Parameterization of Size of Organic and Secondary Inorganic Aerosol for Efficient Representation of Global Aerosol Optical Properties

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Abstract Accurate representation of aerosol optical properties is essential for modeling and remote sensing of atmospheric aerosols. Although aerosol optical properties are strongly dependent upon the aerosol size distribution, use of detailed aerosol microphysics schemes in global atmospheric models is inhibited by associated computational demands. Computationally efficient parameterizations for aerosol size are needed. In this study, airborne measurements over the United States (DISCOVER-AQ) and South Korea (KORUS-AQ) are interpreted with a global chemical transport model (GEOS-Chem) to investigate the variation in aerosol size when organic matter (OM) and sulfate-nitrate-ammonium (SNA) are the dominant aerosol components. The airborne measurements exhibit a strong correlation ($r = 0.83$) between dry aerosol size and the sum of OM and SNA mass concentration (M_{SNAOM}). A global microphysical simulation (GEOS-Chem-TOMAS) indicates that M_{SNAOM}, and the ratio between the two components ($\frac{OM}{SNA}$) are the major indicators for SNA and OM dry aerosol size. A parameterization of dry effective radius (R_{eff}) for SNA and OM aerosol is designed to represent the airborne measurements ($R^2 = 0.74$, slope = 1.00) and the GEOS-Chem-TOMAS simulation ($R^2 = 0.72$, slope = 0.81). When applied in the GEOS-Chem high-performance model, this parameterization improves the agreement between the simulated aerosol optical depth (AOD) and the ground-

34   measured AOD from the Aerosol Robotic Network (AERONET; R^2 from 0.68 to 0.73, slope from 0.75 to 0.96). Thus,

35   this parameterization offers a computationally efficient method to represent aerosol size dynamically.

1   Introduction

37   Aerosol size has numerous effects on aerosol physical and chemical properties and further on atmospheric chemistry.

38   Aerosol size-dependent heterogeneous chemistry affects gaseous oxidants that in turn affect production rates of

39   aerosol components such as sulfate and secondary organic aerosol (Ervens et al., 2011; Estillore et al., 2016). Aerosol

40   size also affects loss rates due to dry and wet deposition (Seinfeld and Pandis, 2016). Both direct and indirect aerosol

41   radiative forcing are sensitive to aerosol size, as aerosol size affects the interaction between particles and radiation,

42   and the rate at which a particle grows to a cloud droplet (Adams and Seinfeld, 2002; Faxvog and Roessler, 1978;

43   Mishchenko et al., 2002; Emerson et al., 2020). The size dependence of aerosol extinction and scattering phase

44   function also affects the retrieval of aerosol properties from satellites (Levy et al., 2013; Kahn et al., 2005; Jin et al.,

45   2023). Aerosol size affects the fraction of particles that deposit in the body when breathing as well as location within

46   the body where they deposit (Hinds and Zhu, 1999). An appropriate representation of aerosol size is essential for

47   modeling aerosol composition and optical properties (Kodros and Pierce, 2017), interpreting satellite data (Levy et al.,

48   2013; Kahn et al., 2005), studying climate processes (Twomey, 2007; Kellogg, 1980), and moving from aerosol

49   exposure towards dose in health studies (Kodros et al., 2018).

50   The evolution of the aerosol size distribution is affected by various processes, such as nucleation, condensation,

51   coagulation, and deposition. Nucleation events contribute to the number of particles in the nucleation mode (diameters

52   less than about 10 nm) and thus tend to decrease the mean aerosol size for a population (Aalto et al., 2001). In polluted

53   areas with high emission rates of aerosol precursors, mean aerosol size tends to increase by condensation and

54   coagulation (Sakamoto et al., 2016; Sun et al., 2011). Dry and wet aerosol deposition have strong size dependencies

55   due to competing physical processes (Emerson et al., 2020; Ruijrok et al., 1995; Reutter et al., 2009). The aerosol size

56   distribution can be simulated using aerosol microphysical schemes, such as the TwO Moment Aerosol Sectional

57   (TOMAS; Adams and Seinfeld, 2002) microphysics model, the Advanced Particle Microphysics (APM; Yu and Luo,

58   2009) model, the Global Model of Aerosol Processes (GLOMAP; Mann et al., 2010), and the Modal Aerosol Module

59   (MAM4; Liu et al., 2016). These schemes have valuable prognostic capabilities; however, their computational cost

60   has limited their use in Chemistry Climate Models (CCMs) or Chemical Transport Models (CTMs). For example, the

61   wall clock time increases by about 2.5 times when APM is enabled in GEOS-Chem CTM relative to the bulk model

62   (GCST et al., 2023). Only 3 of the 10 models that included aerosols, studied by the Atmospheric Chemistry and

63   Climate Model Intercomparison Project, include online size-resolved aerosol microphysics, reflecting its

64   computational cost and complexity (Lamarque et al., 2013; Liu et al., 2012; Szopa et al., 2013; Kodros and Pierce,

65   2017).

66   Methods are needed to better represent aerosol size in CCMs or CTMs without a microphysics scheme (referred to as

67   bulk models). These bulk models usually use prescribed relationships to obtain size-resolved aerosol properties (Croft

68   et al., 2005; Karydis et al., 2011; Zhai et al., 2021), which may insufficiently represent the temporal and spatial

69   variation (Kodros and Pierce, 2017). For example, in the GEOS-Chem CTM, a fixed dry aerosol geometric mean

70   radius (R_g) is assumed for organic matter (OM) and sulfate-nitrate-ammonium (SNA), which is based on analysis of

71   long-term aerosol composition and scattering measurements provided by the IMPROVE network across the

72   continental U.S. (Latimer and Martin, 2019). However, subsequent analysis by Zhai *et al.* (2021) found that this

73   aerosol size underestimated the aerosol mass scattering efficiency and the aerosol extinction coefficients during an

74   aircraft campaign over South Korea (KORUS-AQ). Thus, neglect of aerosol microphysical processes that shape

75   aerosol size distributions can be a significant source of uncertainty in aerosol optical properties in a CTM. A balance

76   between computational cost and representativeness of aerosol size is needed. One option is to use models with size-

77   resolved aerosol microphysics models to inform bulk models, such as was done for the parameterization of biomass

78   burning aerosol size by Sakamoto *et al*. (2016).

79   Recent airborne measurements offer information to evaluate and improve the simulation of aerosol size. DISCOVER-

80   AQ (Deriving Information on Surface Conditions from Column and Vertically Resolved Observations Relevant to Air

81   Quality) was a multi-year campaign over four U.S. cities that provides 3-D resolved measurements of atmospheric

82   gas composition, aerosol composition, size distribution, and optical properties (Choi et al., 2020; Sawamura et al.,

83   2017; Chu et al., 2015). KORUS-AQ (the Korea-United States Air Quality Study) offers similar measurements in a

84   different environment with higher aerosol mass loadings (Choi et al., 2020; Zhai et al., 2021; Nault et al., 2018; Jordan

85   et al., 2020).

86   To study the global variation in aerosol size, we explore airborne measurements from DISCOVER-AQ and KORUS-

87   AQ, as well as output from the GEOS-Chem-TOMAS microphysics model. We focus on OM and SNA, which

88   dominate fine aerosol composition in populated areas (Weagle et al., 2018; Geng et al., 2017; Meng et al., 2019; Van

89   Donkelaar et al., 2019; Li et al., 2017). The driving factors for variation in aerosol size are examined. A

90   parameterization of aerosol size using these driving factors is proposed. This parameterization is then applied to a

91   GEOS-Chem high-performance model bulk simulation for global aerosol optical depth (AOD), which is evaluated by

92   ground-measured AOD from the Aerosol Robotic Network (AERONET).

93   **2   Observations and Models**

94   **2.1   Observations**

95   **2.1.1   Aircraft measurements**

96   We examine airborne measurements from two NASA campaigns, DISCOVER-AQ and KORUS-AQ. DISCOVER-

97   AQ includes four deployments in Maryland (MD), California (CA), Texas (TX), and Colorado (CO). KORUS-AQ is

98   an international cooperative field study program conducted in South Korea (KO), sponsored by NASA and the South

99   Korean government through the National Institute of Environmental Research. The year as well as the date and altitude

100 ranges of each deployment are in Table 1.

101

Table 1. Temporal and spatial coverage of each aircraft deployment

Campaign	Year	Date Range	Altitude from surface
MD	2011	07/01-07/29	0 to 5 km
TX	2013	09/04-09/29	0 to 5 km
CA	2013	01/16-02/06	0 to 4 km
CO	2014	07/17-08/10	0 to 6 km
KO	2016	05/02-06/11	0 to 8 km

Measurements used in this study include aerosol composition, ambient aerosol extinction, aerosol number size distribution, gas tracer species, and meteorological data. Measurement methods are listed in Table 2. Measured aerosol mass is converted from standard to ambient condition before analysis using ambient temperature and pressure. We use OM directly measured during KORUS-AQ. We use water soluble organic carbon (OC) and a parameterized ratio between OM and OC (Philip et al., 2014) to calculate OM for DISCOVER-AQ. The parameterized OM is evaluated with KORUS-AQ data, and overall consistency is found (Figure A1; Appendix A). For both campaigns, dust concentration is derived from Ca2+ and Na+ assuming non-sea salt Ca2+ accounts for 7.1% of dust mass (Shah et al., 2020):

$$Dust = \frac{\left([Ca^{2+}] - 0.0439\frac{[Na^+]}{2}\right)}{0.071} \qquad \text{Eqn. (1)}$$

Sea salt is calculated from measured Na^+ following previous studies (Remoundaki et al., 2013; Malm et al., 1994; Snider et al., 2016). The crustal component is removed by subtracting 10 % of $[Al^{3+}]$ (Remoundaki et al., 2013). A 2.54 scalar is applied to $[Na^+]_{ss}$ to account for $[Cl^-]$ (Malm et al., 1994):

$$Sea\ Salt = 2.54([Na^+] - 0.1[Al^{3+}]) \qquad \text{Eqn. (2)}$$

Effective radius (R_{eff}) (Hansen and Travis, 1974), defined as the area-weighted mean radius of a particle population, is used as a surrogate for aerosol size:

$$R_{eff} = \frac{\int r\pi r^2 n(r)dr}{\int \pi r^2 n(r)dr} \qquad \text{Eqn. (3)}$$

Measurement data are screened for dust influence by excluding data with the sum of SNA and OM (M_{SNAOM}) < 4 × dust mass.

