



1 Combining low-cost, surface-based aerosol monitors with 2 size-resolved satellite data for air quality applications

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4 Priyanka deSouza^{1†}, Ralph A Kahn², James A Limbacher², Eloise A. Marais^{3*}, Fábio Duarte^{1,4}, Carlo Ratti¹

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6 ¹ Senseable City Lab, Massachusetts Institute of Technology, Cambridge MA, United States

7 ² Earth Sciences Division, NASA Goddard Space Flight Center, Greenbelt, Maryland 20771, United States

8 ^{3*} School of Engineering and Applied Sciences, Harvard University, Cambridge, MA, United States

9 ⁴ Pontifícia Universidade Católica do Paraná, Brazil

10 * Now at: School of Physics and Astronomy, University of Leicester, Leicester, UK.

11 [†] Correspondence to: Priyanka deSouza (desouzap@mit.edu)

12

13 **Abstract:**

14 Poor air quality is the world's single largest environmental health risk, and air quality monitoring is crucial for
15 developing informed air quality policies. Efforts to monitor air pollution in different countries are uneven, largely
16 due to the high capital costs of reference air quality monitors (AQMs), especially for airborne particulate matter
17 (PM). In sub-Saharan Africa, for example, few cities operate AQM systems. It is thus important to examine the
18 potential of alternative monitoring approaches. Although PM measurements can be obtained from *low-cost optical*
19 *particle counters (OPCs)*, data quality can be an issue.

20 This paper develops a new method using raw aerosol size distributions from multiple, surface-based low-cost
21 Optical Particle Counters (OPCs) to calibrate the Multi-angle Imaging SpectroRadiometer (MISR)
22 component-specific, column aerosol optical depth (AOD) data, that contain some particle-size-resolved information.
23 The combination allows us to derive surface aerosol concentrations for particles as small as $\sim 0.1 \mu\text{m}$ in diameter that
24 MISR detects but are below the OPC detection limit of $\sim 0.5 \mu\text{m}$. As such, we obtain better constraints on the
25 near-surface particulate matter (PM) concentration, especially as the smaller particles tend to dominate urban
26 pollution.

27 We test our method using data from five low-cost OPCs deployed in the city of Nairobi, Kenya, from May 1
28 2016 to March 2 2017. As MISR passes over Nairobi only once in about eight days, we use the size-resolved MISR
29 AODs to scale the more frequent Moderate Resolution Imaging Spectrometer (MODIS)-derived AODs over our
30 sites. The size distribution derived from MISR and MODIS agrees well with that from the OPCs in the size range
31 where the data overlap (adjusted- $R^2 \sim 0.80$). We then calculate surface-PM concentration from the combined data.
32 The situation for this first demonstration of the technique had significant limitations. We thus identify factors that



33 will reduce the uncertainty in this approach for future experiments. Within these constraints, the approach has the
34 potential to greatly expand the range of cities that can afford to monitor long-term air quality trends and help inform
35 public policy.

36

37 **Key words:** MISR, MODIS, MAIAC, aerosol optical depth, low-cost air quality monitor, particulate matter,
38 Nairobi, public health

39

40 **1 Introduction**

41 Near-surface particulate matter (PM), airborne particles, also known as aerosol, is a major pollutant that affects air
42 quality, and many countries are taking measures to decrease PM levels. However, efforts to monitor air pollution in
43 different countries are uneven. In sub-Saharan Africa, for example, few countries operate air quality monitoring
44 systems, and most countries lack any air quality monitoring capabilities at all, even though the limited observations
45 that do exist show PM levels harmful to human health (Petkova et al., 2013). This is because air quality monitoring
46 equipment tends to be costly to purchase (capital costs are in the range of ~USD \$100,000 -USD \$200,000) and
47 maintain, and data processing and analysis requires additional expertise and resources (deSouza, 2017; Kumar et al.,
48 2015; Mead et al., 2013).

49

50 Given this context, other technologies, such as low-cost air quality sensors and satellite imagery, are being examined
51 as alternative means of monitoring air quality. Low-cost air quality sensors, usually costing less than \$2,000
52 (Morawska et al., 2018), have the potential to move us from a paradigm of high-cost, highly accurate, sparse
53 reference air quality monitoring to low-cost, more widely available air quality monitoring networks. One of the
54 major drawbacks of using the lower-cost sensors is that no standards or certification criteria exist for these
55 instruments yet, and consequently, the quality of the data they produce is of special concern (Lewis and Edwards,
56 2016; US EPA, 2016).

