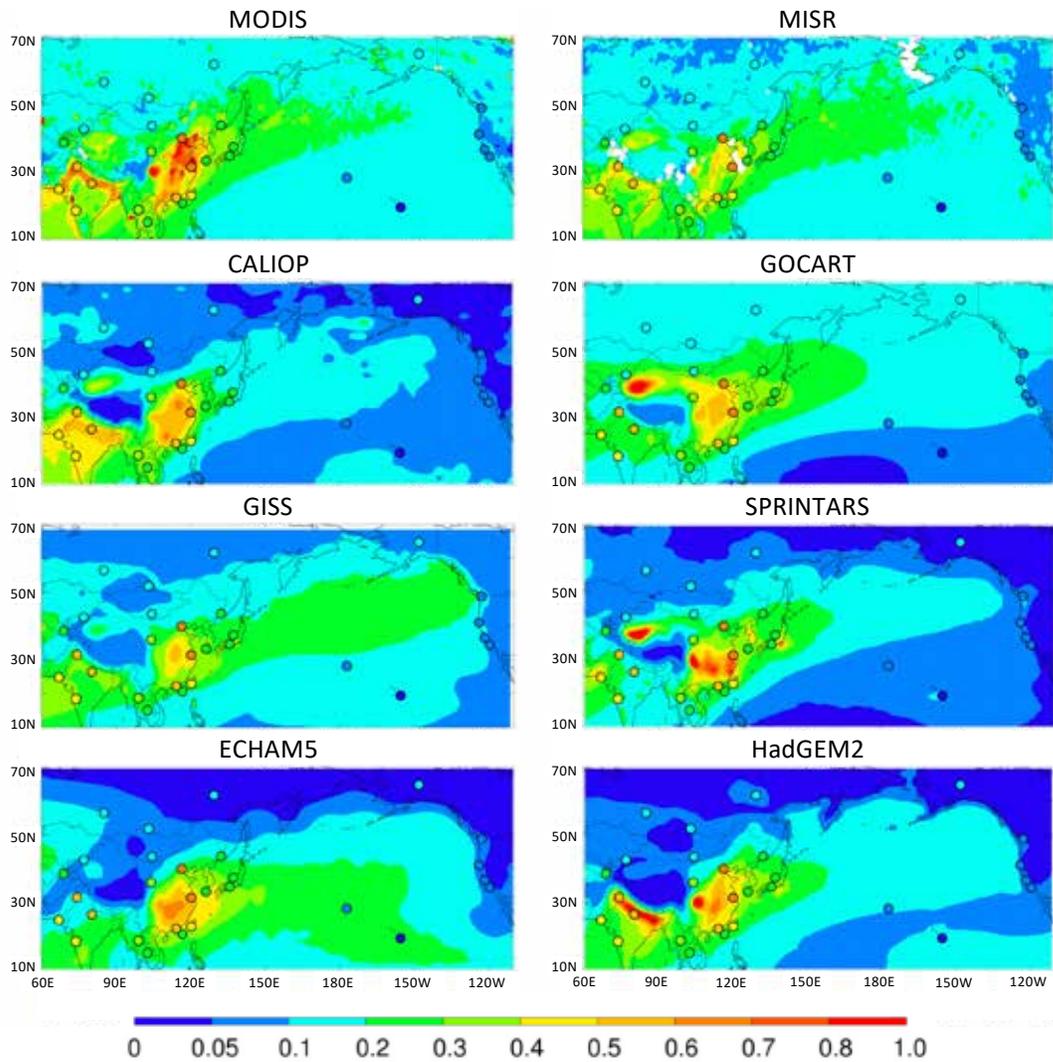


Figure 2. Spatial distribution of mean AOD from satellites (MODIS, MISR, and CALIOP) and models (GOCART, GISS, SPRINTARS, ECHAM5, and HadGEM2) averaged over 2000-2005. CALIOP including clear-air samples is averaged for 2007-2011. Color circles superimposed on the map represent AERONET observed AOD.

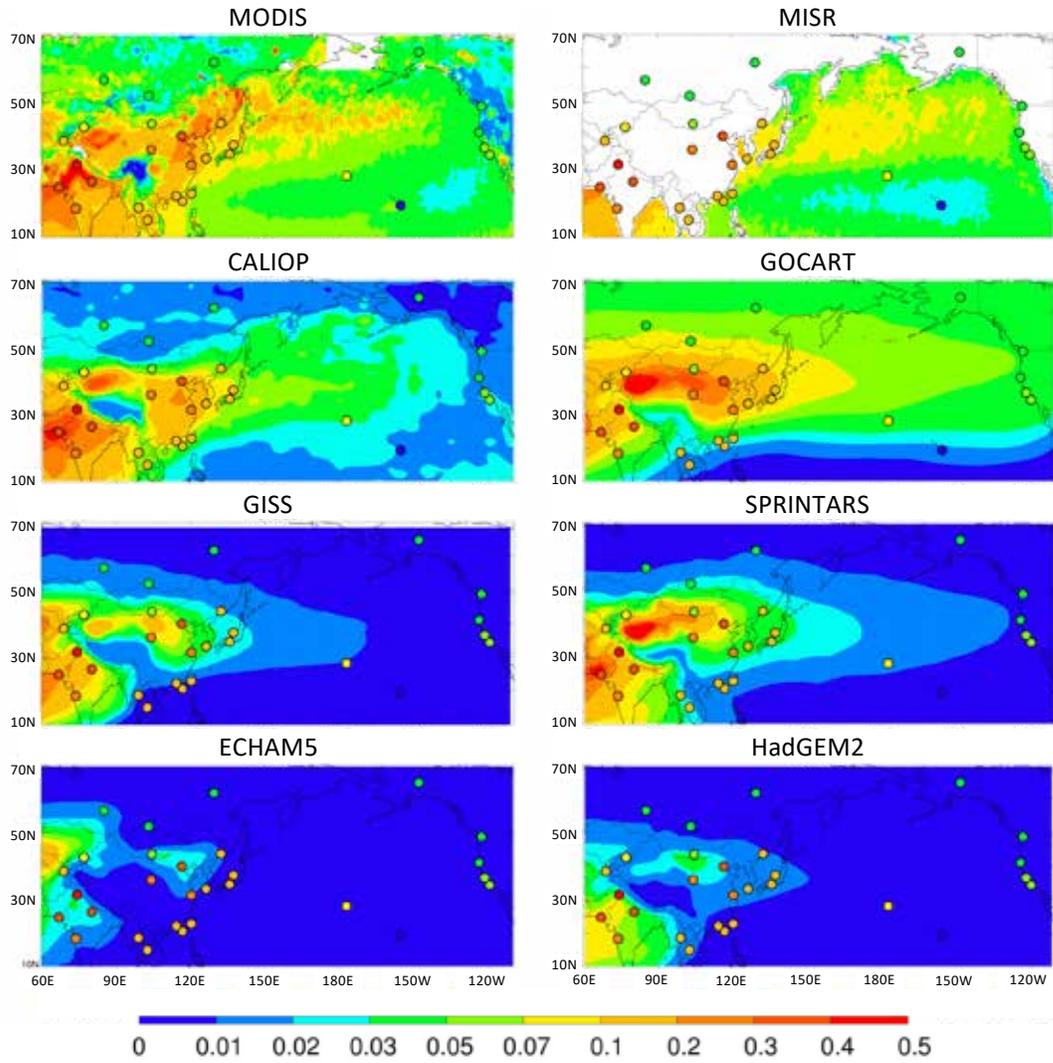


Figure 3. Spatial distribution of mean dust optical depth (DOD) from satellites (MODIS, MISR, and CALIOP) and models (GOCART, GISS, SPRINTARS, ECHAM5, and HadGEM2) averaged over 2000-2005. CALIOP including clear-air samples and is averaged for 2007-2011. Color circles superimposed on the map are the AERONET retrieved coarse mode AOD.