120 **Table 2. Aircraft observations used in this study**[*]

Variables	DISCOVER-AQ	KORUS-AQ
Bulk aerosol ionic composition	IC-PILS [a]	SAGA [b]
Sub-micron non-refractory aerosol composition	TOC-PILS [c]	HR-ToF-AMS [d]
Refractory black carbon concentration	SP2 [e]	
Dry aerosol size distribution	UHSAS [f] or LAS [g]	LAS [g]
Aerosol extinction profile at 532 nm	HSRL [h]	
NO$_2$	4-Channel Chemiluminescence Instrument [i]	
Relative humidity (RH)	DLH [j]	

121 [*] Adapted from Zhai et al. (2021)

122 [a] Ion Chromatography Particle-Into-Liquid Sampler, with a 1.3 µm inlet cutoff aerodynamic diameter (Lee et al., 2003;
123 Hayes et al., 2013).

124 [b] Soluble Acidic Gases and Aerosol (SAGA) instrument (Dibb et al., 2003). The cutoff aerodynamic diameter of the
125 inlet is around 4 µm (McNaughton et al., 2007).

126 [c] Water-soluble organic carbon Particle-Into-Liquid Sampler, with a 1 µm inlet cutoff diameter at 1 atmosphere
127 ambient pressure (Sullivan et al., 2019; Timonen et al., 2010).

128 [d] University of Colorado Boulder High-Resolution Time-of-Flight Aerosol Mass Spectrometer (HR-ToF-AMS) with
129 a 1 µm inlet cutoff diameter (Nault et al., 2018; Guo et al., 2021; Canagaratna et al., 2007).

130 [e] Single-Particle Soot Photometer (SP2), measuring refractory black carbon with a volume equivalent diameter of 100-
131 500 nm (Lamb et al., 2018; Schwarz et al., 2006).

132 [f] Particles with mobility diameters between 60 to 1000 nm can be measured by Ultra-High Sensitivity Aerosol
133 Spectrometer (UHSAS), which illuminates particles with a laser and relate the single-particle light scattering intensity
134 and count rate measured over a wide range of angles to the size-dependent particle concentration (Moore et al., 2021).
135 Particles in the sample are dried to less than 20 % RH.

136 [g] Particles between 100 to 5000 nm measured by Laser Aerosol Spectrometer (LAS, TSI model 3340). The principle
137 of LAS is the same as that of UHSAS, but with a different laser wavelength (1054 nm for the UHSAS and 633 nm for
138 the LAS) and intensity (about 100 times higher for the UHSAS). These differences affect how the instrument sizes
139 non-spherical or absorbing aerosols (Moore et al., 2021). Particles in the sample are dried to less than 20 % RH.

140 [h] NASA Langley airborne High Spectral Resolution Lidar (HSRL) (Hair et al., 2008).

141 [i] National Center for Atmospheric Research (NCAR) 4-Channel Chemiluminescence Instrument (Weinheimer et al.,
142 1993)

143   [j] NASA Diode Laser Hygrometer (DLH) (Podolske et al., 2003).

2.1.2   AERONET AOD

145   We use ground-based AOD observations to evaluate our parameterization and simulated AOD. The Aerosol Robotic

146   Network (AERONET) is a worldwide network that provides long-term sun photometer measured AOD, and is

147   conventionally considered as the ground truth for evaluating model-simulated (Zhai et al., 2021; Meng et al., 2021;

148   Jin et al., 2023) or satellite-retrieved AOD (Levy et al., 2013; Wang et al., 2014a; Kahn et al., 2005; Lyapustin et al.,

149   2018). We use the Version 3 Level 2 database, which includes an improved cloud screening algorithm (Giles et al.,

150   2019). AOD at 550 nm wavelength, interpolated based on the local Ångström exponent at 440 and 670 nm channels,

151   is used in this study. For each site, we use data for the year 2017, excluding months with less than 20 days of

152   measurements and excluding sites with less than 4 months of observations.

2.2   GEOS-Chem simulation

154   We interpret the aircraft observations with the GEOS-Chem chemical transport model (www.geos-chem.org, last

155   access: 30 October 2022). GEOS-Chem is driven by offline meteorological data from the Goddard Earth Observing

156   System (GEOS) of the NASA Global Modeling and Assimilation Office (Schubert et al., 1993). We use the high-

157   performance implementation of GEOS-Chem (GCHP) (Eastham et al., 2018; Bindle et al., 2021) to examine the

158   effect of variation in aerosol size on AOD. We also use the TOMAS microphysical scheme, coupled with the standard

159   GEOS-Chem implementation (GEOS-Chem Classic), to explicitly resolve aerosol microphysics. The bulk and the

160   microphysics simulations share common emissions and chemical mechanisms. They are both conducted for the year

161   2017 and driven by MERRA-2 meteorological fields.

162   The GEOS-Chem aerosol simulation includes the sulfate-nitrate-ammonium system (Fountoukis and Nenes, 2007;

163   Park, 2004), primary and secondary carbonaceous aerosols (Park et al., 2003; Wang et al., 2014b; Marais et al., 2016;

164   Pye et al., 2010), sea salt (Jaeglé et al., 2011), and mineral dust (Fairlie et al., 2007). The primary emission data are

165   from the Community Emissions Data System (CEDS$_{GBD-MAPS}$; McDuffie et al., 2020). Dust emission inventories

166   include updated natural dust emission (Meng et al., 2021b), and anthropogenic fugitive, combustion, and industrial

167   dust (AFCID; Philip et al., 2017). Resolution-dependent soil NO_x, sea salt, biogenic VOC, and natural dust emissions

168   are calculated offline at native meteorological resolution to produce consistent emissions across resolution (Weng et

169   al., 2020; Meng et al., 2021b). Biomass burning emissions use the Global Fire Emissions Database, version 4 (GFED4)

170   (Van Der Werf et al., 2017). We estimate organic matter (OM) from primary organic carbon using the same OM/OC

171   parameterizations as applied for DISCOVER-AQ (Philip et al., 2014; Canagaratna et al., 2015). Dry and wet

172   deposition follows Amos *et al.* (2012), with a standard resistance-in-series dry deposition scheme (Wang et al., 1998).

173   Wet deposition includes scavenging processes from convection and large-scale precipitation (Liu et al., 2001).

174   Global relative humidity dependent aerosol optical properties are based on the Global Aerosol Data Set (GADS)

175   (Kopke P., 1997; Martin et al., 2003) with updates for SNA and OM (Latimer and Martin, 2019), mineral dust (Zhang

176   et al., 2013), and absorbing brown carbon (Hammer et al., 2016). In the current GEOS-Chem model, the SNA and

177 OM R$_{eff}$ of particular interest here are based on co-located measurements of aerosol scatter and mass from the

178 IMPROVE network at U.S. national parks over the period 2000-2010, together with a κ-Kohler framework for aerosol

179 hygroscopicity (Kreidenweis et al., 2008) as implemented by Latimer and Martin (2019). Aerosol extinction is

180 calculated as the sum of extinction from each aerosol component with aerosol optical properties listed in Table A1, as

181 described in Appendix A2.

182 A global GCHP simulation (Eastham et al., 2018) version 13.0.0 (DOI: 10.5281/zenodo.4618180) that includes

183 advances in performance and usability (Martin et al., 2022), is conducted on a C90 cubed-sphere grid corresponding

184 to a horizontal resolution of about 100 km, with a spin-up time of 1 month.

185 The TOMAS microphysics scheme, coupled with the GEOS-Chem simulation, conserves aerosol mass, and tracks

186 particles with diameters from approximately 1 nm to 10 μm (Adams and Seinfeld, 2002). Microphysical processes in

187 TOMAS include nucleation, condensation, evaporation, coagulation, and wet and dry deposition (Adams and Seinfeld,

188 2002). Nucleation in TOMAS follows a ternary scheme (sulfuric acid, ammonia, and water) when ammonia mixing

189 ratios are greater than 0.1 ppt; otherwise, a binary nucleation scheme is used (Napari et al., 2002). The nucleation rate

190 is scaled by 10^{-5} to better match the observations (Westervelt et al., 2013). The condensation and evaporation algorithm

191 is based on a study from Tzivion *et al.* (1989), including interaction with secondary organic aerosol (D'Andrea et al.,

192 2013). Interstitial coagulation in clouds is also included (Pierce et al., 2015).

