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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 proposed, which well represents 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

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ground-measured AOD from the Aerosol Robotic Network (AERONET; R^2 from 0.68 to 0.73, slope from 0.75 to 0.96). Thus, this parameterization offers a computationally efficient method to represent aerosol size dynamically.

1 Introduction

Aerosol size has numerous effects on aerosol physical and chemical properties and further on atmospheric chemistry. Aerosol size-dependent heterogeneous chemistry affects gaseous oxidants that in turn affect production rates of aerosol components such as sulfate and secondary organic aerosol (Ervens et al., 2011; Estillore et al., 2016). Aerosol size also affects loss rates due to dry and wet deposition (Seinfeld & Pandis, 2016). Both direct and indirect aerosol radiative forcing are sensitive to aerosol size due to the strong size dependence of aerosol extinction and of the number of cloud condensation nuclei (Adams & Seinfeld, 2002; Emerson et al., 2020; Faxvog & Roessler, 1978; Mishchenko et al., 2002). The size dependence of aerosol extinction and scattering phase function also affects the retrieval of aerosol properties from satellites (Jin et al., 2022; Kahn et al., 2005; Levy et al., 2013). Aerosol size affects the fraction of particles that deposit in the body when breathing as well as location within the body where they deposit (Hinds & Zhu, 1999). An appropriate representation of aerosol size is essential for modeling aerosol composition and optical properties (Kodros & Pierce, 2017), interpreting satellite data (Kahn et al., 2005; Levy et al., 2013), studying climate processes (Kellogg, 1980; Twomey, 2007), and moving from aerosol exposure towards dose in health studies (Kodros et al., 2018).

The evolution of the aerosol size distribution is affected by various processes, such as nucleation, condensation, coagulation, and deposition. Nucleation events contribute to the number of particles in the nucleation mode (diameters less than about 10 nm) and thus tend to decrease the mean aerosol size for a population (Aalto et al., 2001). In polluted areas with high emission rates of aerosol precursors, mean aerosol size tends to increase by condensation and coagulation (Sakamoto et al., 2016; Sun et al., 2011). Dry and wet aerosol deposition have strong size dependencies due to competing physical processes (Emerson et al., 2020; Reutter et al., 2009; Ruijrok et al., 1995). The aerosol size distribution can be simulated using aerosol microphysical schemes, such as the TwO Moment Aerosol Sectional (TOMAS; Adams & Seinfeld, 2002) microphysics model, the Advanced Particle Microphysics (APM; Yu & Luo, 2009) model, the Global Model of Aerosol Processes (GLOMAP; Mann et al., 2010), and the Modal Aerosol Module (MAM4; X. Liu et al., 2016). These schemes have valuable prognostic capabilities; however, their computational cost has limited their use in Chemistry Climate Models (CCMs) or Chemical Transport Models (CTMs). For example, only 3 of the 10 models that included aerosols, studied by the Atmospheric Chemistry and Climate Model Intercomparison Project, include online size-resolved aerosol microphysics (Kodros & Pierce, 2017; Lamarque et al., 2013).

Methods are needed to better represent aerosol size in CCMs or CTMs without a microphysics scheme (referred to as bulk models). These bulk models usually use prescribed relationships to obtain size-resolved aerosol properties (Croft et al., 2005; Karydis et al., 2011; Zhai et al., 2021), which may insufficiently represent the temporal and spatial variation (Kodros & Pierce, 2017). For example, in the GEOS-Chem CTM, a fixed dry aerosol geometric mean radius (R_g) is assumed for organic matter (OM) and sulfate-nitrate-ammonium (SNA), which is based on analysis of long-

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term aerosol composition and scattering measurements provided by the IMPROVE network across the continental U.S. (Latimer & Martin, 2019). However, subsequent analysis by Zhai *et al.* (2021) found that this aerosol size underestimated the aerosol mass scattering efficiency and the aerosol extinction coefficients during an aircraft campaign over South Korea (KORUS-AQ). Thus, neglect of aerosol microphysical processes that shape aerosol size distributions can be a significant source of uncertainty in aerosol optical properties in a CTM. A balance between computational cost and representativeness of aerosol size is needed. One option is to use models with size-resolved aerosol microphysics models to inform bulk models, such as was done for the parameterization of biomass burning aerosol size by Sakamoto *et al*. (2016).

Recent airborne measurements offer information to evaluate and improve the simulation of aerosol size. DISCOVER-AQ (Deriving Information on Surface Conditions from Column and Vertically Resolved Observations Relevant to Air Quality) was a multi-year campaign over four U.S. cities that provides 3-D resolved measurements of atmospheric gas composition, aerosol composition, size distribution, and optical properties (Choi et al., 2020; Chu et al., 2015; Sawamura et al., 2017). KORUS-AQ (the Korea-United States Air Quality Study) offers similar measurements in a different environment with higher aerosol mass loadings (Choi et al., 2020; Jordan et al., 2020; Nault et al., 2018; Zhai et al., 2021).

To study the global variation in aerosol size, we explore airborne measurements from DISCOVER-AQ and KORUS-AQ, as well as output from the GEOS-Chem-TOMAS microphysics model. We focus on OM and SNA, which dominate fine aerosol composition in populated areas. The driving factors for variation in aerosol size are examined. A parameterization of aerosol size using these driving factors is proposed. This parameterization is then applied to a GEOS-Chem high-performance model bulk simulation for global aerosol optical depth (AOD), which is evaluated by ground-measured AOD from the Aerosol Robotic Network (AERONET).

2 Observations and Models

2.1 Observations

2.1.1 Aircraft measurements

We examine airborne measurements from two NASA campaigns, DISCOVER-AQ and KORUS-AQ. DISCOVER-AQ includes four deployments in Maryland (MD), California (CA), Texas (TX), and Colorado (CO). KORUS-AQ is an international cooperative field study program conducted in South Korea (KO), sponsored by NASA and the South Korean government through the National Institute of Environmental Research. The year as well as the date and altitude ranges of each deployment are in Table 1.