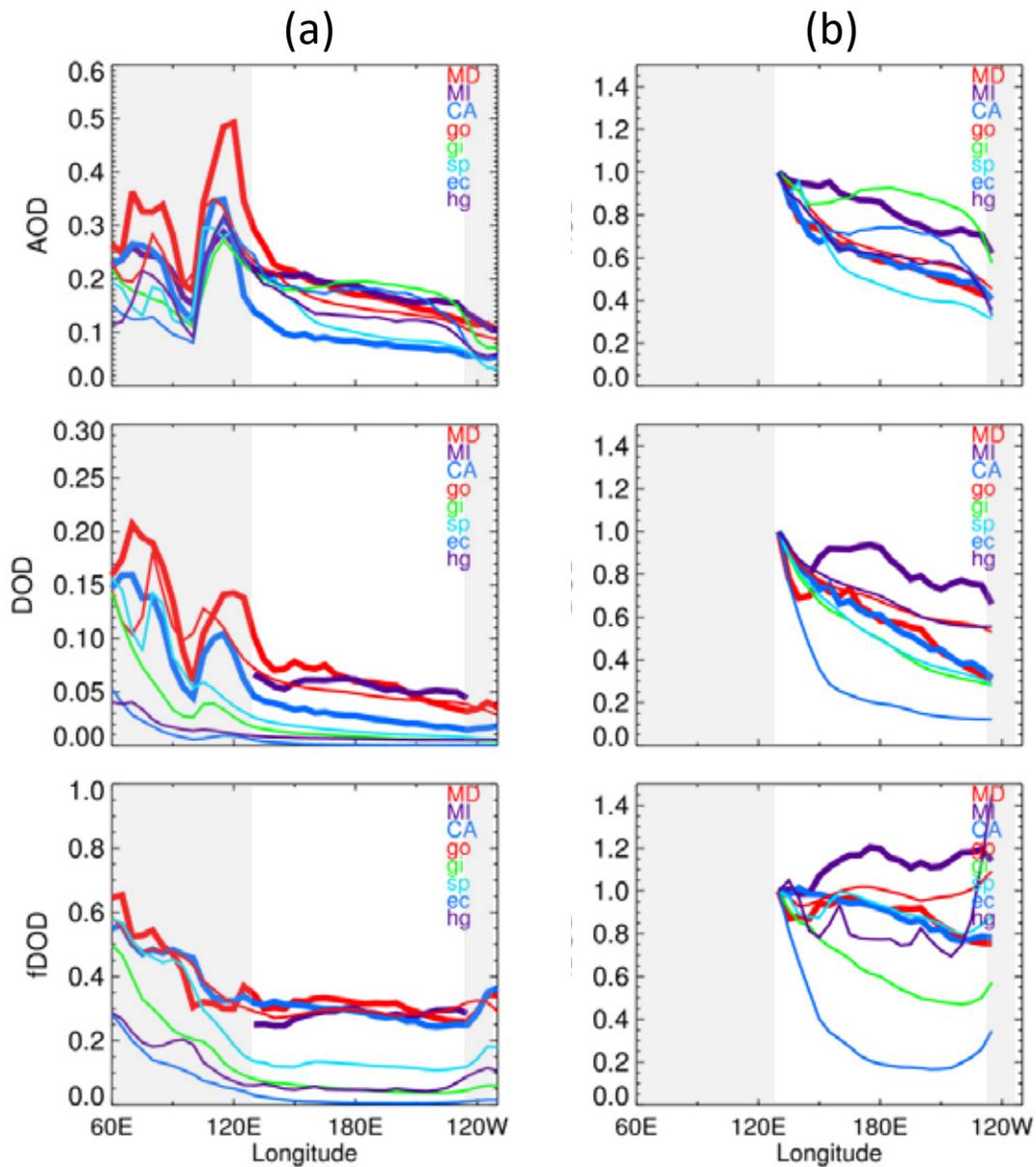


Figure 4. (a) Meridional mean of AOD, DOD, and  $f_{DOD}$  averaged from 20°N to 60°N. Thick lines are satellite retrievals from MODIS (MD), MISR (MI), and CALIOP (CA), and thin lines are model simulations. No DOD is available over land in MISR products. Asia and North America is shaded in gray. (b) Same as (a), except for normalized to values of each variable at the Asian coast of 130°E.

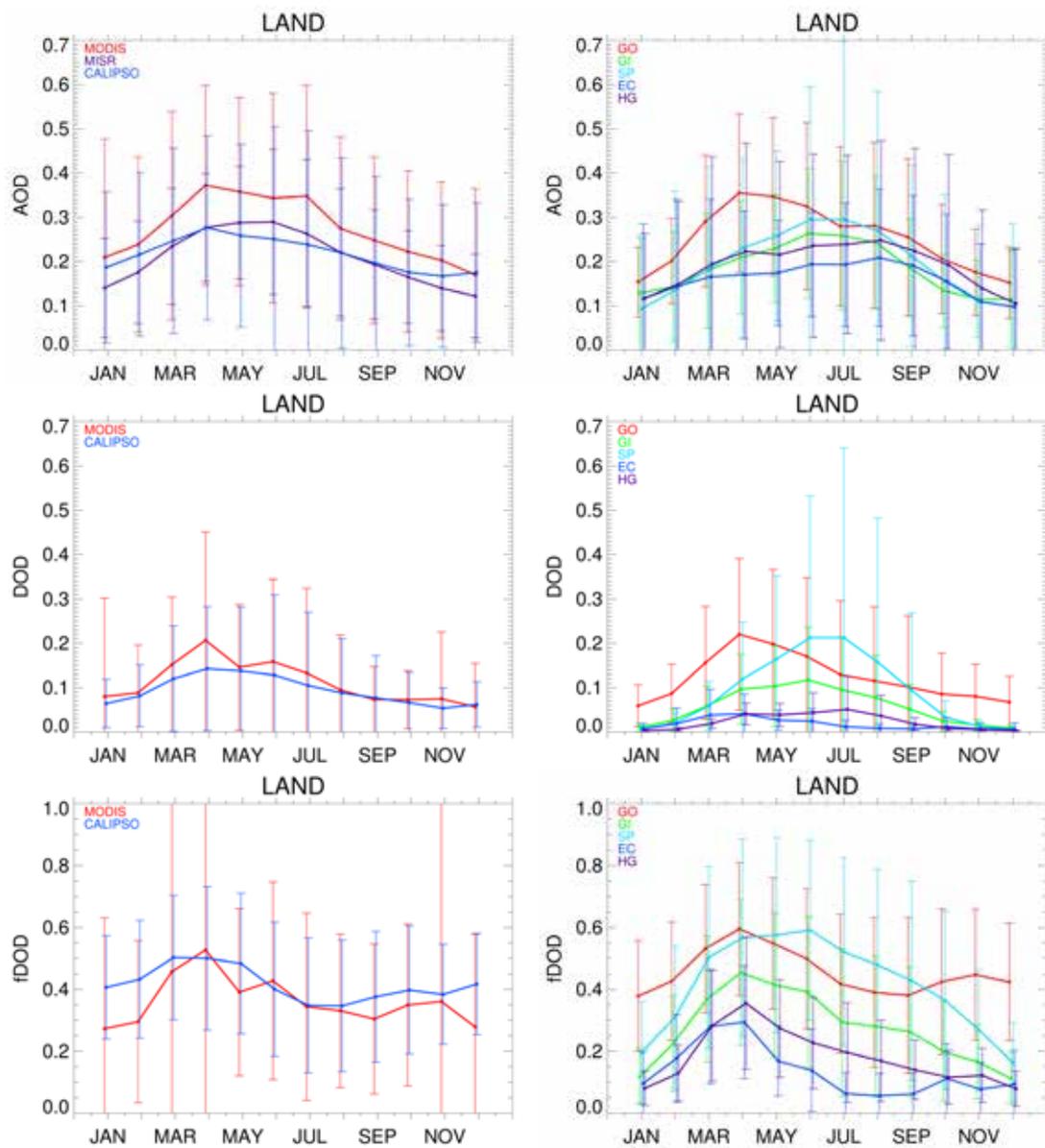


Figure 5. Monthly mean of (top) AOD, (middle) DOD, (bottom)  $f_{DOD}$  for land [60°E-140°E; 20°N-60°N]. Left- and right-columns are from satellites and model, respectively. All model plots are averaged from 2000 to 2005. Vertical bars are the standard deviation of monthly mean values.