193 For each size bin, TOMAS tracks the mass and number of sulfate, sea salt, black carbon, OC, dust, and water. Primary

194 sulfate emissions have 2 lognormal modes: 15% of the mass with a number median diameter (NMD) of 10 nm and

195 geometric standard deviation (σ) of 1.6 and the remainder with a NMD of 70 nm and σ of 2 (Adams and Seinfeld,

196 2003). The size of emitted carbonaceous particles varies depending on the source: those produced by fossil fuel have

197 a NMD of 30 nm and σ of 2, while biofuel and biomass burning particles are emitted with a NMD of 100 nm and σ

198 of 2 (Pierce et al., 2007). Meteorology and most of the emissions in GEOS-Chem-TOMAS follow the bulk simulation,

199 except that online schemes are used for dust (Zender et al., 2003) and sea salt (Jaeglé *et al.* 2011).

200 The GEOS-Chem-TOMAS (version 13.2.1. DOI: 10.5281/zenodo.5500717) is used to provide insights into global

201 scale aerosol size variation and the driving factors. For computational feasibility, a one-year global simulation is

202 conducted with a horizontal resolution of 4º × 5º and 47 vertical layers from surface to 0.01 hPa. The spin-up time is

203 1 month. Aerosols are tracked in 15 size bins with particle diameters ranging from about 3 nm to 10 μm. We also

204 conducted a 2º × 2.5º simulation for October to evaluate the sensitivity of our conclusions to the resolution of the

205 aerosol microphysics simulation.

3   Development of a Parameterization of Aerosol Size

207 We first examine the aircraft measurements for insight into the observed variation in aerosol size. Then we apply the

208 size-resolved GEOS-Chem-TOMAS model to extend our analysis to the global scale and identify driving factors of

209 aerosol size. We subsequently develop and test a parameterization of aerosol size for use in bulk models.

 3.1   Observed variation in aerosol size

211   Figure 1 shows the daily-mean dry effective radius from DISCOVER-AQ and KORUS-AQ as a function of aerosol

212   mass. Aerosol size, in terms of dry R_{eff}, ranges from 90 nm to 179 nm for DISCOVER-AQ, which is generally smaller

213   than for KORUS-AQ that ranges from 135 nm to 174 nm. M_{SNAOM} from DISCOVER-AQ (1.4 μg/m^3 to 27.4 μg/m^3)

214   is also generally less than that from KORUS-AQ (5.5 μg/m^3 to 33.2μg/m^3). A strong correlation (r = 0.83) between

215   aerosol size and M_{SNAOM} is evident. R_{eff} from KORUS-AQ is less sensitive to M_{SNAOM} (slope = 1.23) compared to

216   DISCOVER-AQ (slope = 3.57). The relatively large particle size at low mass concentration during KORUS-AQ might

217   reflect the influence of aged aerosol transported from upwind (Jordan et al., 2020; Zhai et al., 2021; Nault et al., 2018).

218
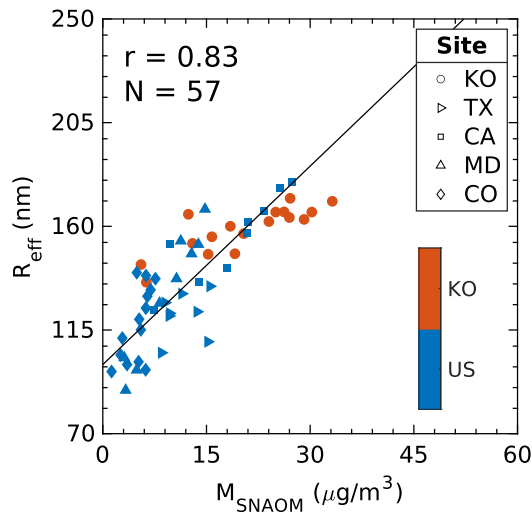
Figure 1. Airborne measurements of dry effective radius (R_{eff}) versus the sum of SNA and OM mass

(M_{SNAOM}) for DISCOVER-AQ (Maryland is abbreviated as MD, California as CA, Texas as TX, Colorado as

CO) and for KORUS-AQ (KO) campaigns. Each point represents a daily average for the entire flight profile.

Only data with $M_{SNAOM} > 4 \times$ Dust mass is used.

223   The positive relationship between dry aerosol size and mass of SNA and OM reflects the roles of emission,

224   condensation, and coagulation in simultaneously increasing aerosol size and mass. This general tendency is also

225   observed by many other studies (e.g., Sakamoto et al., 2016; Rodríguez et al., 2007; Sun et al., 2012; Bahreini et al.,

226   2003) despite variable aerosol sources and growth mechanisms. In cities, the joint increases in aerosol size and mass

227   are usually attributable to anthropogenic emissions and condensation (Tian et al., 2019; Sun et al., 2011; Huang et al.,

228   2013). In remote areas, biomass burning shifts the particle size distribution toward larger radii due to high emission

229   rates and coagulation in plumes (Rissler et al., 2006; Ramnarine et al., 2019) that, for example, increase both aerosol

230   size and mass from the wet season to the dry season in Amazonia (Rissler et al., 2006; Andreae et al., 2015). The

231   positive relationship between aerosol size and mass suggests the possibility of using aerosol mass as a predictor of

232   R_{eff}.

233 We examine the ability of the GEOS-Chem bulk model to reproduce the observed extinction. The top panel of Figure
234 2 compares the measured aerosol extinction profiles to calculated aerosol extinction profiles using default R_{eff}. Details
235 about the calculation are described in Appendix A2. Both measured and calculated extinction profiles exhibit
236 increasing extinction toward the surface associated with increasing aerosol mass concentrations. However, biases are
237 apparent for both DISCOVER-AQ and KORUS-AQ. The R_{eff} from KORUS-AQ shown in Figure 1 have a mean value
238 of 164 nm, larger than the value of 101 nm inferred by Latimer & Martin (2019) based on measurements of aerosol
239 scatter and mass by the U.S. IMPROVE network. This bias was previously noted by Zhai *et al.* (2021). The mean R_{eff}
240 from DISCOVER-AQ of 138 nm is also larger than the inferred value. This likely reflects representativeness
241 differences since the DISCOVER-AQ deployments focused on major urban areas during months of high aerosol
242 loadings, while the IMPROVE measurements were at national parks throughout the year. The middle panel shows the
243 calculated extinction using the measured aerosol size distribution. Applying the measured aerosol size distribution
244 addresses most discrepancies between the calculated and measured aerosol extinction profile for both KORUS-AQ
245 and DISCOVER-AQ. The corresponding discrepancies in AOD estimation also significantly decreased (from 0.09 to
246 0.03 for DISCOVER-AQ and from 0.17 to 0.02 for KORUS-AQ). The reduced discrepancies support the conclusions
247 from Zhai *et al.* (2021) that the GEOS-Chem aerosol size is underestimated for KORUS-AQ and motivate
248 parameterization of R_{eff} for efficient representation of aerosol size for global scale aerosol modeling.
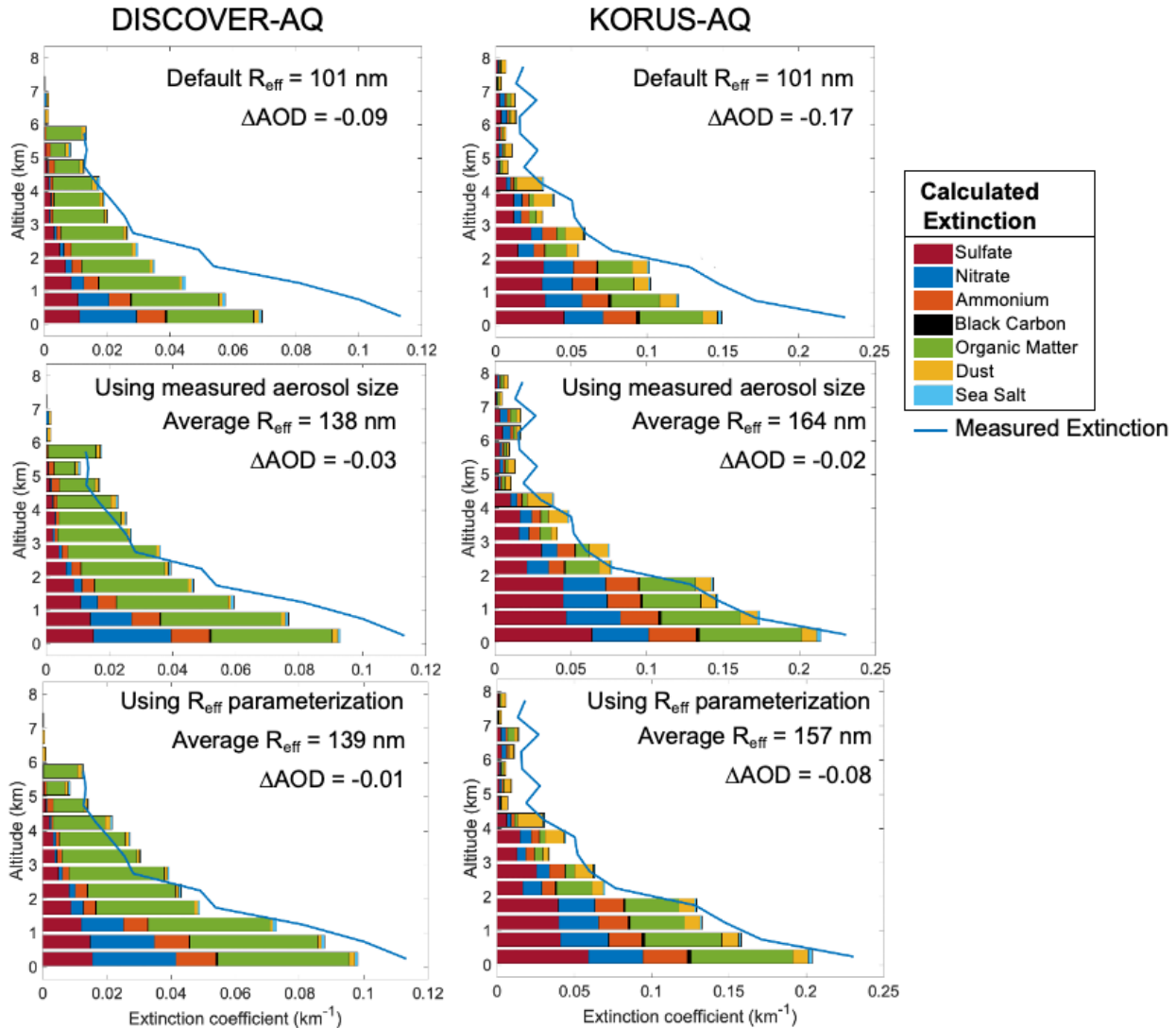
Figure 2. Aerosol extinction profile for the DISCOVER-AQ and KORUS-AQ aircraft campaigns. Blue lines are the measured extinction profiles. Horizontal bars are calculated extinction using (top) default GEOS-Chem R_{eff}, (middle) measured R_{eff}, and (bottom) parameterized R_{eff} (described in Section 3.3), together with measured aerosol composition and RH. The aerosol extinction calculation is described in Appendix A.