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

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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 coefficients, 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 Ca^{2+} and Na^{+} assuming non-sea salt Ca^{2+} 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 (Malm et al., 1994; Remoundaki et al., 2013; 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 & 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.

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]

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Aerosol extinction profile at 532 nm	HSRL [h]
NO_2	4-Channel Chemiluminescence Instrument [i]
Relative humidity (RH)	DLH [j]

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

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

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

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

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

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

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

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

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

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

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

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2.1.2 AERONET AOD

We use ground-based AOD observations to evaluate our parameterization and simulated AOD. Aerosol Robotic Network (AERONET) is a worldwide network that provides long-term sun photometer measured AOD. We use the Version 3 Level 2 database, which includes an improved cloud screening algorithm (Giles et al., 2019). AOD at 550 nm wavelength, interpolated based on the local Ångström exponent at 440 and 670 nm channels, is used in this study. For each site, we use data for the year 2017, excluding months with less than 20 days of measurements and excluding sites with data less than 4 months.

2.2 GEOS-Chem simulation

We interpret the aircraft observations with the GEOS-Chem chemical transport model (www.geos-chem.org, last access: 30 October 2022). GEOS-Chem is driven by offline meteorological data from the Goddard Earth Observing System (GEOS) of the NASA Global Modeling and Assimilation Office (Schubert et al., 1993). We use the high-performance implementation of GEOS-Chem (GCHP; Eastham et al. 2018) to examine the effect of variation in aerosol size on AOD. We also use the TOMAS microphysical scheme, coupled with the standard GEOS-Chem implementation (GEOS-Chem classic), to explicitly resolve aerosol microphysics. The bulk and the microphysics simulations share common emissions and chemical mechanisms. They are both conducted for the year 2017 and driven by MERRA-2 meteorological fields.

The GEOS-Chem aerosol simulation includes the sulfate-nitrate-ammonium system (Fountoukis & Nenes, 2007; Park, et al., 2004), primary and secondary carbonaceous aerosols (Marais et al., 2016; Park et al., 2003; Pye et al., 2010; Wang et al., 2014), sea salt (Jaeglé et al., 2011), and mineral dust (Fairlie et al., 2007). The primary emission data are from the Community Emissions Data System ($CEDS_{GBD-MAPS}$; McDuffie et al. 2020). Dust emission inventories include updated natural dust emission (Meng et al., 2021), and anthropogenic fugitive, combustion, and industrial dust (AFCID; Philip et al., 2017). Resolution-dependent soil NO_x, sea salt, biogenic VOC, and natural dust emissions are calculated offline at native meteorological resolution to produce consistent emissions across resolution (Meng et al., 2021; Weng et al., 2020). Biomass burning emissions use the Global Fire Emissions Database, version 4 (GFED4) (Van Der Werf et al., 2017). We estimate organic matter (OM) from primary organic carbon using the same OM/OC parameterizations as applied for DISCOVER-AQ (Canagaratna et al., 2015; Philip et al., 2014). Dry and wet deposition follows Amos *et al.* (2012), with a standard resistance-in-series dry deposition scheme (Wang et al., 1998). Wet deposition includes scavenging processes from convection and large-scale precipitation (Liu et al., 2001).

Global relative humidity dependent aerosol optical properties are based on the Global Aerosol Data Set (GADS; Koepke et al. 1997; Martin et al. 2003) with updates for SNA and OM (Latimer & Martin, 2019), mineral dust (Zhang et al., 2013), and absorbing brown carbon (Hammer et al., 2016). In the current GEOS-Chem model, the SNA and OM R_{eff} of particular interest here are based on co-located measurements of aerosol scatter and mass from the IMPROVE network at U.S. national parks over the period 2000-2010, together with a κ-Kohler framework for aerosol hygroscopicity (Kreidenweis et al., 2008) as implemented by Latimer and Martin (2019). Aerosol extinction is

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calculated as the sum of extinction from each aerosol component with aerosol optical properties listed in Table A1, as described in Appendix A2.

A global GCHP simulation (Eastham et al. 2018) version 13.0.0 (DOI: 10.5281/zenodo.4618180) that includes advances in performance and usability (Martin et al., 2022), is conducted on a C90 cubed-sphere grid corresponding to a horizontal resolution of about 100 km.

The TOMAS microphysics scheme, coupled with the GEOS-Chem simulation, conserves aerosol mass, and tracks particles with diameters from approximately 1 nm to 10 µm (Adams & Seinfeld, 2002). Microphysical processes in TOMAS include nucleation, condensation, evaporation, coagulation, and wet and dry deposition (Adams & Seinfeld, 2002). Nucleation in TOMAS follows a ternary scheme (sulfuric acid, ammonia, and water) when ammonia mixing ratios are greater than 0.1 ppt; otherwise, a binary nucleation scheme is used (Napari et al., 2002). The nucleation rate is scaled by 10^{-5} to better match the observations (Westervelt et al., 2013). The condensation and evaporation algorithm is based on a study from Tzivion *et al.* (1989), including interaction with secondary organic aerosol (D'Andrea et al., 2013). Interstitial coagulation in clouds is also included (Pierce et al., 2015).

For each size bin, TOMAS tracks the mass and number of sulfate, sea salt, black carbon, OC, dust, and water. Primary sulfate emissions have 2 lognormal modes: 15% of the mass with a number median diameter (NMD) of 10 nm and geometric standard deviation (σ) of 1.6 and the remainder with a NMD of 70 nm and σ of 2 (Adams & Seinfeld, 2003). The size of emitted carbonaceous particles varies depending on the source: those produced by fossil fuel have 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 of 2 (Pierce et al., 2007). Meteorology and most of the emissions in GEOS-Chem-TOMAS follow the bulk simulation, except that online schemes are used for dust (Zender et al., 2003) and sea salt (Jaeglé *et al.* 2011).