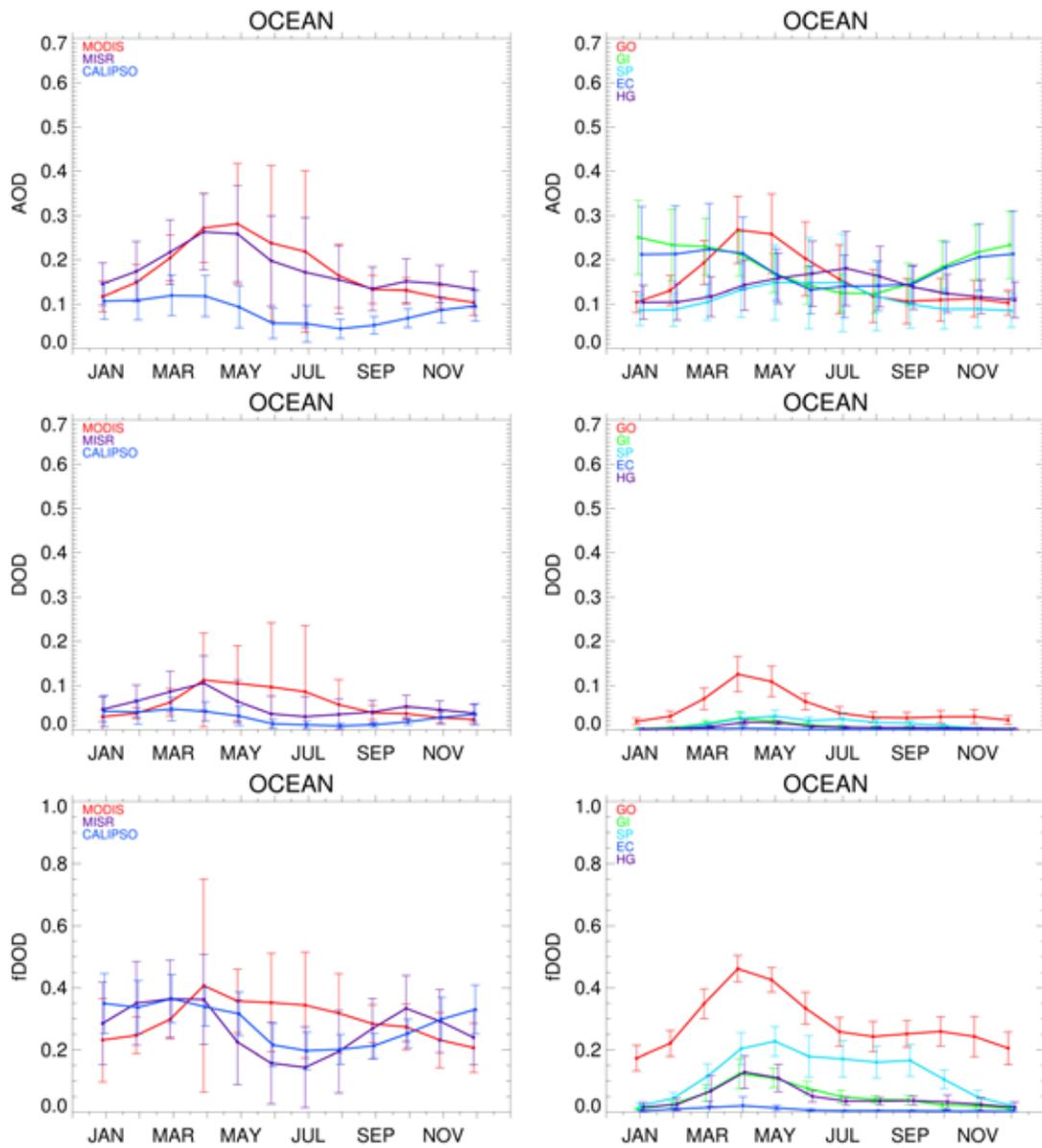


Figure 6. Monthly mean of (top) AOD, (middle) DOD, (bottom)  $f_{DOD}$  for ocean [140°E-140°W; 20°N-60°N]. Left- and right-columns are from satellites and model, respectively. All model plots are averaged from 2000 to 2005. Vertical bars are the standard deviation of monthly mean values.

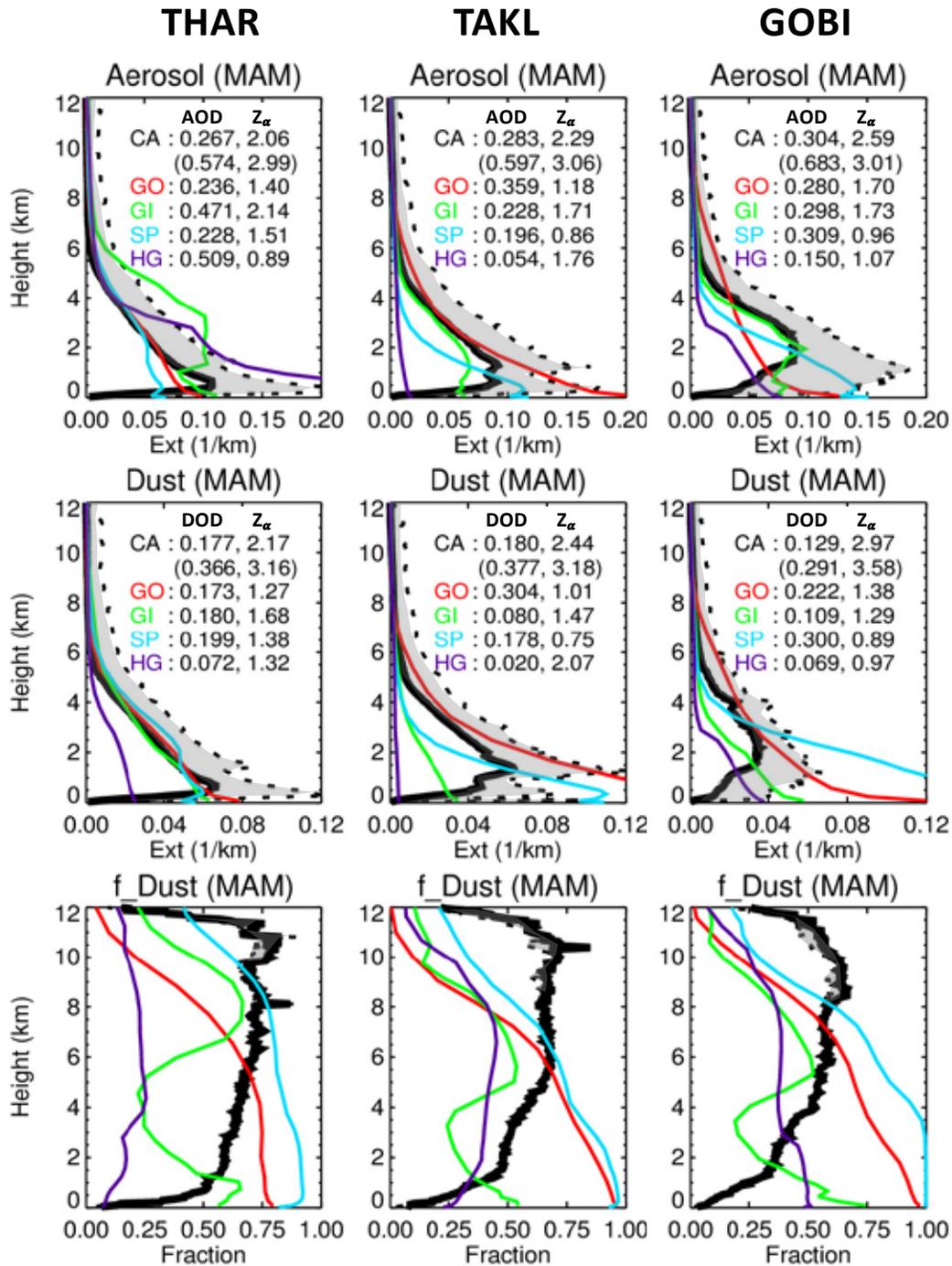


Figure 7. Mean spring season vertical profile of extinction coefficient of total aerosol ( $\sigma_{\text{aer}}$  in  $\text{km}^{-1}$ ), extinction coefficient of dust ( $\sigma_{\text{du}}$  in  $\text{km}^{-1}$ ), and  $f_{\text{Dust}}$ , the ratio of  $\sigma_{\text{du}}$  to  $\sigma_{\text{aer}}$  for THAR (Thar desert), TAKL (Taklimakan desert), and GOBI (Gobi desert) domains. Model simulations are for 2006. CALIOP data is averaged from 2007 to 2011. Black solid and dashed-lines are the means of CALIOP data including clear-air samples and excluding clear-air samples, respectively, representing the lower and upper limits for the

CALIOP data (range shaded in grey). Numbers in parenthesis are CALIOP data excluding clear-air samples.

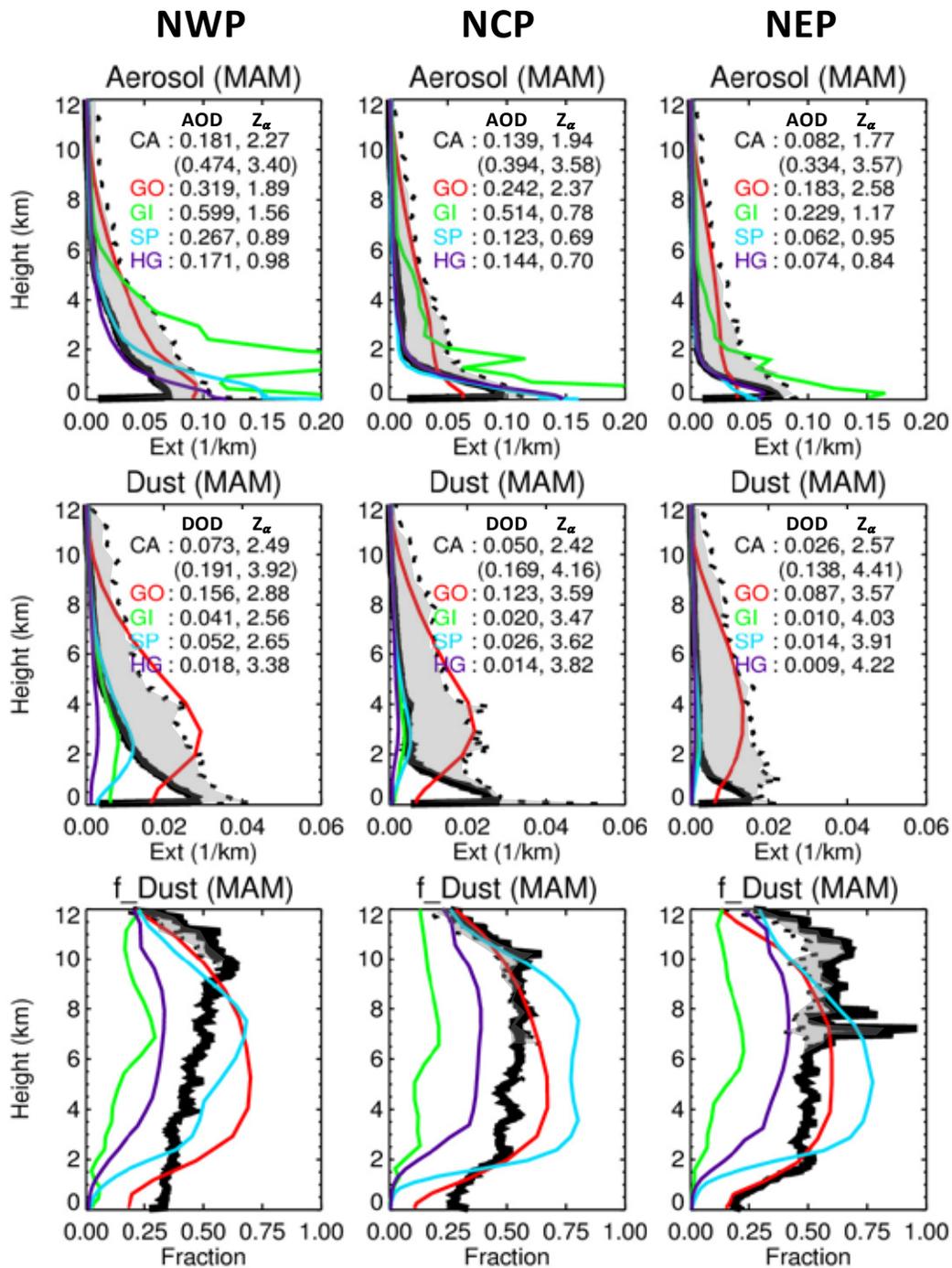


Figure 8. Same as Figure 7 except for (left) north-west Pacific domain, (middle) north-center Pacific, (right) north-east Pacific domains.