3.2 Driving factors

Given the strong positive correlation of aerosol mass with aerosol size, we further examine this relationship globally using GEOS-Chem coupled with the TOMAS aerosol microphysics scheme. To focus on areas that are dominated by SNA and OM, we only include grid boxes with $M_{SNAOM} > 90\%$ of the aerosol mass. Inspection of the GEOS-Chem-TOMAS size distribution across continental regimes reveals a general tendency for the distribution to shift toward smaller sizes as R_{eff} decreases and toward larger sizes as R_{eff} increases, thus supporting the use of the single summary statistic of R_{eff} for aerosol size. The top panel of Figure 3 shows the geographic distribution of annual mean surface layer dry R_{eff} for ~~locations and months~~grid boxes that meet the criterion ~~where aerosol mass is dominated by SNA and~~

262 ~~OM, as indicated by M_{SNAOM} > 90% of the aerosol mass~~. Among the areas of interest, biomass burning regions of

263 Central Africa, South America, and boreal forests of North America exhibit the highest surface R_{eff} of about 180 nm.

264 Industrial areas such as East Asia and South Asia also exhibit high R_{eff} of about 130 nm, given an abundance of particle

265 emissions and gaseous precursors. The lowest surface R_{eff} of about 80 nm is found in North America, where aerosol

266 mass concentrations are low.

267 The middle panel of Figure 3 shows the simulated M_{SNAOM} from GEOS-Chem-TOMAS. Enhanced M_{SNAOM}

268 concentrations of over 40 μg/m^3 are apparent over East Asia and South Asia, reflecting intense anthropogenic

269 emissions. Another M_{SNAOM} hotspot can be seen in Central Africa, driven by biomass burning during the dry season

270 (Van Der Werf et al., 2017; McDuffie et al., 2021) and sometimes exacerbated by anthropogenic emissions (Ngo et

271 al., 2019). Moving from North America to Europe, and then to Asia (defined by boxes in the middle panel), M_{SNAOM}

272 concentrations exhibit a generally increasing tendency (mean value of 11, 17, and 25 μg/m^3, respectively), consistent

273 with the R_{eff} tendency (mean value of 124, 133, and 136 nm, respectively) in the top panel and aligning with the

274 relationship between aircraft measurements over the U.S. and South Korea.

275 However, in South America, where R_{eff} is among the highest, M_{SNAOM} is relatively low. This discrepancy motivates

276 the search for other factors, such as aerosol composition, that are associated with aerosol size. In South America,

277 aerosol mass is mostly from natural sources, particularly biomass burning during the dry seasons. R_g for a particle

278 population from biomass burning ranges from 60 nm to 170 nm (Rissler et al., 2006; Reid et al., 2005; Janhäll et al.,

279 2010), usually larger than that of primary sulfate aerosol (5 to 35 nm) (Whitey, 1978; Plaza et al., 2011). Therefore,

280 the relative abundance of OM in the total M_{SNAOM} can serve as another predictor of R_{eff}. The bottom panel of Figure

281 3 shows the ratio between OM and SNA mass. In addition to the Amazon basin, the biomass burning regions of Central

282 Africa and boreal forests in Asia and North America are all areas with high OM mass fractions, which contribute to

283 their high R_{eff}.

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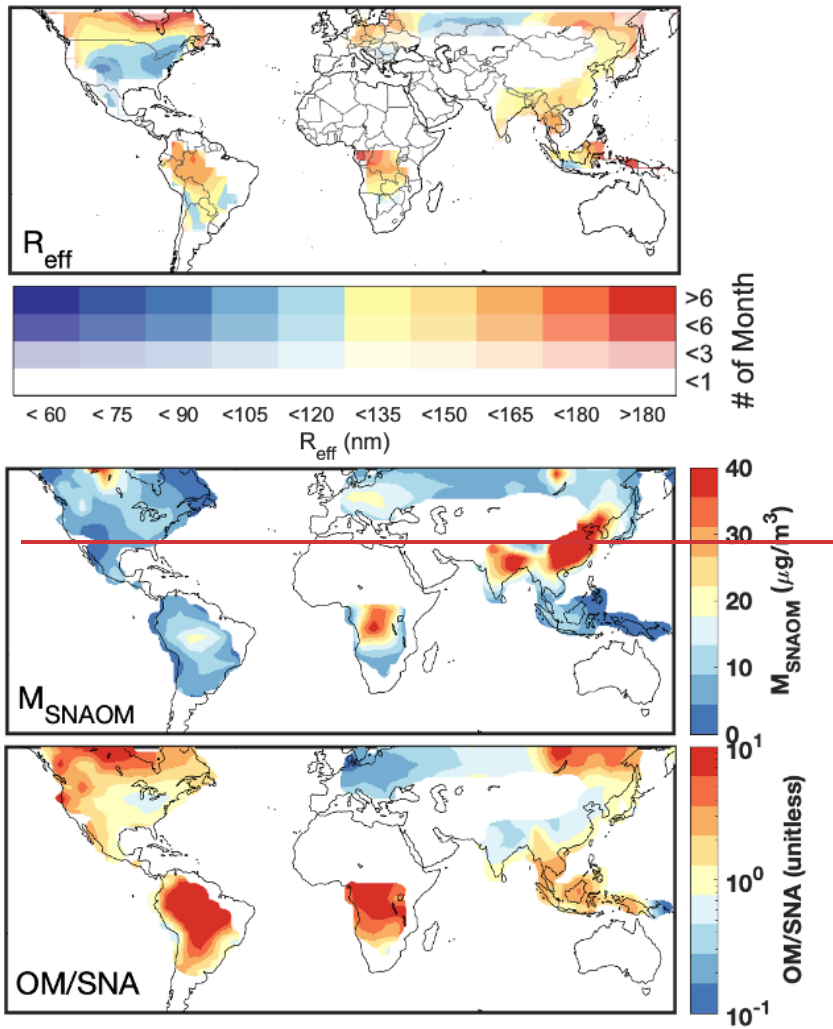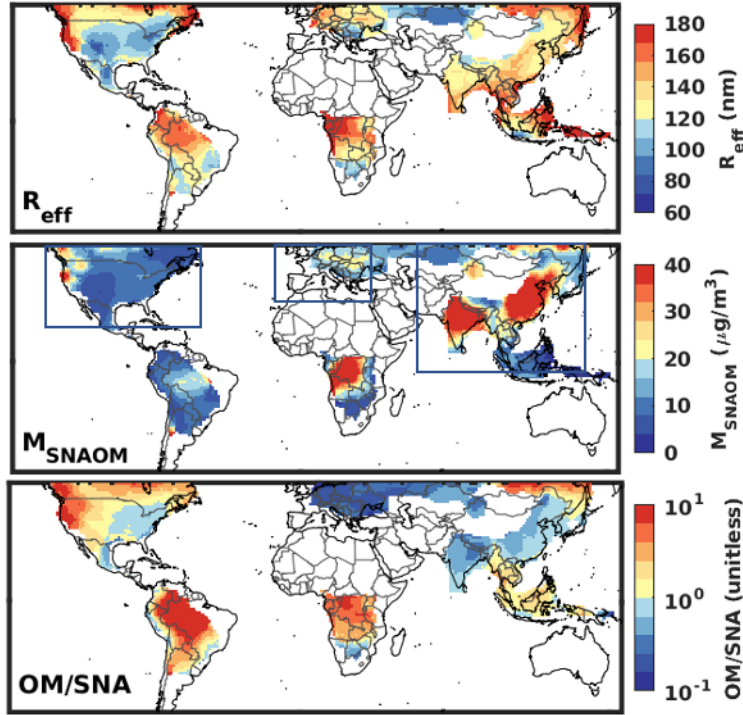
Figure 3: Geographic distribution of GEOS-Chem-TOMAS-simulated annual mean surface layer aerosol properties; (top) R$_{eff}$ when M$_{SNAOM}$ > 90% of aerosol mass, (middle) the sum of SNA and OM mass (M$_{SNAOM}$), and (bottom) OM/SNA.