A one-year global GEOS-Chem-TOMAS (version 13.2.1. DOI: 10.5281/zenodo.5500717) simulation is conducted with a horizontal resolution of 4º × 5º and 47 vertical layers from surface to 0.01 hPa. Aerosols are tracked in 15 size bins with particle diameters ranging from about 3 nm to 10 µm.

3 Development of a Parameterization of Aerosol Size

We first examine the aircraft measurements for insight into the observed variation in aerosol size. Then we apply the size-resolved GEOS-Chem-TOMAS model to extend our analysis to the global scale and identify driving factors of aerosol size. We subsequently develop and test a parameterization of aerosol size for use in bulk models.

3.1 Observed variation in aerosol size

Figure 1 shows the daily-mean dry effective radius from DISCOVER-AQ and KORUS-AQ as a function of aerosol mass. Aerosol size, in terms of dry R_{eff}, ranges from 90 nm to 179 nm for DISCOVER-AQ, which is generally smaller 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) 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 aerosol size and M_{SNAOM} is evident.

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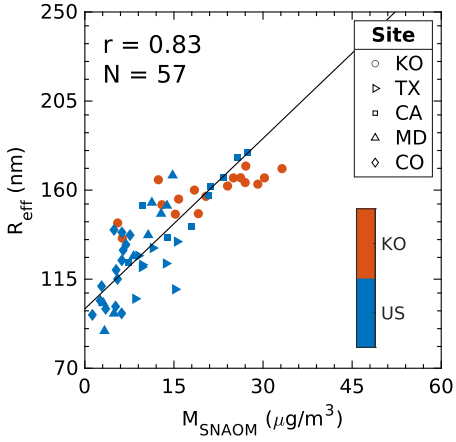

Figure 1. Airborne measurements of dry effective radius (R_{eff}) versus the sum of SNA and OM mass (M_{SNAOM}) for DISCOVER-AQ (Maryland is abbreviated as MD, California as CA, Texas as TX, Colorado as CO) and for KORUS-AQ (KO) campaigns. Each point represents a daily average for the entire flight profile. Only data with M_{SNAOM} > 4 × Dust mass is used.

The positive relationship between dry aerosol size and mass of SNA and OM reflects the roles of emission, condensation, and coagulation in simultaneously increasing aerosol size and mass. This general tendency is also observed by many other studies (e.g., Bahreini et al., 2003; Rodríguez et al., 2007; Sakamoto et al., 2016; Sun et al., 2010) despite variable aerosol sources and growth mechanisms. In cities, the joint increases in aerosol size and mass are usually attributable to anthropogenic emissions and condensation (Huang et al., 2013; Sun et al., 2011; Tian et al., 2019). In remote areas, biomass burning shifts the particle size distribution toward larger radii due to high emission rates and coagulation in plumes (Ramnarine et al., 2019; Rissler et al., 2006) that, for example, increase both aerosol size and mass from the wet season to the dry season in Amazonia (Andreae et al., 2015; Rissler et al., 2006). The positive relationship between aerosol size and mass suggests the possibility of using aerosol mass as a predictor of R_{eff}.

We examine the ability of the GEOS-Chem bulk model to reproduce the observed extinction. The top panel of Figure 2 compares the measured aerosol extinction profiles to calculated aerosol extinction profiles using default R_{eff}. Details about the calculation are described in Appendix A2. Both measured and calculated extinction profiles exhibit increasing extinction toward the surface associated with increasing aerosol mass concentrations. However, biases are apparent for both DISCOVER-AQ and KORUS-AQ. The R_{eff} from KORUS-AQ shown in Figure 1 have a mean value of 164 nm, larger than the value of 101 nm inferred by Latimer & Martin (2019) based on measurements of aerosol scatter and mass by the U.S. IMPROVE network. This bias was previously noted by Zhai *et al.* (2021). The mean R_{eff} from DISCOVER-AQ of 138 nm is also larger than the inferred value. This likely reflects representativeness differences since the DISCOVER-AQ deployments focused on major urban areas during months of high aerosol loadings, while the IMPROVE measurements were at national parks throughout the year. The middle panel shows the

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calculated extinction using the measured aerosol size distribution. Applying the measured aerosol size distribution addresses most discrepancies between the calculated and measured aerosol extinction profile for both KORUS-AQ and DISCOVER-AQ. The corresponding discrepancies in AOD estimation also significantly decreased (from 0.09 to 0.03 for DISCOVER-AQ and from 0.17 to 0.02 for KORUS-AQ). The reduced discrepancies support the conclusions from Zhai *et al.* (2021) that the GEOS-Chem aerosol size is underestimated for KORUS-AQ and motivate parameterization of R_{eff} for efficient representation of aerosol size for global scale aerosol modeling.