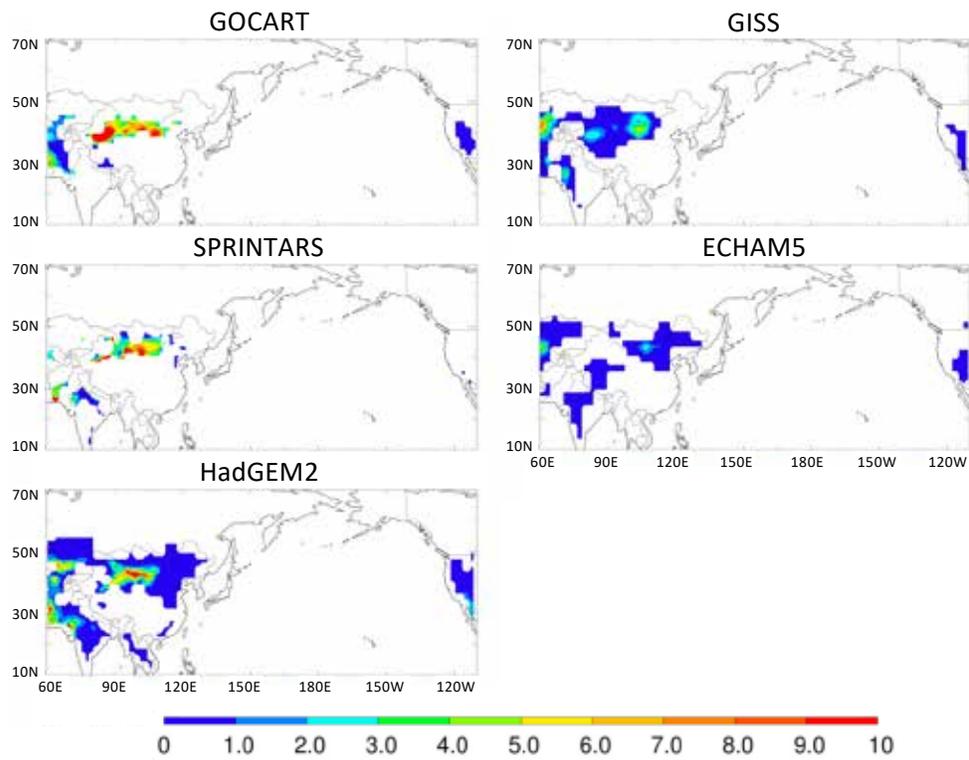


Figure 9. Mean dust emissions from models averaged from 2000 to 2005. Color contour unit is in  $\text{gkm}^{-2}\text{s}^{-1}$ .

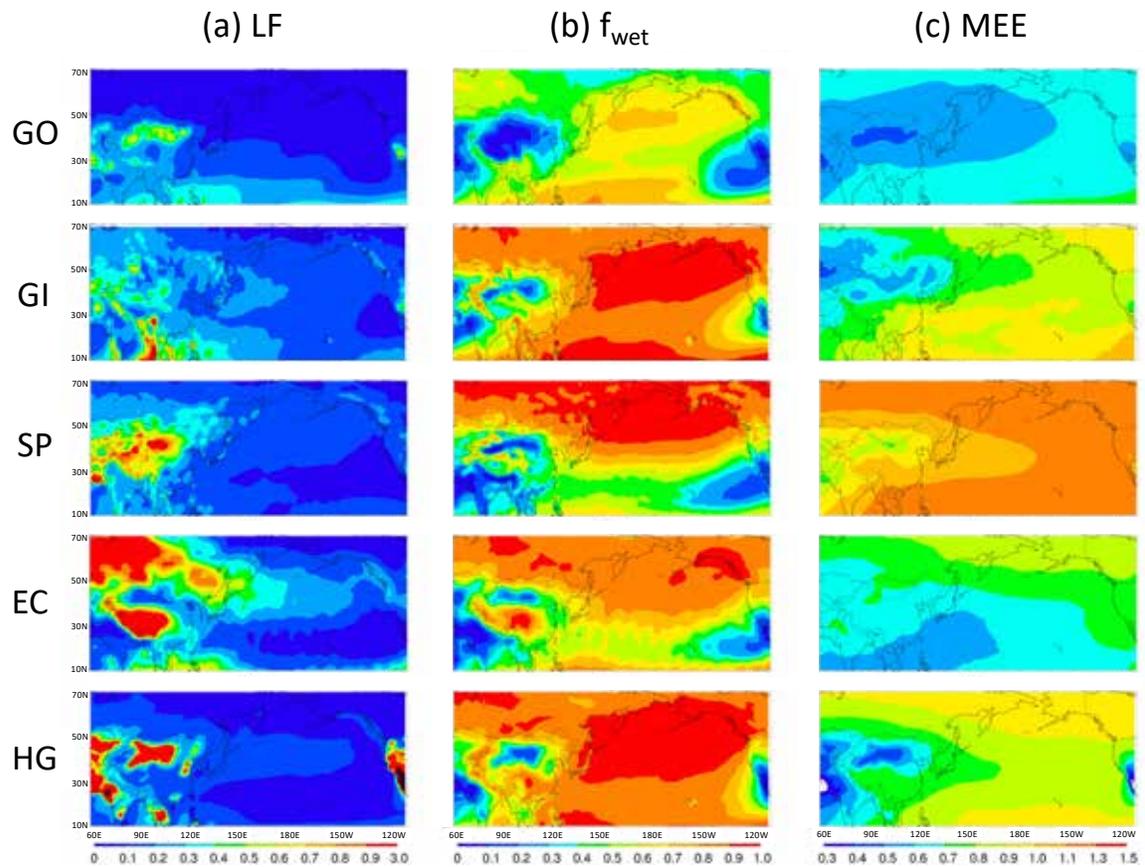


Figure 10. Map of loss frequency,  $f_{\text{wet}}$ , and MEE for dust from models averaged from 2000 to 2005. (a) Loss frequency is the ratio of total removal rate to LOAD ( $\text{day}^{-1}$ ), (b)  $f_{\text{wet}}$  is the fraction of wet removal to the total removal, and (c) MEE is dust mass extinction efficiency at 550 nm ( $\text{m}^2\text{g}^{-1}$ ).

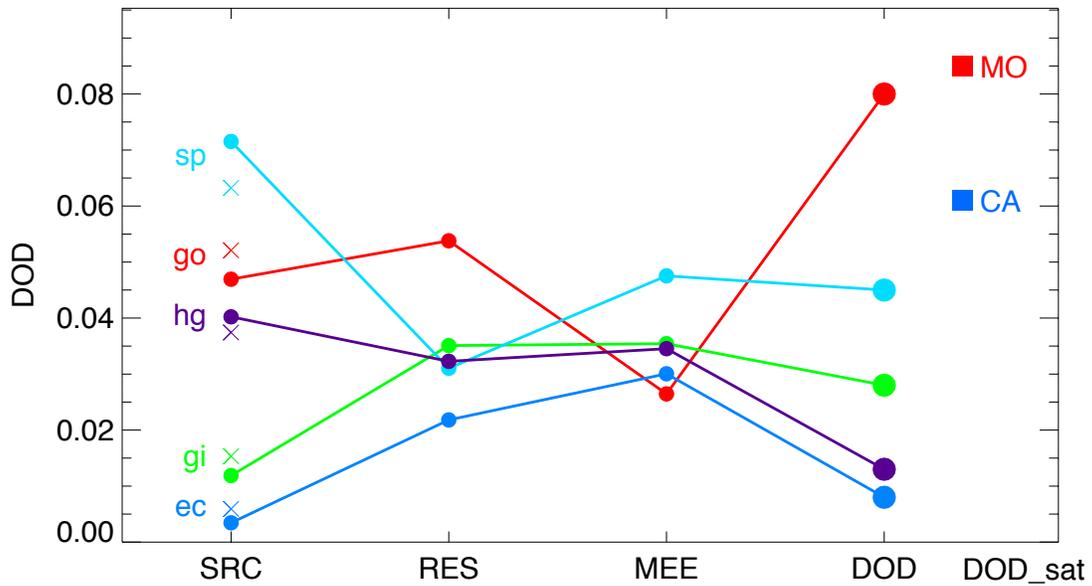


Figure 11. The partial sensitivity of DOD to various determining factors of Source (SRC = EMI + mass imbalance), residence time (RES), and mass extinction efficiency (MEE). Model values (GOCART, SPRINTARS, ECHAM5, HadGEM2, and GISS) are averaged for 2000-2005 over the domain (60°E-140°W, 20°N-60°N). “x” symbol of each model is the partial sensitivity of DOD to EMI within the domain. MO and CA are the mean DOD from MODIS and CALIOP averaged over the same time and domain, respectively.