57

58 Satellite imagery, in particular space-based aerosol datasets derived from the NASA Earth Observing System's
59 Moderate Resolution Imaging Spectrometer (MODIS) and Multiangle Imaging Spectro-Radiometer (MISR), have
60 also been used to estimate near-surface particulate matter concentrations from the retrieved total-column aerosol
61 optical depth (AOD), with the help of aerosol transport modelling (e.g., Liu et al., 2007; Martin, 2008; van
62 Donkelaar et al., 2010). The advantages of satellite technology for air quality monitoring arise from the spatially
63 extensive measurements over time (2000-present for MISR and MODIS), and include global coverage, instrument
64 calibration stability, and the low incremental cost of data acquisition.

65



66 However, the challenges of using these datasets for air-quality applications are also considerable. Among the main
67 challenges in using satellite-derived AOD for this application are:

68 (1) The low temporal frequency of measurements from polar-orbiting instruments (i.e., at most, about once daily for
69 MODIS, and between two and nine days for MISR, depending on latitude) compared to diurnally varying pollution
70 levels in many settings

71 (2) Inaccuracies introduced in satellite aerosol retrieval algorithms by uncertain aerosol and surface optical
72 properties

73 (3) The relatively coarse retrieval-product spatial resolution and aerosol species discrimination

74 (4) Inability to retrieve aerosol in the presence of cloud cover, and possible sub-pixel cloud contamination elsewhere
75 (Duncan et al., 2014; Martonchik et al., 2009).

76 (5) The relationship between satellite-derived AOD and $PM_{2.5}$ is not straightforward. AOD is the integral of
77 atmospheric *optical* extinction from the surface to the top of the atmosphere under ambient temperature and
78 humidity conditions, whereas $PM_{2.5}$ is the near-surface aerosol *mass* concentration of dry particles with diameters <
79 $2.5 \mu\text{m}$. The relationship depends upon the aerosol vertical distribution, hygroscopic growth factor, mass extinction
80 efficiency, and ambient atmospheric relative humidity profile (Gupta et al., 2006). The relationship is also time
81 dependent and can vary across typical satellite grid-cells (Engel-Cox et al., 2004; Hu, 2009; Lee et al., 2011).
82

83 Some recent studies that apply models to derive near-surface $PM_{2.5}$ from satellite AOD measurements combine AOD
84 with ground-based $PM_{2.5}$ measurements from reference air quality monitors. Many early methods derived simple
85 empirical relationships between $PM_{2.5}$ and AOD (Engel-Cox et al., 2004; Wang and Christopher, 2003; Zhang et al.,
86 2009). More advanced approaches applied chemical transport models to derive near-surface $PM_{2.5}$ from the
87 total-column aerosol optical depths of different aerosol components, which can be done, e.g., using model-simulated
88 aerosol vertical distribution and aerosol-type constraints from MISR (Friberg et al., 2018; Liu et al., 2007; Patadia,
89 2013).
90

91 Many studies have focused on continental US due to the extensive surface measurements available for model
92 validation (Al-Saadi et al., 2005; Liu et al., 2005; Tai et al., 2010). Gupta et al., (2006) were among the first to
93 examine the derivation of $PM_{2.5}$ from AOD in cities on different continents: Sydney, Delhi, Hong Kong and New
94 York. van Donkelaar et al., (2010) used the GEOS-Chem model to determine the scaling factors between AOD and
95 $PM_{2.5}$ for the entire globe. Because the AOD- $PM_{2.5}$ relationship varies by region and season, it is particularly
96 important to test existing models, and modify them appropriately in the data-sparse regions of the world.
97

98 To respond to this challenge, the SPARTAN network is adding numerous reference-grade surface stations in poorly
99 sampled areas, to evaluate and enhance satellite-derived PM results (Snider et al., 2016; Weagle et al., 2018). Given
100 that it is unlikely many cities will have access to reference air quality monitoring instruments due to their high cost,
101 it is important to start examining the fusion of data from low-cost air quality monitors with that from satellites, and



102 to develop insights from the combination of these measurements. This paper represents the first attempt, to the best
103 of our knowledge, to do so.

104

105 Part of the challenge of attempting to combine these datasets is that low-cost air quality monitors on the market are
106 not very reliable, and their measurements tend to be much less accurate than reference monitors (Lewis and
107 Edwards, 2016). Many PM monitors, termed Optical Particle Counters (OPCs), measure particle counts instead of
108 particulate mass, and do so reliably only for particles within certain diameter ranges. For example, assumptions
109 about particle density as well as the number of ultrafine particles not sampled by these instruments must be made to
110 convert the particle counts to $PM_{2.5}$. These assumptions introduce additional uncertainties into the results.