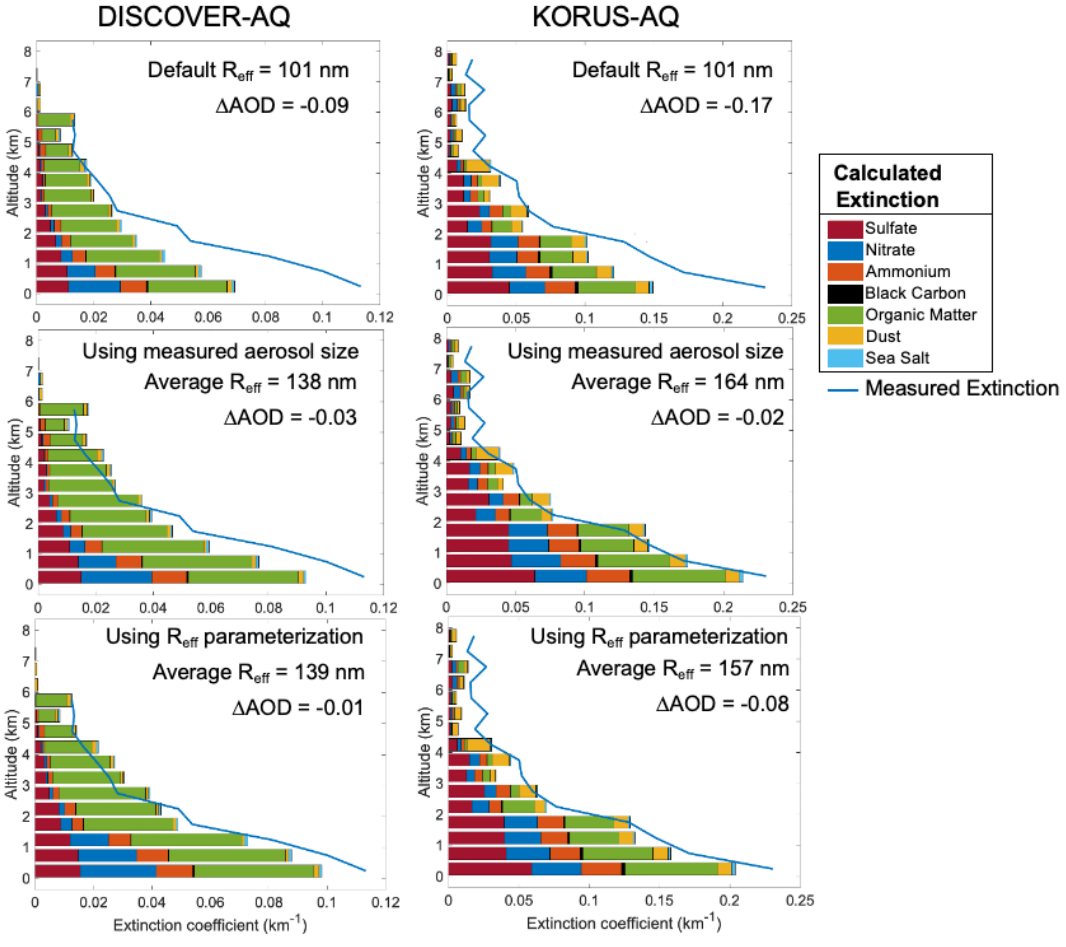

Figure 2. Aerosol extinction profile for the DISCOVER-AQ and KORUS-AQ aircraft campaigns. Blue lines are the measured extinction profiles. Horizontal bars are calculated extinction using (top) default GEOS-Chem R_{eff}, (middle) measured R_{eff}, and (bottom) parameterized R_{eff} (described in Section 3.3), together with measured aerosol composition and RH. The aerosol extinction calculation is described in Appendix A.

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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. The top panel of Figure 3 shows the geographic distribution of annual mean surface layer dry R_{eff} for locations and months where aerosol mass is dominated by SNA and OM, as indicated by M_{SNAOM} > 90% of the aerosol mass. Among the areas of interest, biomass burning regions of Central Africa, South America, and boreal forest of North America exhibit the highest surface R_{eff} of about 180 nm. Industrial areas such as East Asia and South Asia also exhibit high R_{eff} of about 130 nm, given an abundance of particle emissions and gaseous precursors. The lowest surface R_{eff} of about 80 nm is found in North America, where aerosol mass concentrations are low.

The middle panel of Figure 3 shows the simulated M_{SNAOM} from GEOS-Chem-TOMAS. Enhanced M_{SNAOM} concentrations of over 40 μg/m^3 are apparent over East Asia and South Asia, reflecting intense anthropogenic emissions. Another M_{SNAOM} hotspot can be seen in Central Africa, driven by biomass burning during the dry season (McDuffie et al., 2021; Van Der Werf et al., 2017) and sometimes exacerbated by anthropogenic emissions (Ngo et al., 2019). Moving from North America, to Europe, and then to Asia, M_{SNAOM} concentrations exhibit a generally increasing tendency, consistent with the R_{eff} tendency in the top panel and aligning with the relationship between aircraft measurements over the U.S. and South Korea.

However, in South America, where R_{eff} is among the highest, M_{SNAOM} is relatively low. This discrepancy motivates the search for other factors, such as aerosol composition, that are associated with aerosol size. In South America, aerosol mass is mostly from natural sources, particularly biomass burning during the dry seasons. R_g for a particle population from biomass burning ranges from 60 nm to 170 nm (Janhäll et al., 2010; Reid et al., 2005; Rissler et al., 2006), usually larger than that of primary sulfate aerosol (5 to 35 nm; Plaza et al., 2011; Whitey, 1978). Therefore, the relative abundance of OM in the total M_{SNAOM} can serve as another predictor of R_{eff}. The bottom panel of Figure 3 shows the ratio between OM and SNA mass. In addition to the Amazon basin, the biomass burning regions of Central Africa and boreal forests in Asia and North America are all areas with high OM mass fractions, which contribute to their high R_{eff} despite the low M_{SNAOM}.