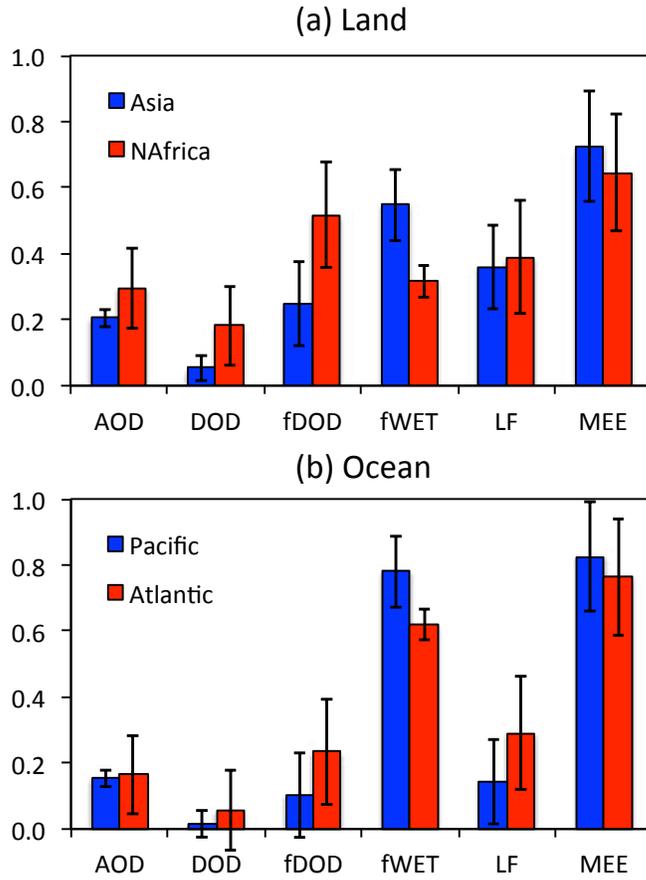


Figure 12. Multi-model mean of optical and physical parameters over (a) Asia and North Africa and (b) Pacific ocean and Atlantic ocean. Models (GOCART, SPRINTARS, ECHAM5, HadGEM2, and GISS) are averaged from 2000 to 2005. Error bars are the standard deviation of model values.

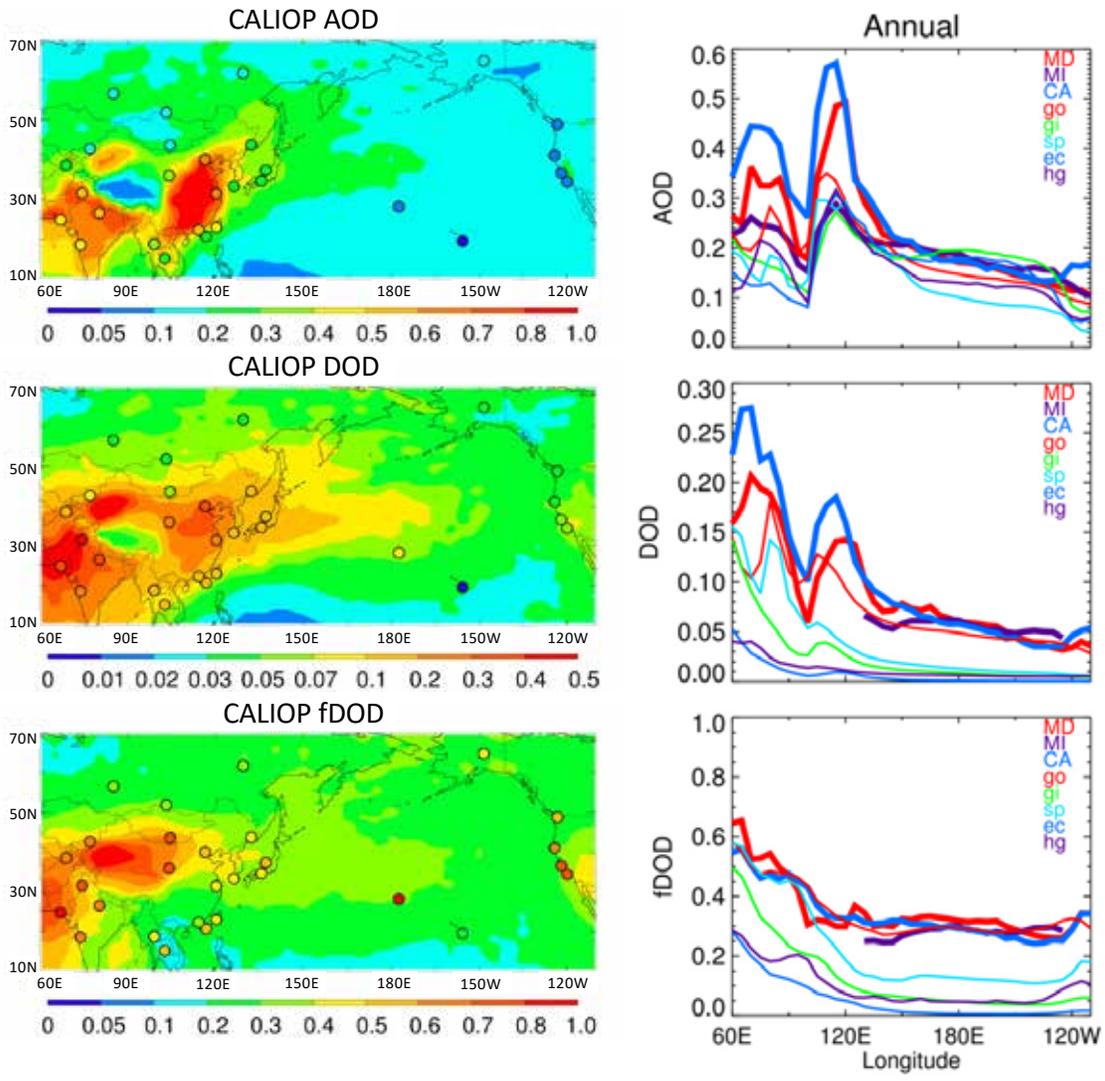


Figure 13. (left) Spatial distribution of mean AOD, DOD, and  $f_{DOD}$  from CALIOP averaged for 2007-2011, where, CALIOP excludes clear-air samples. Color circles superimposed on the map represent AERONET data. (right) same as Figure 4a except for CALIOP excludes clear-air samples.

Auxiliary Material for

# Asian and trans-Pacific Dust: A multi-model and multi-remote sensing observation analysis

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Takemura<sup>9</sup>, Luca Pozzoli<sup>10</sup>, Nicolas Bellouin<sup>11</sup>, and Michael Schulz<sup>12</sup>

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## Introduction

There are a supplement table and six supplement figures. File names and figure captions are presented.

1. Table\_S1.docx: AERONET site name, longitude, and latitude.
2. Table\_S2.docx: Mean emissions from the Taklimakan desert (75°E-90°E, 35°N-45°N), Gobi Desert (95°E-115°E, 40°N-50°N), and Thar desert (60°E-80°E, 20°N-40°N). SRC<sub>all</sub> is the sum of TAKL, GOBI and THAR deserts; SRC<sub>TAGO</sub> is the sum of TAKL, GOBI; Total is the entire domain (60°E-140°W, 20°N-60°N) and the values are taken from Figure 4.
3. Suppliment\_Figirures.docx

## Supplement Figure Captions

Figure S1. Number of data samples (ncount) in million for January 2007 - December 2011: (a)  $-100 < CAD < -20$  and include clear-air; (b)  $-100 < CAD < -70$  and include clear-air; (c)  $-100 < CAD < -20$  and exclude clear-air; (d)  $-100 < CAD < -70$  and exclude clear-air. (e) ncount ( $-100 < CAD < -20$ , include clear-air) minus ncount ( $-100 < CAD < -70$ , include clear-air), (f) ratio of exclude clear-air to include clear-air ( $-100 < CAD < -70$ ), (g) percent ratio of  $CAD < -20$  to  $CAD < -70$  (exclude clear-air).

Figure S2. Comparison of monthly mean AOD between AEROENT and other satellite data and model values over the study domain. Number of total data point is 474 between 2000 and 2005. R, B, and E are the correlation coefficient, mean bias, and root-mean-square-error, respectively. Mean bias is defined as the sum of the ratio of the modeled or satellite AOD to AERONET AOD.

Figure S3. Monthly mean AOD over Land-West (60°E-100°E), Land-East (100°E-140°E), Ocean-West (140°E-180°E), Ocean-East (180°E-140°W) domains from top to bottom. Latitudinal ranges are 20°N to 60°N. Left- and right-columns are from satellites and models, respectively. All model plots are averaged from 2000 to 2005. Vertical bars are the standard deviation of monthly mean values.

Figure S4. Same as Figure S3 except for DOD.

Figure S5. Same as Figure S3 except for  $f_{DOD}$ .

Figure S6. Monthly mean DOD for 2000-2005 over the Taklimakan desert.

Figure S7. Map of precipitation (mm day<sup>-1</sup>) of each season from models averaged from 2000 to 2005.