111

112 This paper presents a novel method linking the size-resolved information in MISR AOD component-specific
113 retrievals with the ground-based aerosol size distribution derived from the raw particle counts of surface-based
114 OPCs. As MISR passes over countries near the equator only once in about 8 days, we use monthly-MISR aerosol
115 climatology to scale the more frequent (twice-daily near the equator) MODIS-derived AOD.

116

117 As a first attempt at testing the method, we apply it to five Alphasense OPC-N2 low-cost monitors¹ deployed from
118 May 2016 to March 2017 in Nairobi, a growing metropolitan area in sub-Saharan Africa. The Nairobi case entails
119 some important limitations for the current application; the AOD over the region was relatively low, there were no
120 independent measurements of aerosol vertical distribution or any surface-based, high-quality reference air quality
121 monitors to help with validation. However, it is the only location where we have a significant record of coincident,
122 ground-based low-cost OPC data. As such, we have to make assumptions in this first demonstration of the
123 technique, which we detail, and mitigate to the extent possible, in this paper.

124

125 Section 2 provides an overview of the ground-based and satellite datasets involved in this study, as well as the model
126 simulations used to constrain the aerosol vertical distribution. Section 3 describes in detail the method we developed
127 for combining the surface and satellite data. Section 4 contains the results of applying this method in Nairobi. Our
128 conclusions appear in section 5, where we also summarize the factors that will reduce the uncertainties involved in
129 combining data from low cost monitors with satellite observations in future deployments.

130 ¹ Alphasense OPC-N2 product page URL: <http://www.alphasense.com/index.php/products/optical-particle-counter/>
131 Last accessed 15.12.2016)

132



133 **2 Data**

134 **2.1 Ground-Based measurements:**

135 The Alphasense OPC-N2 monitor is a low-cost Optical Particle Counter, costing USD \$450, that works by using
136 focused light from a (~ 5V, 175 mA, 658 nm) laser to illuminate one aerosol particle at a time, and then measuring
137 the intensity of light scattered. The amount of scattering is a function of the size, shape, and composition of the
138 aerosol, and especially for spherical particles such as those most likely to dominate in the study region, the
139 measurements can be calibrated using monodisperse particles of known size (Sousan et al., 2016). The Alphasense
140 OPC-N2 is unique among low-cost sensors as in addition to PM estimates, it reports the raw particle counts in 16
141 bins based on particle diameter, ranging from 0.38 μm to 17.5 μm , which is critical to our method. The bins are
142 tabulated in Table S1 in Supplementary Information. Sousan et al. (2016) discuss the accuracy of these count
143 measurements in detail, and note that they agree well with reference instrument measurements for coarser particles
144 ($> 0.78 \mu\text{m}$ in diameter), but underestimate the particle counts for finer particles.

145

146 As the OPCs cannot detect particles with diameters $< 0.38 \mu\text{m}$, Alphasense provides software to extrapolate the
147 particle counts, as needed to estimate the contribution from aerosols having diameters $< 0.38 \mu\text{m}$. The number of
148 particles per volume of air in all bins can be obtained by dividing the particle counts of each bin by the flow rate and
149 sampling duration. The Alphasense company proprietary data reduction algorithm makes assumptions about the
150 particle density and volume of aerosols in each bin to calculate PM_1 , $\text{PM}_{2.5}$ and PM_{10} data from the particle count
151 data.

152

153 Details about the Nairobi OPC deployment can be found in section S1.1 in Supplementary Information.

154 **2.2 Satellite Data**

155 Although passive remote sensing has significant limitations for air quality applications at present, it offers
156 substantially more frequent, global-scale aerosol constraints than any other measurement technique. Starting in
157 December 1999, the National Aeronautics and Space Administration (NASA) launched a series of Earth Observing
158 System satellite sensors, including the two instruments we use in this experiment: the Multiangle Imaging
159 Spectroradiometer (MISR) on board the Terra satellite (Diner et al., 1998), and two Moderate Resolution Imaging
160 Spectroradiometer (MODIS) sensors (e.g., Remer et al., (2005)), one each aboard the Terra and Aqua satellite
161 platforms.