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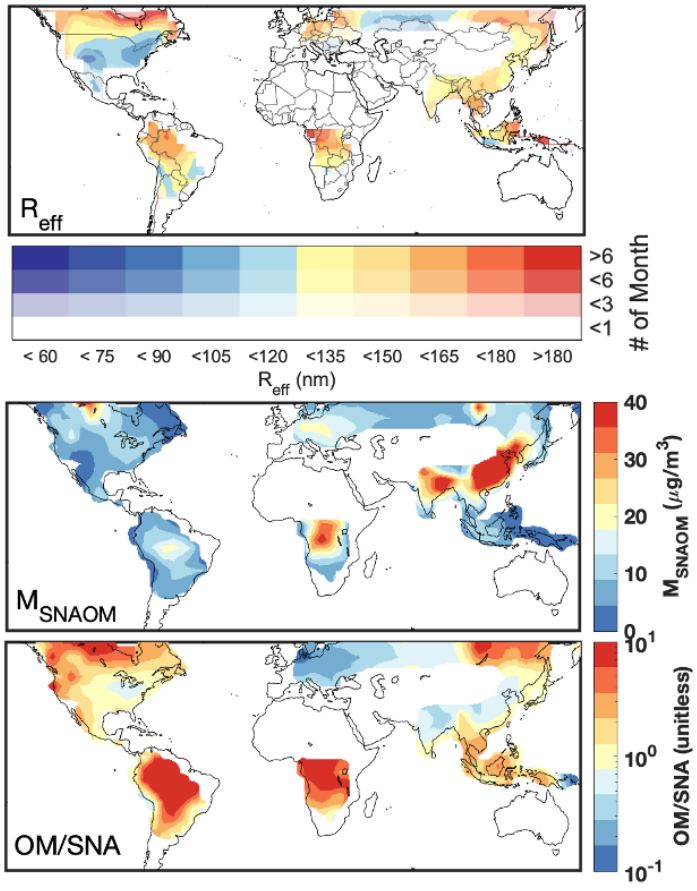

Figure 3: Geographic distribution of GEOS-Chem-TOMAS-simulated annual mean surface layer aerosol properties; (top) R_{eff} with color intensity indicating the number of months included (Mass of SNA and OM > 90% of aerosol mass), (middle) the sum of SNA and OM mass (M_{SNAOM}), and (bottom) OM/SNA.

3.3 Parameterization and evaluation

We use Multiple Linear Regression (MLR) to derive a parameterization of dry R_{eff} 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; Tian et al., 2019; Zhai et al., 2021). Second, the PBL is the domain where the model-measurement difference exists (Figure 2, top panel).

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

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

Figure 4 shows the distribution of dry R_{eff} based on GEOS-Chem-TOMAS and Eqn. (5). Circles in Figure 4 show the mean values of the sampled GEOS-Chem-TOMAS simulated R_{eff} as a function of simulated M_{SNAOM} concentrations, 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 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 (about 44 μg/m^3 and 14 respectively). The background color indicates our parameterized R_{eff}. A high degree of consistency exists between the parameterized R_{eff} and simulated R_{eff}, especially in the free troposphere where large 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). Despite the overall consistency, a few differences exist. When aerosol mass concentration is high, the parameterization tends to yield a higher R_{eff} than in the GEOS-Chem-TOMAS simulation, since the adjustment using aircraft measurements led to 11% increase in R_{eff}. At M_{SNAOM} near 10 μg/m^3 and OM/SNA near 10, the simulation indicates higher R_{eff} than the parameterization, reflecting dilution downwind of biomass burning that reduces the aerosol mass concentration but has little influence on particle size in GEOS-Chem-TOMAS. A 10-20% underestimation in the parameterization at low OM/SNA reflects the advection and dilution of downwind of urban areas and in the free troposphere.

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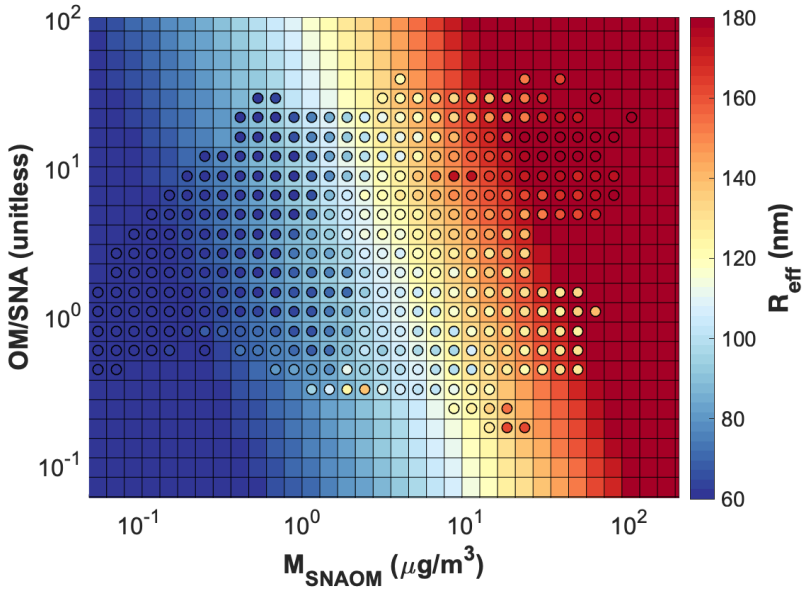

Figure 4. Dry R_{eff} as a function of M_{SNAOM} and OM/SNA when SNA and OM are dominant (>90%). Each circle represents the mean value of the GEOS-Chem-TOMAS simulated R_{eff} in each bin. Background color indicates the parameterized R_{eff}.

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). Most discrepancies between calculated and measured extinction from aircraft campaigns are eliminated (Figure 2, bottom panel) with AOD discrepancies reduced to 0.01 and 0.08 for DISCOVER-AQ and KORUS-AQ, respectively.

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 with the color intensity indicating the ratio of SNA and OM mass to total aerosol mass at the surface. 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 spatial pattern well represents the GEOS-Chem-TOMAS simulation, with high R_{eff} found in biomass burning regions in South America and Central Africa, as well as industrial regions in Asia. The horizontal variation diminishes with altitude (Figure B2), with the mean R_{eff} decreasing from 85 nm (surface) to 43 nm (10 km).