Table S1. AERONET site name, longitude, and latitude.

<b>Site Name</b>	<b>Longitude (°E)</b>	<b>Latitude (°N)</b>
Issyk-Kul	76.98	42.62
Dushanbe	68.86	38.55
SACOL	104.14	35.95
Kanpur	80.23	26.51
Pimai	102.56	15.18
Dalanzadgad	104.42	43.58
Tomsk	85.05	56.48
Karachi	67.03	24.87
Lahore	74.33	31.54
Pune	73.81	18.54
Chiang_Mai_Met_Sta	98.97	18.77
Dongsha_Island	116.73	20.70
Hong_Kong_PolyU	114.18	22.30
Chen-Kung_Univ	120.22	23.00
Irkutsk	103.09	51.80
Yakutsk	129.37	61.66
Midway_Island	-177.38	28.21
Mauna_Loa	-155.58	19.54
Bonanza_Creek	-148.32	64.74
Trinidad_Head	-124.15	41.05
Saturn_Island	-123.13	48.78
UCSB	-119.85	34.42
Monterey	-121.86	36.59
Taihu	120.22	31.42
Beijing	116.38	39.98
Gosan_SNU	126.16	33.29
Osaka	135.59	34.65
Noto	137.14	37.33
Ussuriysk	132.16	43.70

Table S2. Mean emissions from the Taklimakan desert (75°E-90°E, 35°N-45°N), Gobi Desert (95°E-115°E, 40°N-50°N), and Thar desert (60°E-80°E, 20°N-40°N). SRC<sub>all</sub> is the sum of TAKL, GOBI and THAR deserts; SRC<sub>TAGO</sub> is the sum of TAKL, GOBI; Total is the entire domain (60°E-140°W, 20°N-60°N) and the values are taken from Figure 4.

Model	Emission (Tg yr <sup>-1</sup> )			Ratio		
	TAKL (TA)	GOBI (GO)	THAR (TH)	<u>SRC<sub>all</sub></u> Total	<u>SRC<sub>TAGO</sub></u> Total	<u>TAKL</u> GOBI
GO	252.9	209.4	134.4	0.88	0.68	1.21
GI	30.6	51.0	49.5	0.66	0.41	0.60
SP	208.6	166.0	273.2	0.78	0.45	1.26
EC	1.4	24.7	7.1	0.43	0.34	0.06
HG	31.2	103.5	200.9	0.69	0.28	0.30
Mean	104.9	110.9	133.0	0.7	0.4	0.68
STD	116.5	77.2	108.5	0.2	0.2	0.54
DIV	111.0	69.6	81.6	24.4	35.9	78.30

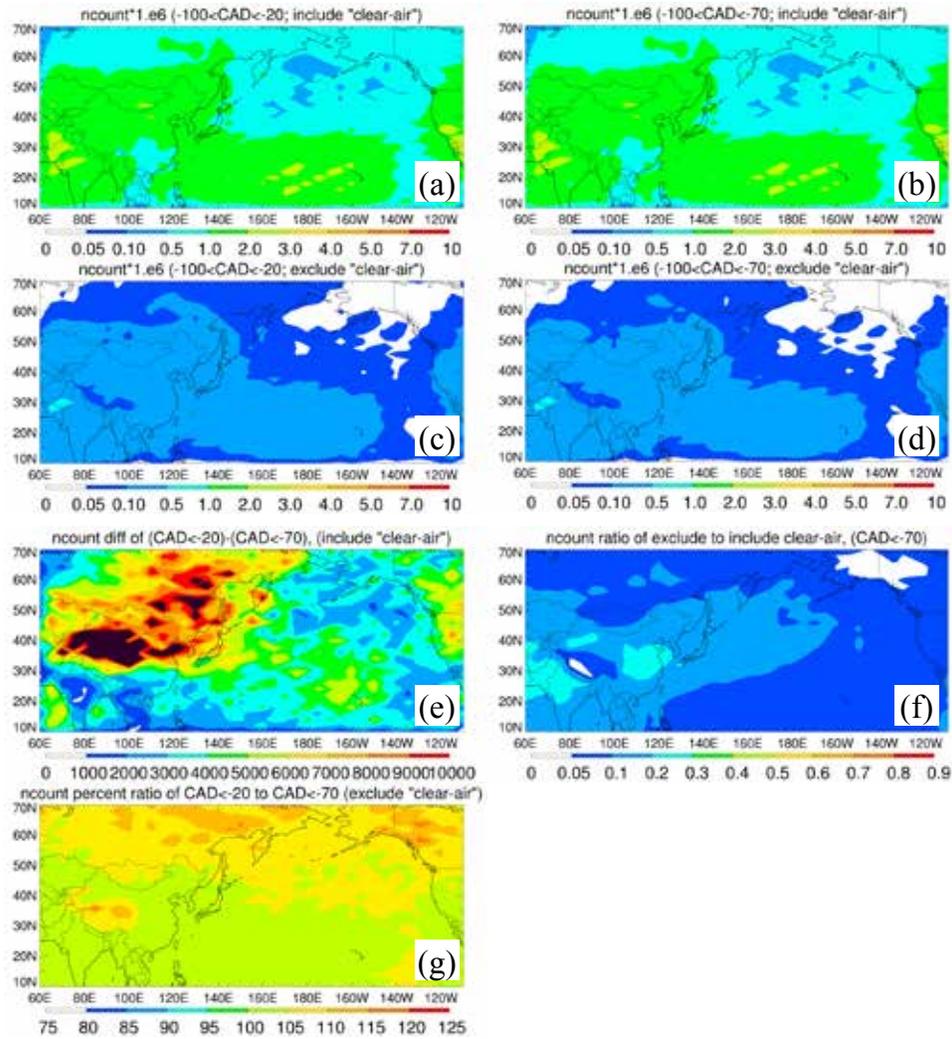


Figure S1. Number of data samples (ncount) in million for January 2007 - December 2011: (a)  $-100 < CAD < -20$  and include clear-air; (b)  $-100 < CAD < -70$  and include clear-air; (c)  $-100 < CAD < -20$  and exclude clear-air; (d)  $-100 < CAD < -70$  and exclude clear-air. (e) ncount ( $-100 < CAD < -20$ , include clear-air) minus ncount ( $-100 < CAD < -70$ , include clear-air), (f) ratio of exclude clear-air to include clear-air ( $-100 < CAD < -70$ ), (g) percent ratio of  $CAD < -20$  to  $CAD < -70$  (exclude clear-air).