3.3   Parameterization and evaluation

We use Multiple Linear Regression (MLR) to derive a parameterization of dry R$_{eff}$ for SNA and OM as a function of M$_{SNAOM}$ and OM/SNA. We sample the GEOS-Chem-TOMAS simulation for locations dominated by M$_{SNAOM}$ (> 90%). We include all qualified data (8,569 grid boxes) from the planetary boundary layer (PBL) to focus on this region, while randomly sample 0.5% of simulations in the free troposphere (217,772 grid boxes) to allow the influence of remote regions in the training set. The reason for focusing on the PBL is twofold. First, the PBL generally has the highest aerosol loading that largely determines the columnar mass and AOD (Koffi et al., 2016; Zhai et al., 2021; Tian et al., 2019). Second, the PBL is the domain where most model-measurement difference exists (Figure 2, top panel).

Taking the logarithm of R$_{eff}$ and the logarithm of the two predictors facilitates linear relationships for regression, which yields the initial parameterization

$$R_{eff} = 78.3 M_{SNAOM}^{0.20} \left(\frac{OM}{SNA}\right)^{0.065} \qquad \text{Eqn. (4)}$$

where R$_{eff}$ has units of nm, M$_{SNAOM}$ has units of µg/m^3, and OM/SNA is unitless. The R$_{eff}$ parameterization is driven primarily by the mass of SNA and OM, modulated by the ratio of OM to SNA. This equation well represents the variation of R$_{eff}$ during the aircraft campaigns with an R^2 of 0.74 (Figure B1, top left). The slope below unity (0.90)

302 likely reflects the effect of coarse model resolution, which dilutes the particle or precursor concentration in turn
303 reducing condensation and coagulation growth (AboEl-Fetouh et al., 2022; Ramnarine et al., 2019; Sakamoto et al.,
304 2016). Adjustment to this parameterization to account for these effects and align the slope with the airborne
305 measurements rather than the model results in a final parameterization of

$$R_{eff} = 87.0 M_{SNAOM}^{0.20} \left(\frac{OM}{SNA}\right)^{0.065} \qquad \text{Eqn. (5)}$$

306 Figure 4 shows the distribution of dry R_{eff} based on GEOS-Chem-TOMAS and Eqn. (5). Circles in Figure 4 show the
307 mean values of the sampled GEOS-Chem-TOMAS simulated R_{eff} as a function of simulated M_{SNAOM} concentrations,
308 ranging from 0.02 to 102 μg/m^3, and OM/SNA ranging from 0.13 to 55. Simulated R_{eff} extends from 15 nm when both
309 M_{SNAOM} and OM/SNA are low (0.09 μg/m^3 and 1.3, respectively), up to 282 nm when M_{SNAOM} and OM/SNA are high
310 (about 44 μg/m^3 and 14 respectively). The background color indicates our parameterized R_{eff}. A high degree of
311 consistency exists between the parameterized R_{eff} and simulated R_{eff}, especially in the free troposphere where large
312 gradients in R_{eff} exist, with overall for the troposphere an R^2 of 0.72, and a slope of 0.81 (Figure B1, bottom right). At
313 the lower end of R_{eff}, the agreement between simulation and the parameterization can also be found in Figure B1,
314 which shows that the small R_{eff} are reproduced by the parameterization. Despite the overall consistency, a few
315 differences exist. When aerosol mass concentration is high, the parameterization tends to yield a higher R_{eff} than in
316 the GEOS-Chem-TOMAS simulation, since the adjustment using aircraft measurements led to 11% increase in R_{eff}.
317 At M_{SNAOM} near 10 μg/m^3 and OM/SNA near 10, the simulation indicates higher R_{eff} than the parameterization,
318 reflecting dilution downwind of biomass burning that reduces the aerosol mass concentration but has less influence
319 on particle size in GEOS-Chem-TOMAS (Park et al., 2013; Rissler et al., 2006; Sakamoto et al., 2016). A 10-20%
320 underestimation in the parameterization at low OM/SNA reflects the advection and dilution of downwind of urban
321 areas and in the free troposphere (Yue et al., 2010; Asmi et al., 2011). Evaluation of our parameterization versus the
322 GEOS-Chem-TOMAS simulation of 2º × 2.5º for October yields similar results but explains an additional 14% of the
323 variance in simulated R_{eff}, providing additional evidence of the fidelity of the parameterization.
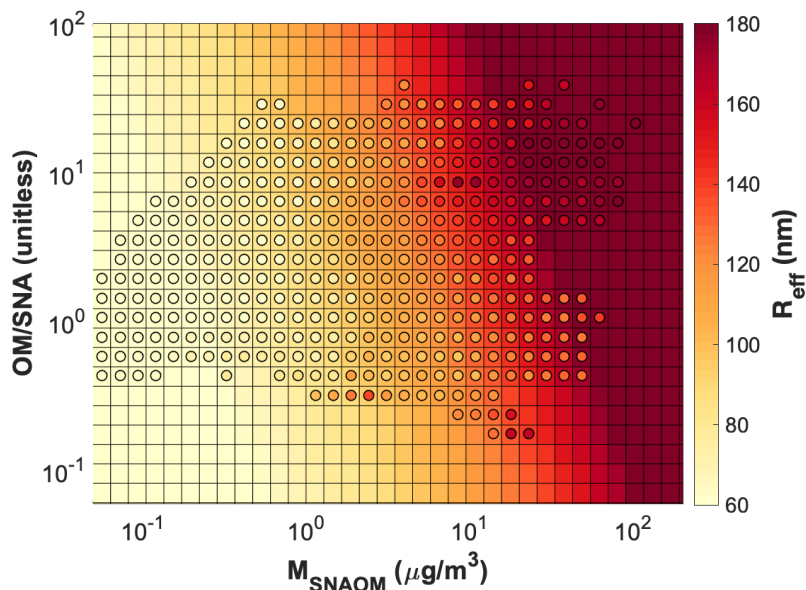
Figure 4. Dry R_{eff} as a function of M_{SNAOM} and OM/SNA when SNA and OM are dominant (>90%). Each circle represents the mean value of the GEOS-Chem-TOMAS simulated R_{eff} in each bin. Background color indicates the parameterized R_{eff}.

When applied to the airborne measurements, this parameterization only slightly overestimates the measured R_{eff} from DISCOVER-AQ (139 nm vs. 138 nm) and slightly underestimates R_{eff} from KORUS-AQ (157 nm vs. 164 nm). Discrepancies between calculated and measured extinction from aircraft campaigns are largely reduced (Figure 2, bottom panel) with AOD biases of 0.01 and 0.08 for DISCOVER-AQ and KORUS-AQ, respectively. Minor differences are still present in aerosol extinction above 4 km for KORUS-AQ, but a physical explanation remains elusive since the calculated extinction is biased even if measured aerosol size and composition are used; instrument uncertainties may play a role. Nonetheless, effects on columnar AOD from these disagreements aloft are minor (<5%).

We then apply Eqn. (5) to a GEOS-Chem bulk simulation to calculate R_{eff} and AOD. The top panel of Figure 5 shows the annual mean dry R_{eff} for surface SNA and OM aerosol. The parameterized R_{eff} is usually higher than the default value of about 100 nm in GEOS-Chem over land, and lower than that over the ocean, with a normalized root mean square deviation (NRMSD) of 43.8%. The parameterized ~~spatial pattern well represents the GEOS-Chem-TOMAS simulation, with high~~ R_{eff} ~~found~~ is the highest in biomass burning regions in South America and Central Africa, as well as industrial regions in Asia, similar to the pattern found in the GEOS-Chem-TOMAS simulation. The parameterized R_{eff} and its horizontal variation diminish~~es~~ with altitude (Figure B2), with the mean R_{eff} ~~decreasing from~~of 85 nm at the surface decreasing by 18.8% to 69 nm at about 5 km~~85 nm (surface) to 43 nm (10 km)~~. By design, the parameterization has little effect in regions and seasons where and when M_{SNAOM} is not dominant, since the parameterization only affects R_{eff} of SNA and OM.