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 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 based on Mie Theory (Mishchenko et al., 1999, 2002). This update generally increases aerosol mass scattering by increasing the mass extinction efficiency, in turn, increasing AOD over regions with strong anthropogenic sources,

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such as East Asia (by 0.13, 35.4%) and South Asia (by 0.13, 28.3%). It also slightly increases AOD over regions influenced by wildfires, such as South America (by 0.02, 12.2%), Central Africa (by 0.03, 17.4%), and the boreal forests in North America, Europe, and Asia (by 0.01-0.03, 12.1 to 16.9%). Most increases occur near the surface (Figure B3), where the highest aerosol mass loading and mass extinction efficiency exist. The NRMSD between original and updated GEOS-Chem simulated AOD is 20.9% globally, and 28.8% over continents.

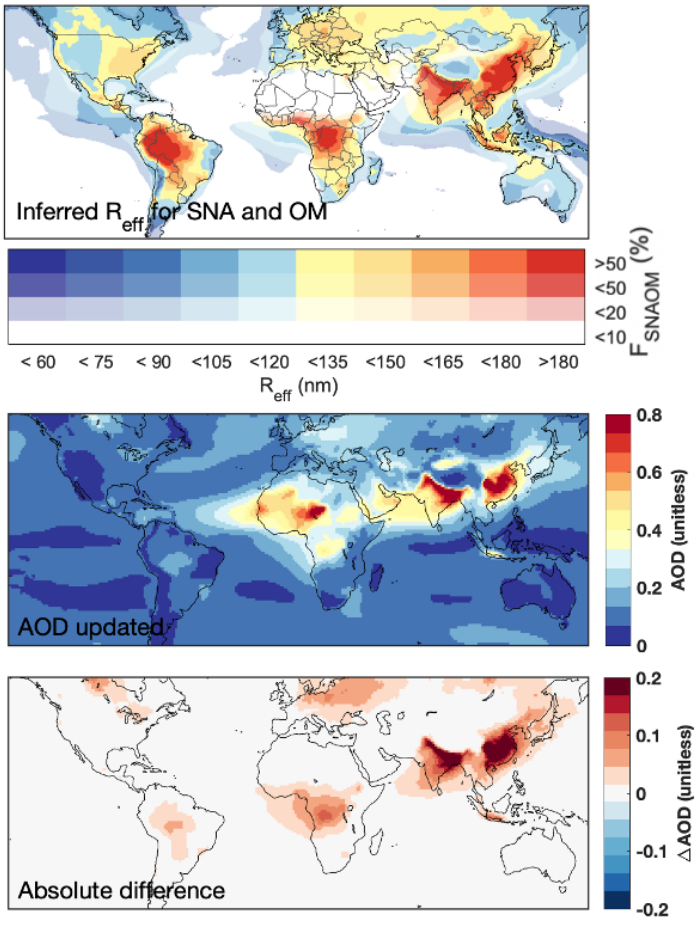

Figure 5. (Top) Surface dry R_{eff} for SNA and OM calculated using Eqn. (5) and GEOS-Chem bulk model simulated SNA and OM mass. F_{SNAOM} is the ratio of SNA and OM mass to the total aerosol mass at the surface. (Middle) The GEOS-Chem simulated AOD using inferred R_{eff}. (Bottom) the absolute difference 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 panel of Figure 6 shows for the default R_{eff}, the

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percent difference 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} slightly overestimates AOD in regions with small parameterized R_{eff} and underestimates AOD in regions 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 0.73, slope from 0.75 to 0.96).

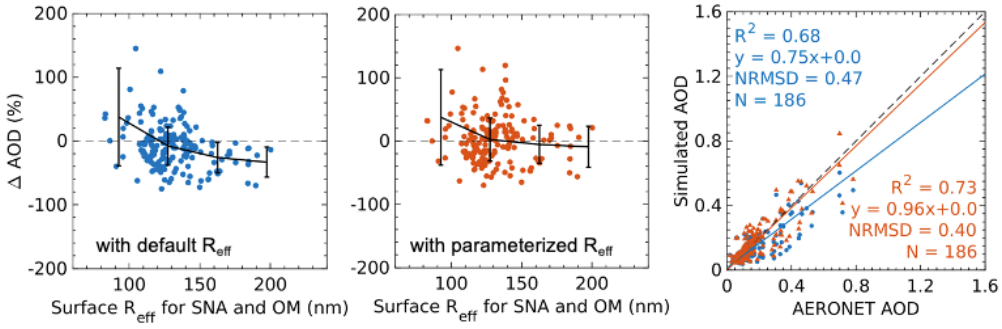

Figure 6. (Left and middle) Percent increase in GEOS-Chem simulated AOD minus AERONET AOD as a function of parameterized surface dry R_{eff} for SNA and OM. Black lines represent the mean values of ΔAOD in each 35 nm bin; error bars represent the corresponding standard deviation. (Right) Scatter plot 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

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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 20.9%, with the most significant regional AOD increase of about 0.13 in South and East Asia, where aerosol mass loadings are high. This parameterization led to improved consistency of GEOS-Chem simulated AOD with AERONET AOD (R^2 from 0.68 to 0.73; slope from 0.75 to 0.96), by increasing AOD at high R_{eff}.

Overall, the simple parameterization of R_{eff} derived in this study improved the accuracy in modeling aerosol optical properties without imposing additional computational expense. Other chemical transport models and modeling of other size-related processes, such as heterogeneous chemistry, photolysis frequencies, and dry deposition, may also benefit from the parameterized R_{eff}. Further developments in computational efficiency of aerosol microphysics models and more abundant measurements of aerosol size and optical properties would both offer opportunities for further advances.