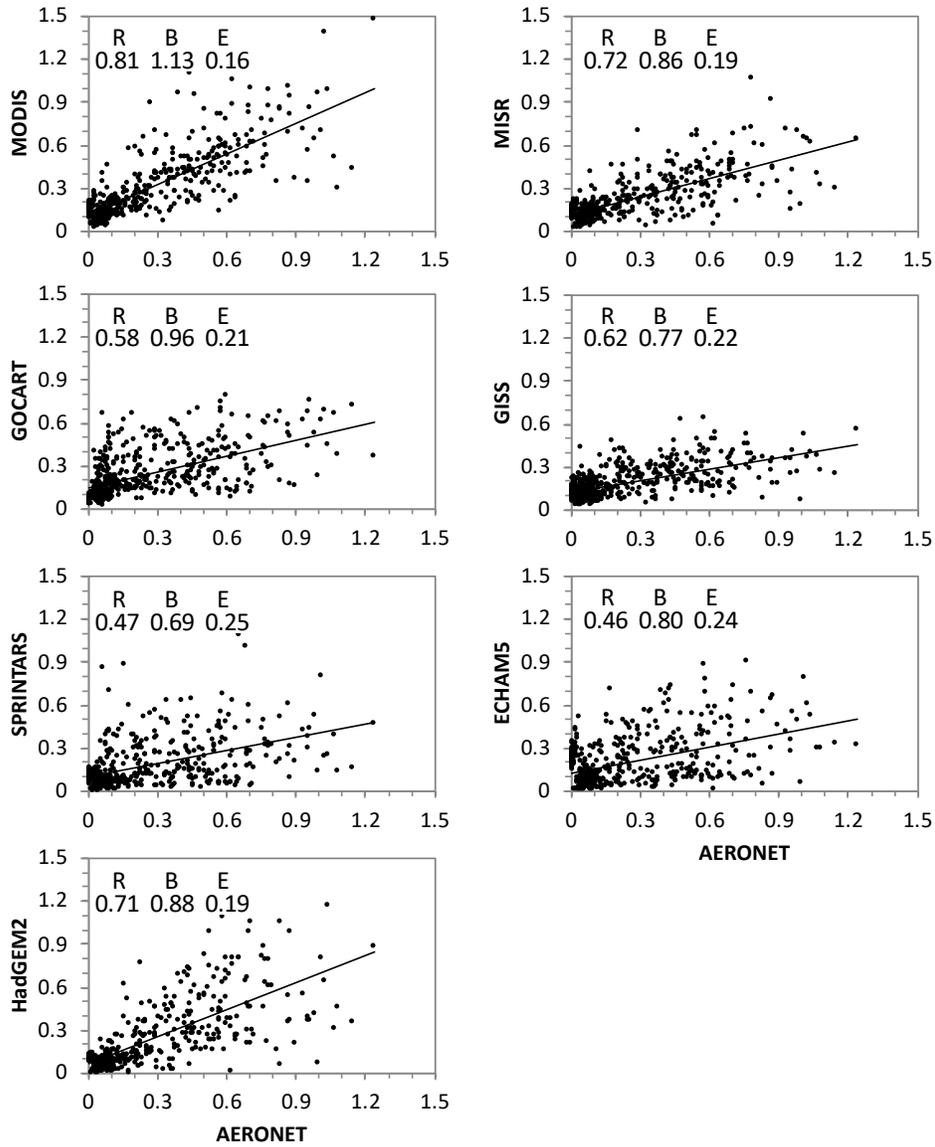


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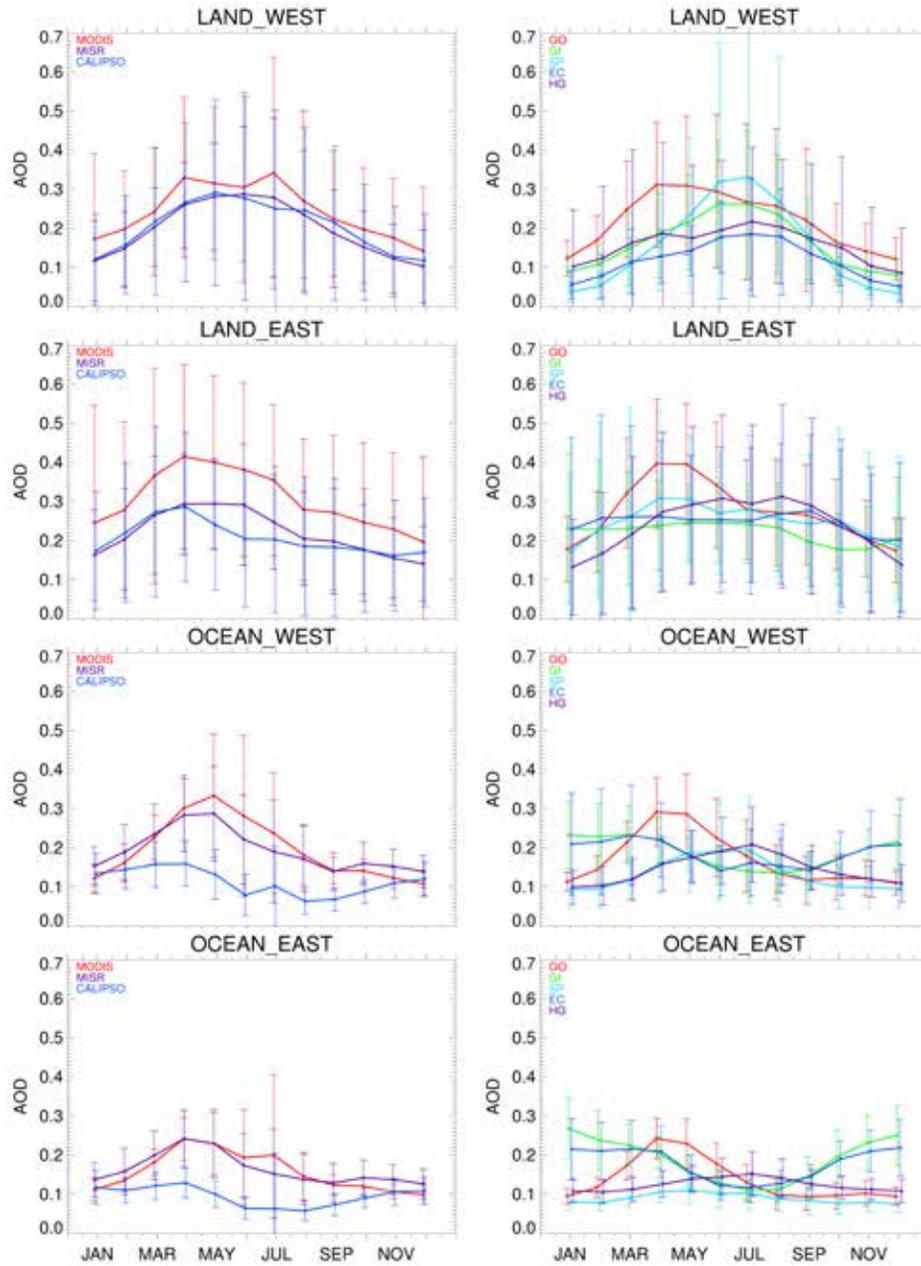


Figure S3. Monthly mean AOD over Land-West (60°E-100°E), Land-East (100°E-140°E), Ocean-West (140°E-180°E), Ocean-East (180°E-140°W) domains from top to bottom. Latitudinal ranges are 20°N to 60°N. Left- and right-columns are from satellites and models, respectively. All model plots are averaged from 2000 to 2005. Vertical bars are the standard deviation of monthly mean values.

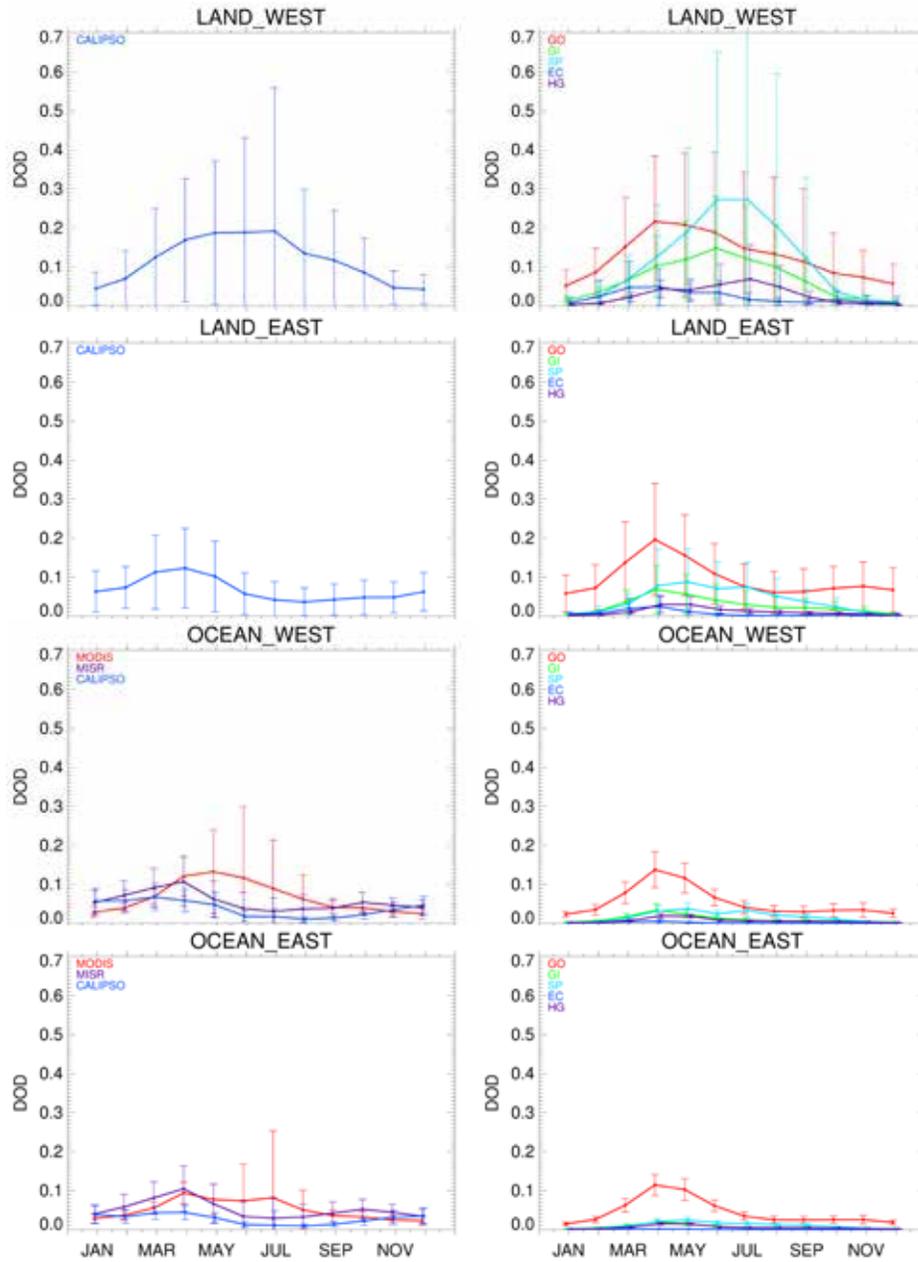


Figure S4. Same as Figure S3 except for DOD.