The middle panel of Figure 5 shows the simulated AOD, with the corresponding difference between the base simulation and the updated simulation in the bottom panel. To accommodate the parameterized R_{eff}, a look-up table

347   with a wide range of R_{eff} (0.02 µm to 1.7 µm) and the corresponding extinction efficiencies for OM and SNA is created

348   based on Mie Theory (Mishchenko et al., 2002, 1999). This update generally increases aerosol mass scattering by

349   increasing the mass extinction efficiency, in turn, increasing AOD over regions with strong anthropogenic sources,

350   such as East Asia (by 0.10, 28.3%) and South Asia (by 0.14, 31.1%). It also slightly increases AOD over regions

351   influenced by wildfires, such as South America (by 0.02, 19.7%), Central Africa (by 0.03, 22.7%), and the boreal

352   forests in Europe (by 0.01, 9.9%). Most increases occur near the surface (Figure B3), where the highest aerosol mass

353   loading and mass extinction efficiency exist. The NRMSD between original and updated GEOS-Chem simulated AOD

354   is 18.9% globally, and 25.6% over continents.
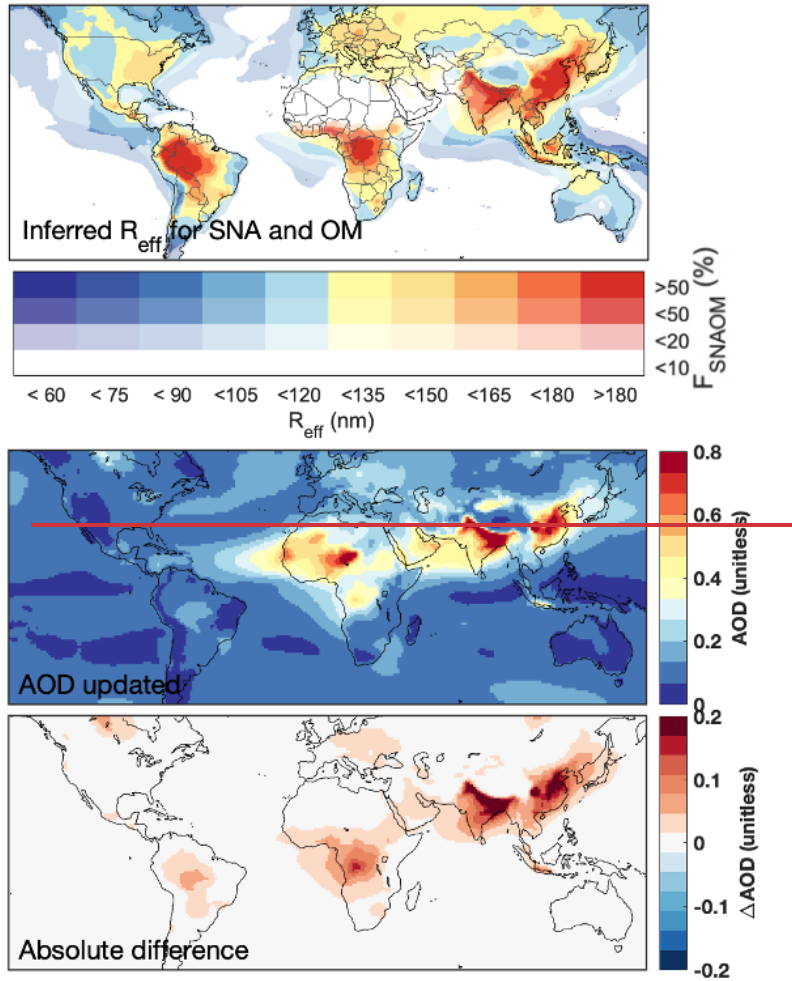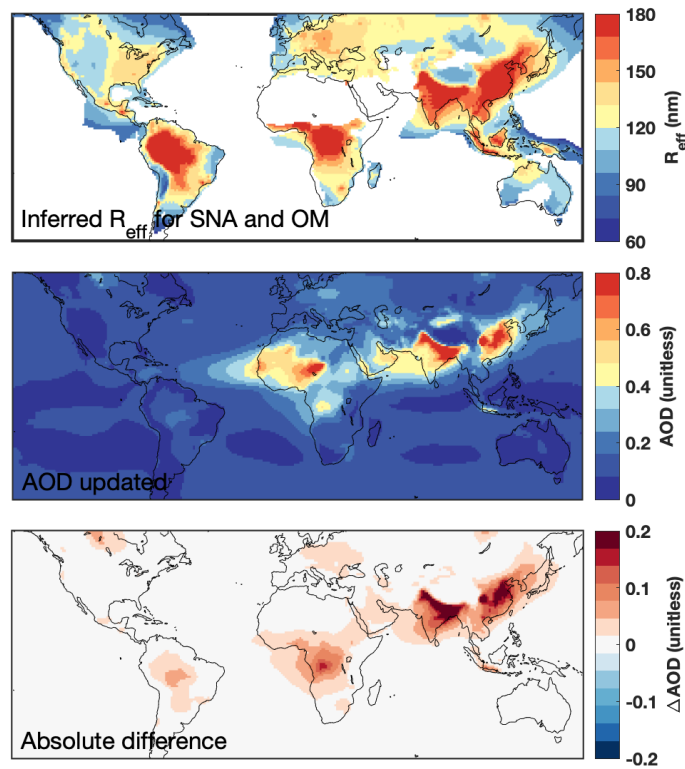
Figure 5. (Top) Surface dry R$_{eff}$ for SNA and OM calculated using Eqn. (5) and GEOS-Chem bulk model simulated SNA and OM mass. ~~F$_{SNAOM}$ is the ratio of SNA and OM mass to the total aerosol mass at the surface~~R$_{eff}$ is shown when M$_{SNAOM}$ is greater than 80% of the total aerosol mass**. (Middle) The GEOS-Chem simulated AOD using inferred R$_{eff}$. (Bottom) the absolute difference between updated AOD and default AOD using dry R$_{eff}$ = 101 nm.**

Although R$_{eff}$ is only one of many processes affecting AOD, we evaluate the effect of the parameterization on the GEOS-Chem simulation of AOD to assess its implications. The left and middle panels of Figure 6 show~~s~~ ~~for the default R$_{eff}$,~~ the ~~percent difference~~discrepancy between GEOS-Chem simulated AOD and AERONET AOD as a function of the parameterized surface R$_{eff}$ for SNA and OM. The simulation using the default R$_{eff}$ (Figure 6, left panel) slightly overestimates AOD at sites with small parameterized R$_{eff}$ and underestimates AOD at sites with large parameterized R$_{eff}$. The overestimates occur primarily in western Europe where SNA and OM concentrations are low, while the underestimates happen mainly over industrial regions in East Asia, Southeast Asia, and biomass burning areas in South America and Central Africa, where the SNA and OM mass loading are high (Figure B4). The underestimates are mitigated when applying the parameterized R$_{eff}$ in GEOS-Chem (Figure 6, middle panel), yielding increased consistency between the measured (AERONET) AOD and simulated AOD (Figure 6, right; R^2 change from 0.68 to 0.74, slope from 0.75 to 0.94).
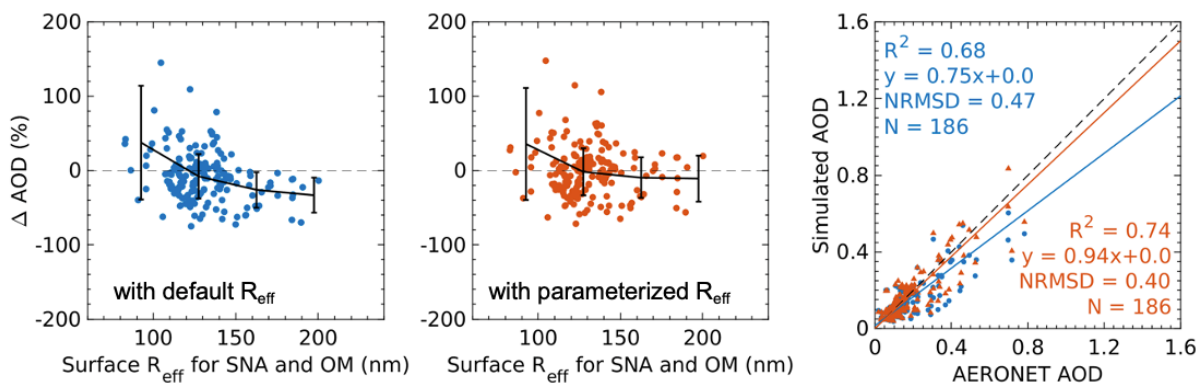
Figure 6. (Left and middle) Percent increase in GEOS-Chem simulated AOD minus AERONET AOD as a function of parameterized surface dry R_{eff} for SNA and OM. Black lines represent the mean values of ΔAOD in each 35 nm bin; error bars represent the corresponding standard deviation. (Right) Scatter plot of AERONET versus simulated AOD with the default R_{eff} (blue dots, line, and text), and with the parameterized R_{eff} (red dots, line, and text). The 1:1 line is dashed. NRMSD is the normalized root mean square deviation between the two datasets. N is the number of points in each dataset.

4   Conclusion

Aerosol size strongly determines mass scattering efficiency with implications for calculation of aerosol optical properties. Prior work found that the global mean dry aerosol size used in a bulk aerosol model induced low bias versus measured extinction in a region with a high aerosol loading (Zhai et al., 2021). We interpreted aircraft measurements from DISCOVER-AQ and KORUS-AQ with a chemical transport model (GEOS-Chem) to better understand regional variation in aerosol size. The measurements had a strong positive correlation (r = 0.83) between aerosol size and mass of sulfate-nitrate-ammonium (SNA) and organic matter (OM), reflecting the high condensation and coagulation rates where emissions of particles and the gaseous precursors are abundant, indicating the possibility of using aerosol mass as a predictor of aerosol size.