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Data availability. AERONET data can be found at https://aeronet.gsfc.nasa.gov/. Aircraft data during DISCOVER-AQ are available at https://asdc.larc.nasa.gov/project/DISCOVER-AQ. KORUS-AQ data can be found at https://doi.org/10.5067/Suborbital/KORUSAQ/DATA01.

Author contributions. HZ and RVM designed the study. HZ performed the data analysis and model simulations with contributions from BC, SZ, CL, LB, JRP, IS, DC, and RYWC. BEA, LDZ, JWH, RAF, CAH, JLJ, PCJ, JED, JSS, AW, and BAN contributed to KORUS-AQ and DISCOVER-AQ campaign measurements. HZ and RVM wrote the paper with input from all authors.

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

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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.

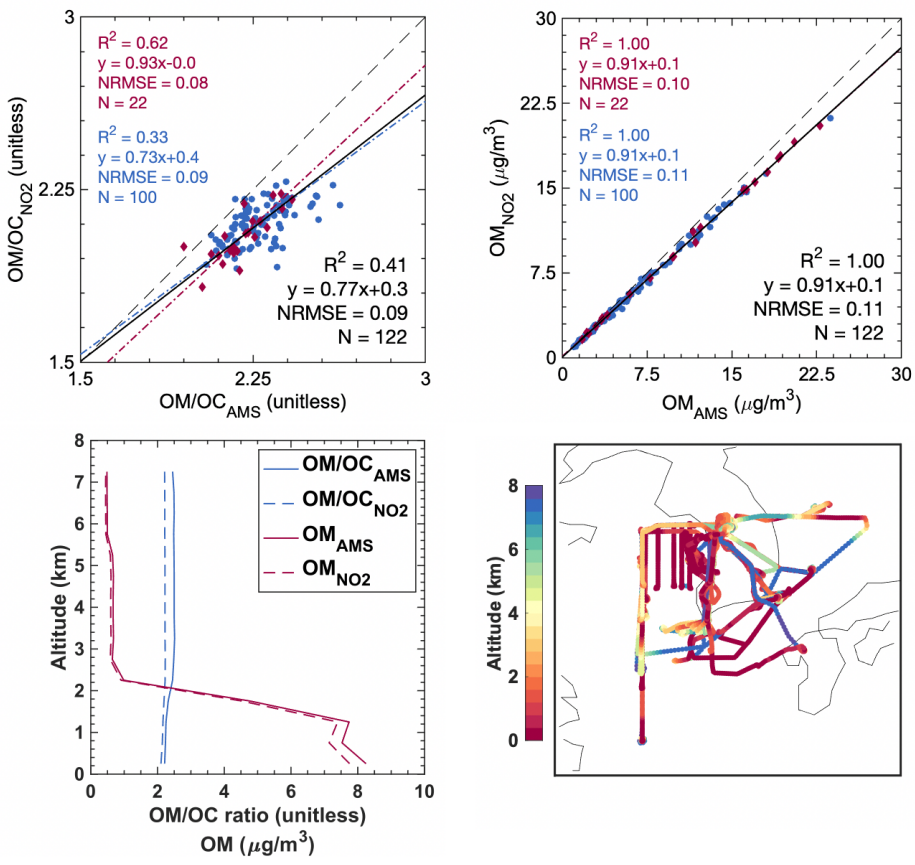

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Figure A1. Scatter plots of estimated and measured OM/OC (top left) and OM (top right) during KORUS-AQ. Each point represents a mean value of AMS measurement for a 1-hour interval. Red diamonds, lines, and texts represent data from 0-500 m altitude. Blue dots, lines, and text represent data above 500 m from the ground. Black solid lines and texts represent the line of best fit for all the data. 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. (Bottom left) Mean values of OM/OC and OM from measurements and estimations along the altitude. (Bottom right) Flight tracks during KORUS-AQ.

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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:

$$Ext_k = \frac{3Q_{ext,k}M_k}{4\rho_k R_{eff,k}} \qquad \text{Eqn. (3)}$$

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 & 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

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Appendix B

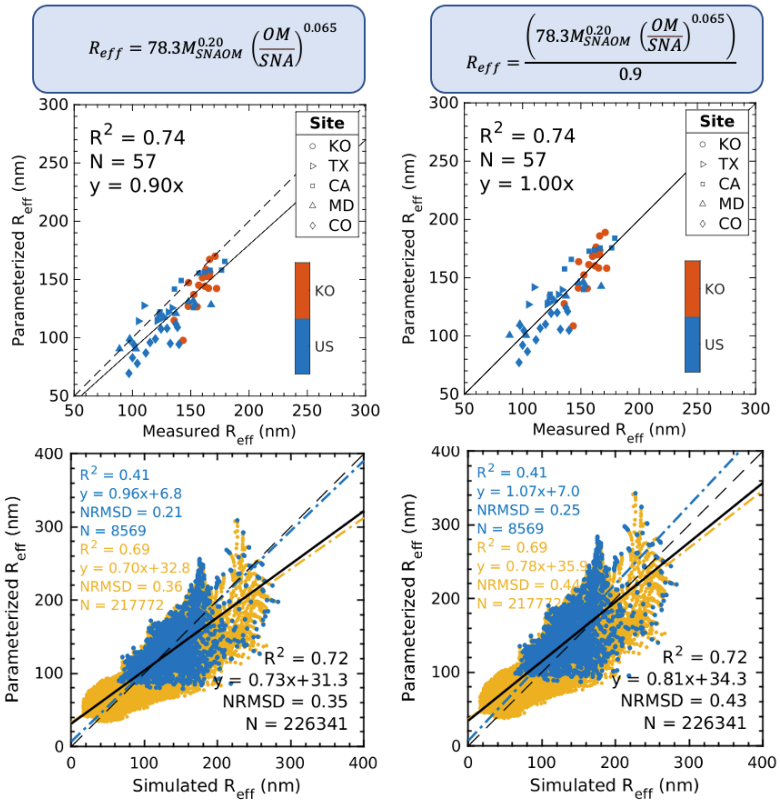

Figure B1. (Top) Scatter plot of parameterized R_{eff} and measured R_{eff} from DISCOVER-AQ and KORUS-AQ. Each point represents a daily mean measurement. (Bottom) Scatter plot of parameterized R_{eff} and GEOS-Chem-TOMAS simulated R_{eff} for the planetary boundary layer (blue dots, line, and texts), and for the free troposphere (yellow dots, line, and texts). Black solid lines and the texts indicate the entire troposphere with the sum of SNA and OM > 90% of aerosol mass. 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. The left panel indicates the original parameterization from multiple linear regression. The right panel shows the adjusted parameterization using aircraft measurements.