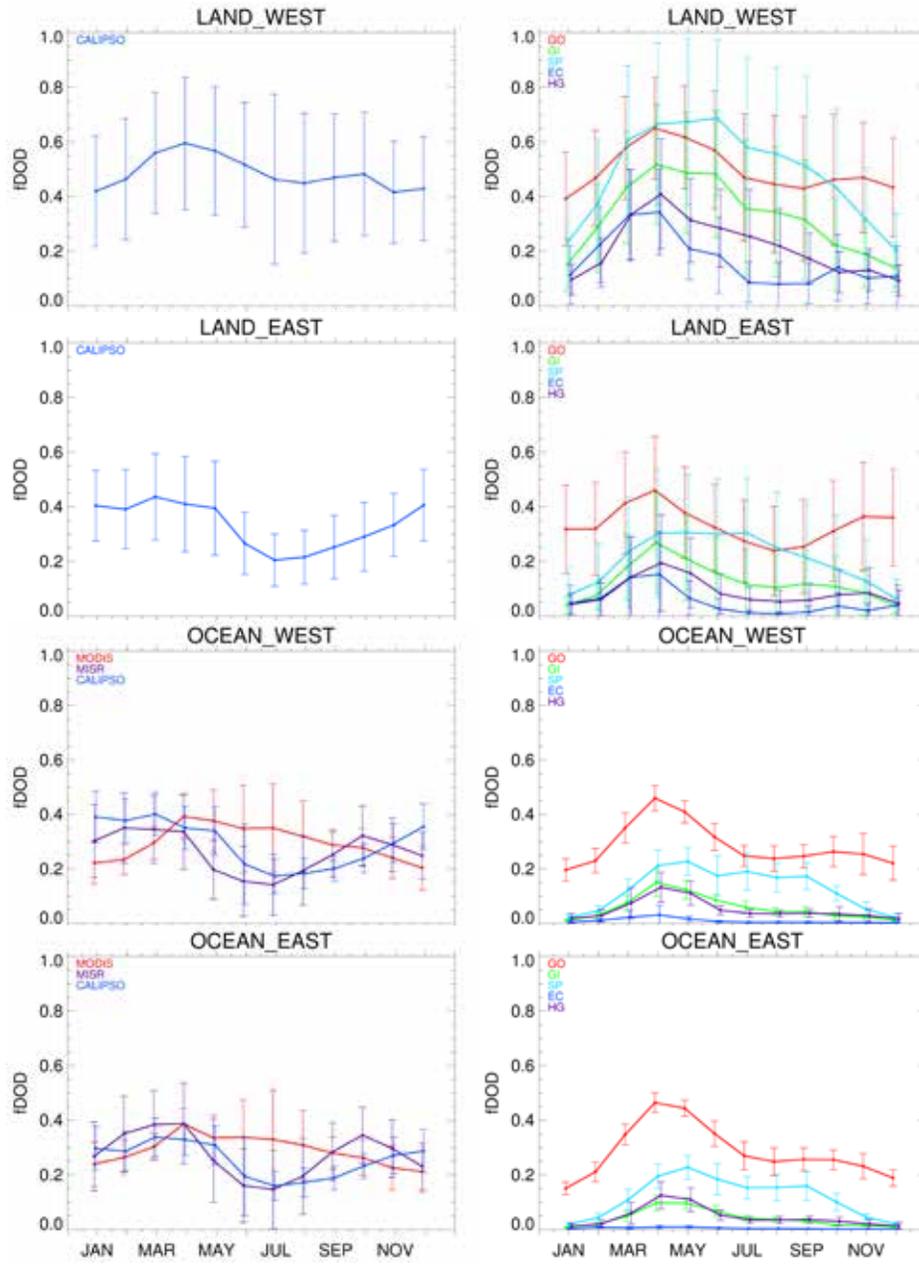


Figure S5. Same as Figure S3 except for  $f_{DOD}$ .

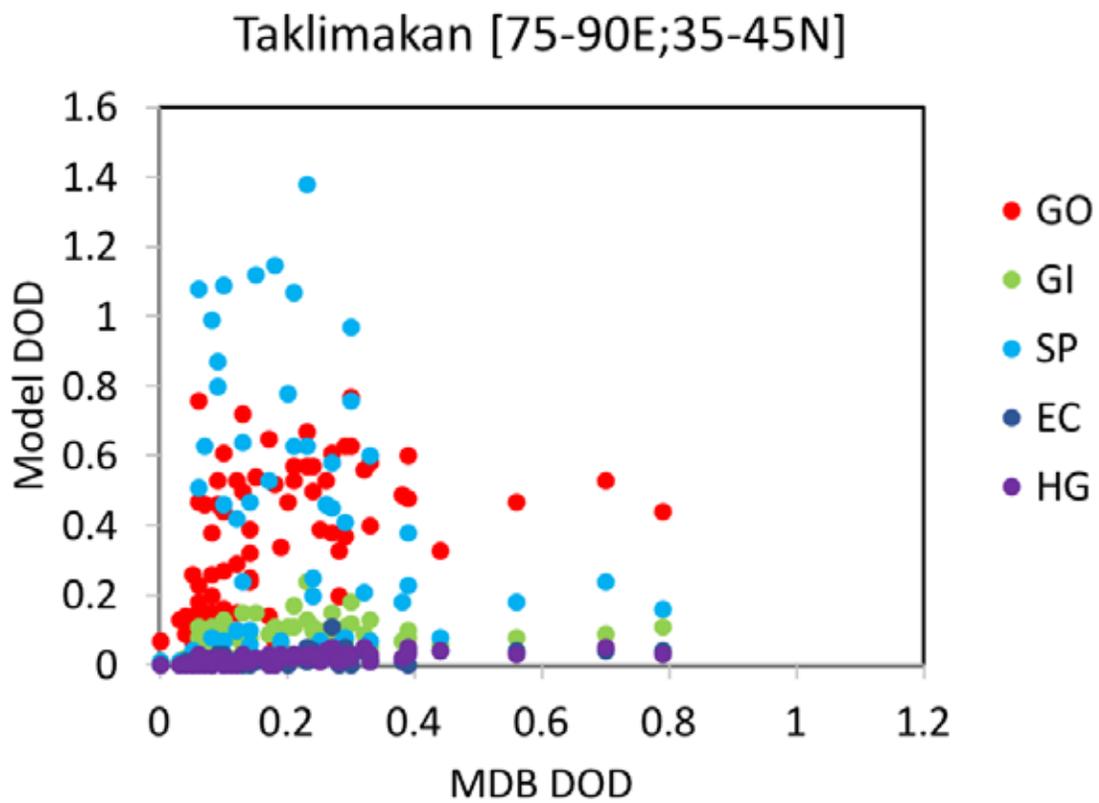


Figure S6. Monthly mean DOD for 2000-2005 over the Taklimakan desert.

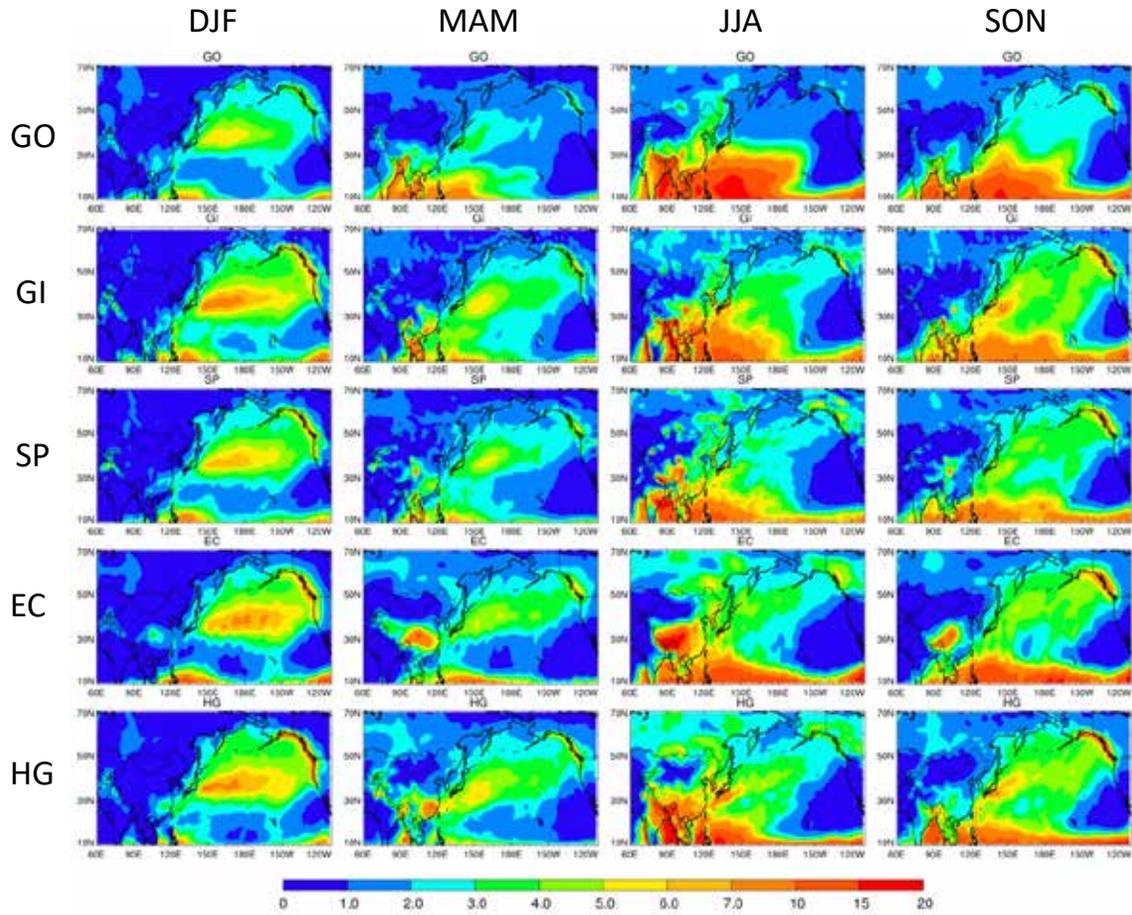


Figure S7. Map of precipitation (mm day<sup>-1</sup>) of each season from models averaged from 2000 to 2005.