To gain a broader perspective of the global variation in aerosol size, we used the TOMAS microphysics package of the GEOS-Chem model to simulate the monthly mean aerosol mass, composition, and size distribution. We used effective radius (R_{eff}) as a surrogate of aerosol size and examined its relationship with aerosol mass and components where SNA and OM were dominant. We found that the sum of SNA and OM concentration, and the ratio between them, were the major predictors of R_{eff}. We used GEOS-Chem-TOMAS model output to derive a parameterization of R_{eff}, which well reproduced R_{eff} measured from the aircraft campaigns ($R^2 = 0.74$). When applied in the bulk GEOS-Chem high-performance model, the parameterization tended to increase R_{eff} of SNA and OM over regions with high concentrations of SNA and OM, and decrease R_{eff} elsewhere relative to the standard model. This led to a global normalized root mean square deviation (NRMSD) of 43.8% between the original and updated surface R_{eff}. The parameterized R_{eff} tended to increase the vertical gradient in extinction relative to the standard model, due to the decrease in R_{eff} with altitude. The NRMSD of global mean AOD between the original and updated simulations was

400   18.9%, with the most significant regional AOD increase of 0.14 in South Asia, where aerosol mass loadings are high.

401   This parameterization led to improved consistency of GEOS-Chem simulated AOD with AERONET AOD (R^2 from

402   0.68 to 0.74; slope from 0.75 to 0.94), by increasing AOD at high R_{eff}.

403   Overall, the simple parameterization of R_{eff} derived in this study improved the accuracy in modeling aerosol optical

404   properties without imposing additional computational expense. Other chemical transport models and modeling of

405   other size-related processes, such as heterogeneous chemistry, photolysis frequencies, and dry deposition, may also

406   benefit from the parameterized R_{eff}. Future work could include additional parameters to better summarize the aerosol

407   size distribution. Further developments in computational efficiency of aerosol microphysics models and more

408   abundant measurements of aerosol size and optical properties would both offer opportunities for further advances.

409

410 *Data availability.* AERONET data can be found at https://aeronet.gsfc.nasa.gov/. Aircraft data during DISCOVER-

411 AQ are available at https://asdc.larc.nasa.gov/project/DISCOVER-AQ. KORUS-AQ data can be found at

412 https://doi.org/10.5067/Suborbital/KORUSAQ/DATA01.

413 *Author contributions.* HZ and RVM designed the study. HZ performed the data analysis and model simulations with

414 contributions from BC, SZ, CL, LB, JRP, IS, DC, and RYWC. BEA, LDZ, JWH, RAF, CAH, JLJ, PCJ, JED, JSS,

415 AW, and BAN contributed to KORUS-AQ and DISCOVER-AQ campaign measurements. HZ and RVM wrote the

416 paper with input from all authors.

417 *Competing interests.* The contact author has declared that neither they nor their co-authors have any competing

418 interests.

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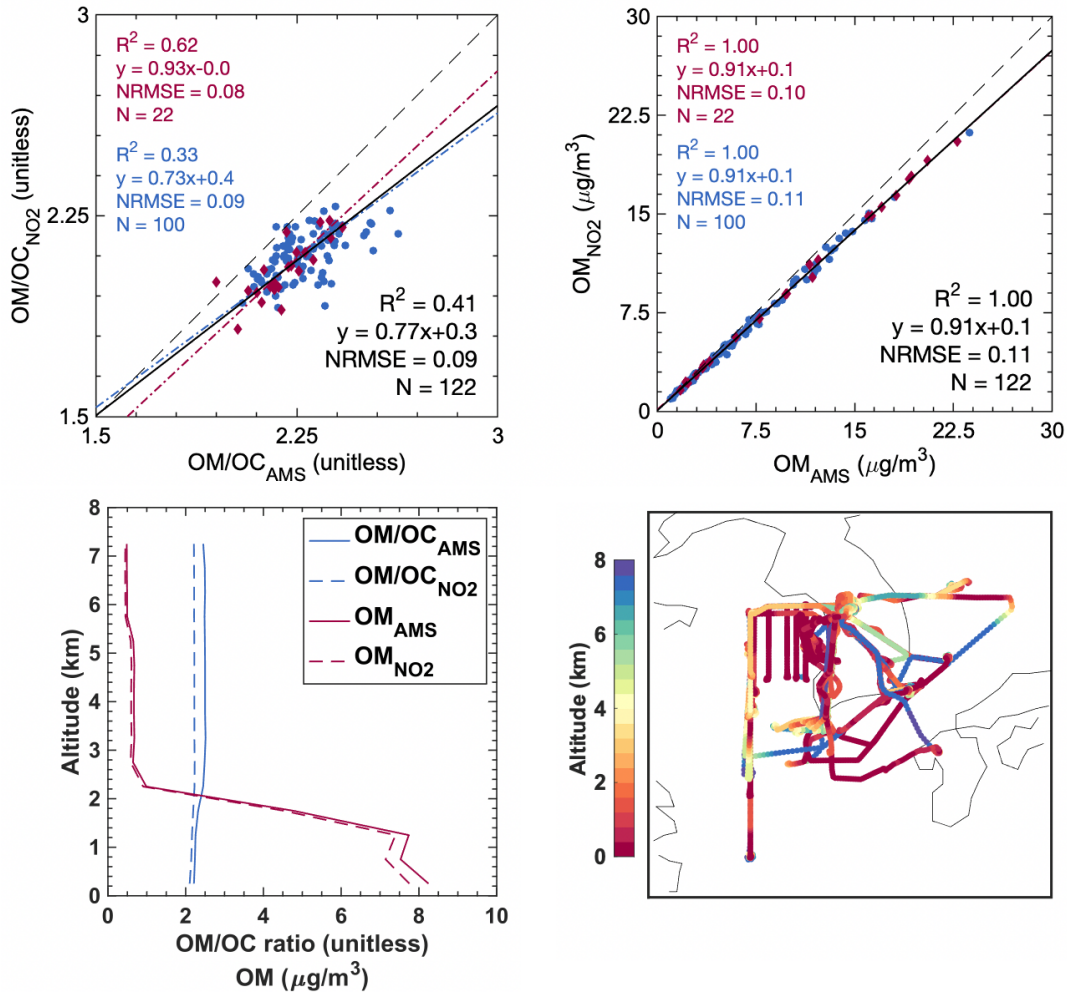
422 by NASA Grant NNX15AT88G.

Appendix A

A1 Application of spatially and temporally varying OM/OC ratio

The top panel of Figure A1 shows scatter plots of the estimated and measured OM/OC and OM during the KORUS-AQ campaign. The estimation is obtained by applying to OC measurement a NO_2 inferred OM/OC from (Philip et al., 2014), with a subsequent correction factor of 1.09 suggested by Canagaratna et al. (2015). Estimated OM is compared with measured OM by AMS during the campaign. Overall consistency is evident between NO_2-derived OM/OC and measured OM/OC. The agreement is better below 500 m than above (left panel, $R^2 = 0.62$ vs. 0.33). The discrepancy at high altitudes is mainly due to the low NO_2 (<0.2 ppbv), where the Philip *et al.* (2014) equation is not applicable. An average OM/OC ratio (2.1) is applied in this case. A high degree of consistency exists between the estimated OM and measured OM, with $R^2 = 0.99$ and slope = 0.91 for data from all altitudes (right panel), thus supporting the use of estimated OM in our analyses. The bottom left panel compares the vertical profile of the estimates and measurements, yielding overall consistency.

435

436   **Figure A1. Scatter plots of estimated and measured OM/OC (top left) and OM (top right) during KORUS-**

437   **AQ. Each point represents a mean value of AMS measurement for a 1-hour interval. Red diamonds, lines,**

438   **and texts represent data from 0-500 m altitude. Blue dots, lines, and text represent data above 500 m from the**

439   **ground. Black solid lines and texts represent the line of best fit for all the data. The 1:1 line is dashed.**

440   **NRMSD is the normalized root mean square deviation between the two datasets. N is the number of points in**

441   **each dataset. (Bottom left) Mean values of OM/OC and OM from measurements and estimations along the**

442   **altitude. (Bottom right) Flight tracks during KORUS-AQ.**

443

A2 Aerosol Extinction Calculation in GEOS-Chem

Extinction (Ext) of radiation by aerosols is represented as the sum of extinction due to each of the aerosol components using the following equation:

$$Ext_k = \frac{3Q_{ext,k}M_k}{4\rho_k R_{eff,k}}$$

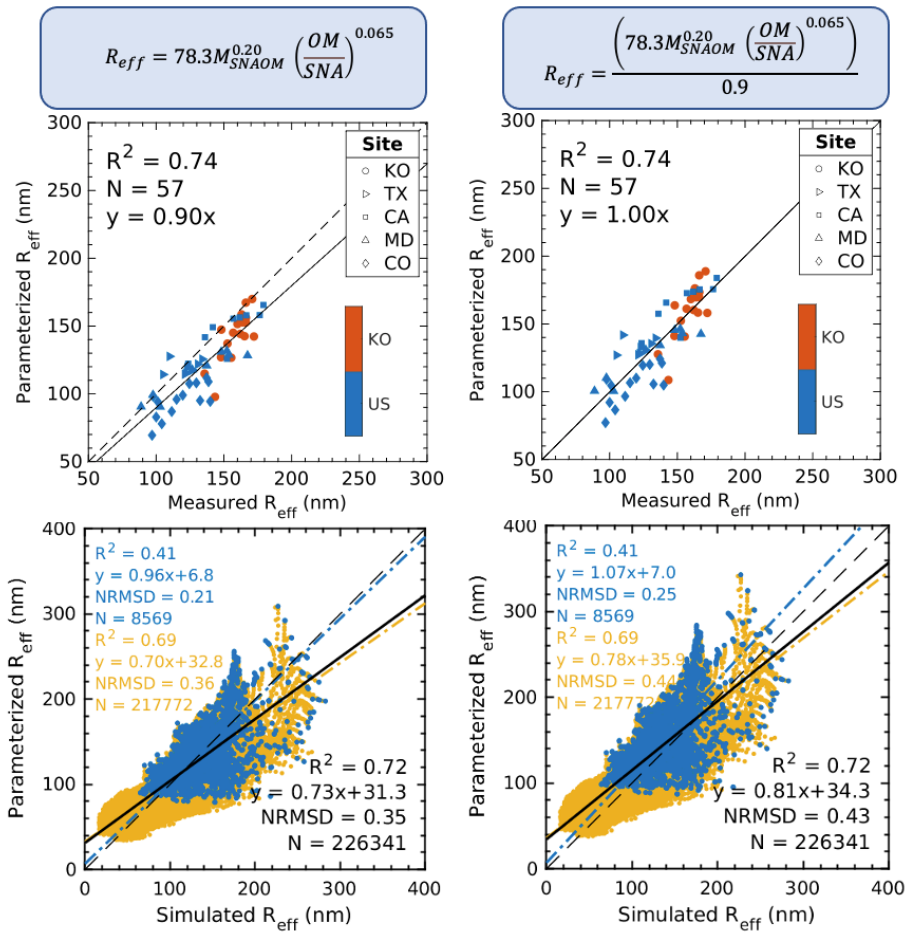
Eqn. (3)

where subscript k indicates the property for the kth component. R_{eff} is the effective radius defined as the area weighted mean radius. Q_{ext} is the area-weighted mean extinction efficiency. M is the aerosol mass loading per unit volume. ρ is the aerosol density. Aerosol optical depth (AOD) is the integral of aerosol extinction across the vertical domain.

For each component, extinction is calculated for assumed log-normal size distribution with corresponding dry geometric mean radius R_g and geometric standard deviation σ, hygroscopicity, refractive index (RI), and density (ρ) for individual aerosol components, as listed in Table A1. Sulfate, nitrate, and ammonium are grouped into SNA for convenience. R_{eff} and Q_{ext} are calculated using Mie Theory (Mishchenko et al., 1999, 2002) based on assumptions in aerosol size and RI. Hygroscopicity for SNA and OM is represented using a κ-Kohler hygroscopic growth scheme (Kreidenweis et al., 2008) as implemented by (Latimer and Martin, 2019).

Table A1. Dry aerosol properties in GEOS-Chem bulk model

Aerosol components	R_g, μm	σ	Hygroscopicity	Refractive Index (dry, 550 nm)	ρ, g cm^{-3}	R_{eff}, μm	Q_{ext}
SNA	0.058	1.6	$\kappa = 0.61$	$1.53 - 6.0\times10^{-3}i$	1.7	0.101	0.603
OM	0.058	1.6	$\kappa = 0.1$	$1.53 - 6.0\times10^{-3}i$	1.3	0.101	0.603

458 **Appendix B**

459

460 **Figure B1. (Top) Scatter plot of parameterized R_{eff} and measured R_{eff} from DISCOVER-AQ and KORUS-**

461 **AQ. Each point represents a daily mean measurement. (Bottom) Scatter plot of parameterized R_{eff} and**

462 **GEOS-Chem-TOMAS simulated R_{eff} for the planetary boundary layer (blue dots, line, and texts), and for the**

463 **free troposphere (yellow dots, line, and texts). Black solid lines and the texts indicate the entire troposphere**

464 **with the sum of SNA and OM > 90% of aerosol mass. The 1:1 line is dashed. NRMSD is the normalized root**

465 **mean square deviation between the two datasets. N is the number of points in each dataset. The left panel**

466 **indicates the original parameterization from multiple linear regression. The right panel shows the adjusted**

467 **parameterization using aircraft measurements.**

468

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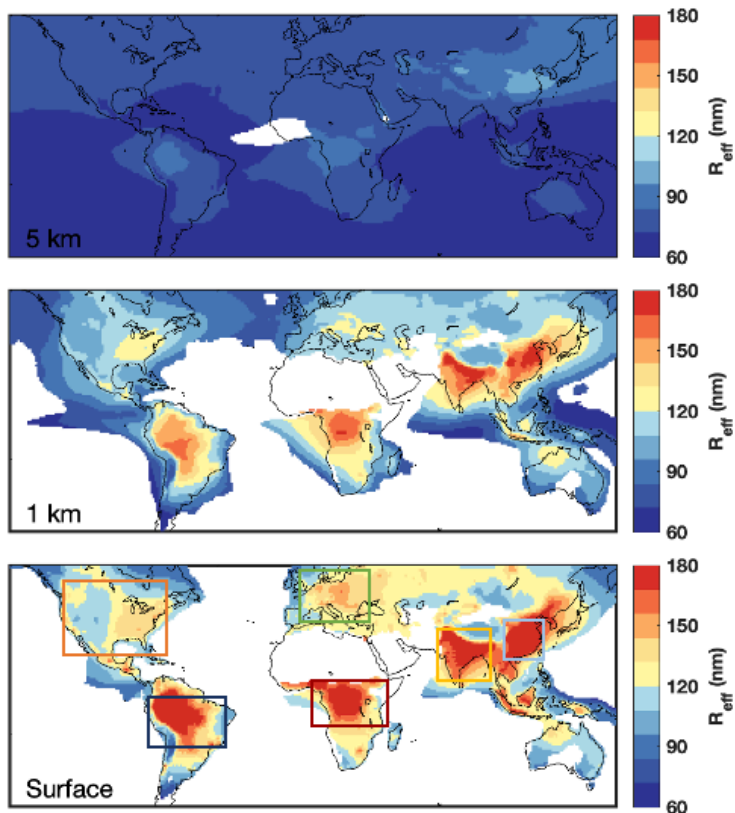


Figure B2. Annual mean R_{eff} for SNA and OM at (top) about 5 km, (middle) about 1 km, and (bottom)

surface, calculated using Eqn. (5) and simulated SNA and OM mass from GEOS-Chem bulk model. R_{eff} is

shown only if M_{SNAOM} is greater than 80% of the total aerosol mass. Boxes in the bottom panel define regions

referred to in Figure B3.

474

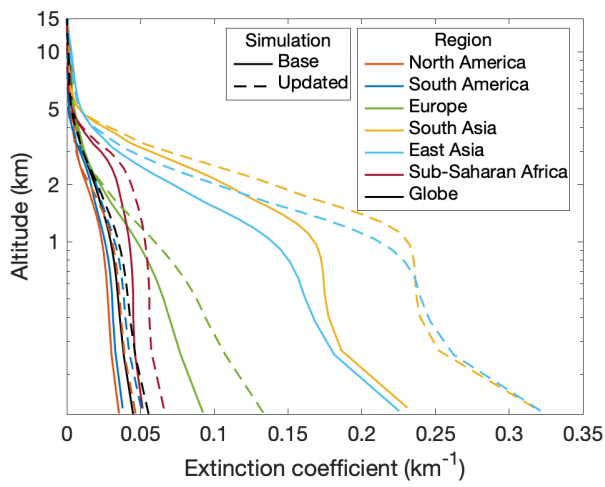
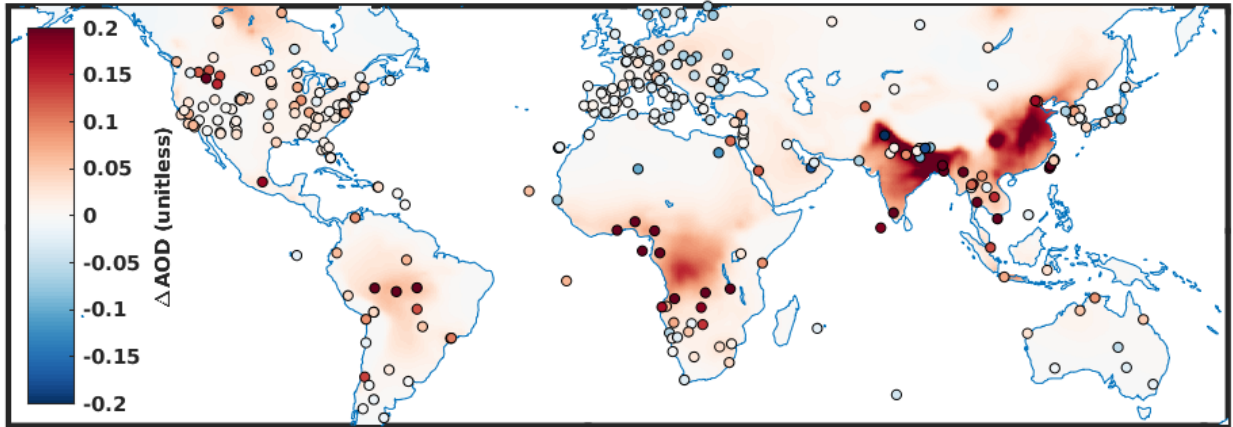



Figure B3. Global and regional aerosol extinction coefficient simulated by GEOS-Chem bulk model with

original R_{eff} (solid lines) and parameterized R_{eff} (dashed lines). Regions are defined by the boxes in Figure B2.

477

478 **Figure B4. Difference between AERONET AOD minus default GEOS-Chem simulated AOD (dots) and**

479 **difference between simulated AOD with the parameterized R_{eff} minus AOD with default R_{eff} (background).**

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