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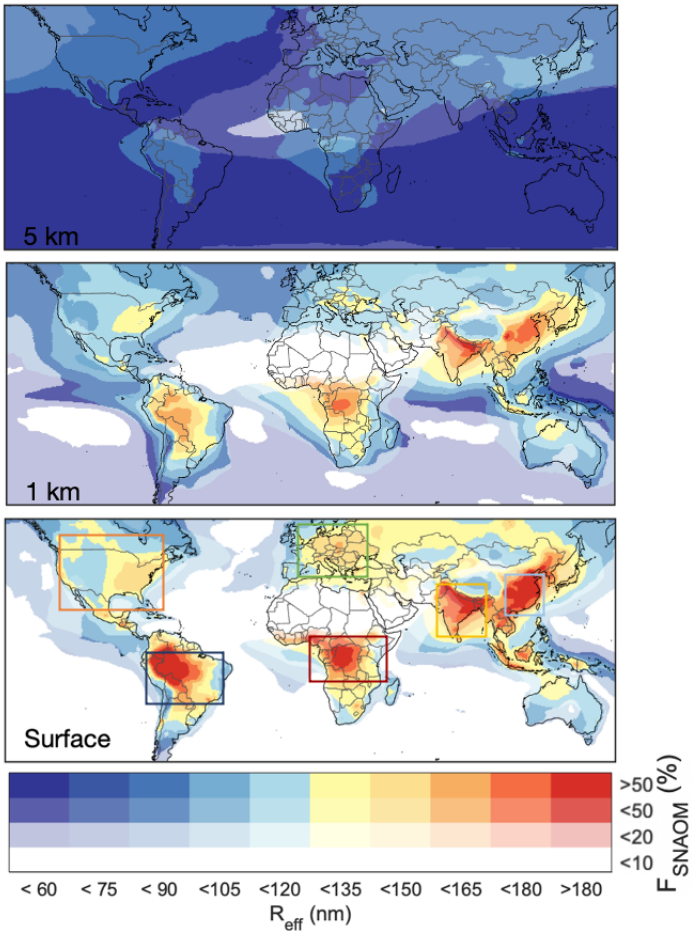

Figure B2. Annual mean R_{eff} for SNA and OM at (top) about 5 km, (middle) about 1 km, and (bottom) surface, calculated using Eqn. (5) and simulated SNA and OM mass from GEOS-Chem bulk model. F_{SNAOM} is the ratio of SNA and OM mass to the total aerosol mass. Boxes in the bottom panel define regions referred to by Figure B3.

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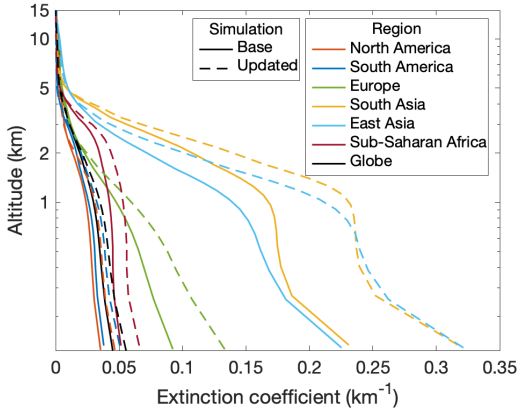

Figure B3. Global and regional aerosol extinction coefficient simulated by GEOS-Chem bulk model with original R_{eff} (solid lines) and parameterized R_{eff} (dashed lines). Regions are defined by the boxes in Figure B2.

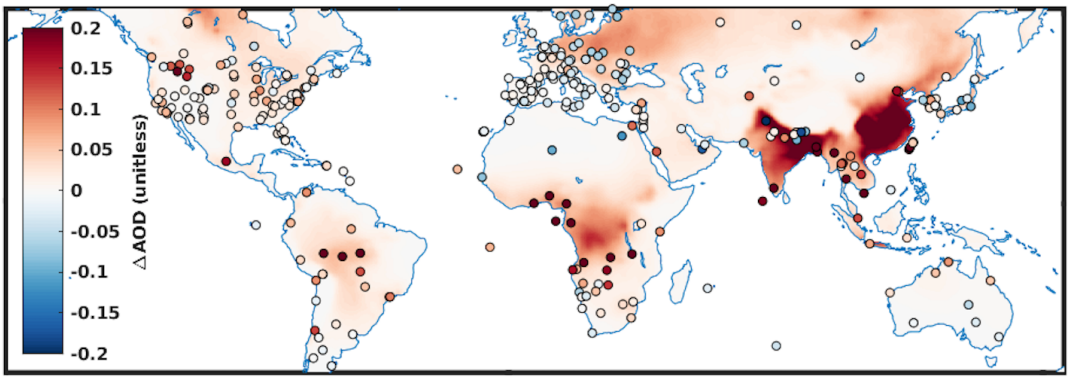

Figure B4. Difference between AERONET AOD minus default GEOS-Chem simulated AOD (dots) and difference between simulated AOD with the parameterized R_{eff} minus AOD with default R_{eff} (background).

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