162



163 2.2.1 MISR Research Algorithm AOD and Particle Properties

164 MISR is one of five instruments aboard the Terra satellite. It measures sunlight reflected from Earth in each of nine
165 cameras pointed at different view angles, from $+70^\circ$ through nadir to -70° along the satellite flight path, in each of
166 four spectral bands (446, 558, 672 and 866nm) (Diner et al., 1998). This multi-angle design allows MISR to observe
167 the atmosphere through effective slant path ranging from one (i.e., vertically down) to three (i.e., at steep forward
168 and aft angles). This geometry produces scattering angles between the sun and viewing vectors ranging from
169 approximately 60° to 160° in mid-latitudes. The combination of multi-spectral and multi-angular observations
170 provides information about aerosol amount and microphysical properties, such as particle size and shape (Kahn et
171 al., 2001; Kahn and Gaitley, 2015).

172

173 MISR algorithms retrieve aerosol properties by selecting from among the optical models for an assumed set of
174 aerosol component mixtures. A “component” is a candidate aerosol type of specified, uniform composition and size
175 distribution. The top-of-atmosphere reflectances simulated for each mixture are calculated and compared with the
176 corresponding MISR observations, to determine the mixtures that fit the data within certain acceptance criteria;
177 these are reported by the algorithm as the “successful mixtures” likely to be present (Diner et al., 2005; Limbacher
178 and Kahn, 2014; Martonchik et al., 2009). Each mixture contains up to three individual aerosol components, where
179 the percent contributions of all the components to the mixture mid-visible AOD sum to 100%.

180

181 The MISR Standard Aerosol retrieval algorithm uses a universe of 74 mixtures. The eight aerosol components in the
182 MISR Standard Version 22 and 23 products are labelled: 1, 2, 3, 6, 8, 14, 19, and 21 as reported in Tables 1 and 2 in
183 Kahn and Gaitley (2015) and reproduced in Table S3 in Supplementary Information. The components are named
184 based on single-scattering albedo (SSA): light-absorbing or non-absorbing, particle shape: spherical, non-spherical
185 grains or spheroids, and effective radius. Under favorable retrieval conditions (e.g., when total-column mid-visible
186 AOD exceeds about 0.15 or 0.2), the MISR algorithm is able to distinguish between three and five bins in
187 column-effective particle size (Kahn and Gaitley, 2015).

188

189 The spectral extinction coefficients for each aerosol component are included in the MISR Aerosol Physical and
190 Optical Properties (APOP) file, available from the NASA Langley Research Center (LARC) Atmospheric Sciences
191 Data Center (ASDC)². The MISR Standard aerosol data product provides AOD values and success flags: (i.e.,
192 whether a mixture is an adequate fit to the observations to be considered a “successful” match) for each aerosol
193 mixture, based on estimated measurement uncertainties.

194

195 ² https://eosweb.larc.nasa.gov/sites/default/files/project/misr/DPS_v32_RevL.pdf (Last accessed on August 12,
196 2019)



197 In this paper, we use the MISR Research Aerosol retrieval algorithm (RA; Limbacher and Kahn, 2014; 2017)
198 applied to MISR Level 1B2 radiance data, to derive AOD estimates for the eight MISR aerosol components. The
199 RA can be run with different sets of aerosol components, including the 74-mixture set used in the MISR Standard
200 Algorithm, and reports column-effective aerosol properties at any desired spatial resolution down to the MISR pixel
201 resolution of 1.1 km x 1.1 km. In addition to producing results at a finer spatial resolution than the MISR Standard
202 aerosol product, the RA also offers significantly better MISR aerosol retrieval results for air quality and other
203 applications because of empirical calibration corrections (Limbacher and Kahn, 2015), better treatment of surface
204 boundary conditions, and other refinements (Limbacher and Kahn, 2017, 2014, 2019).

205

206 Data from MISR on its own rarely contains more detail than qualitative particle size and shape, so
207 particle-composition-related information that could be used to distinguish different sources or to assess particle
208 moisture content is lacking, except where detectable differences in other parameters, such as particle shape (e.g.,
209 non-spherical dust vs. spherical smoke or pollution particles) and particle light-absorption (e.g. “dirty” vs. “clean”)
210 make these distinctions possible (Kahn et al., 2001; Kahn and Gaitley, 2015; Liu et al., 2007). MISR aerosol-type
211 retrieval uncertainty is assessed generally by Kahn and Gaitley (2015), and we rely on these results to indicate the
212 expected uncertainties here. Specifically, we enforce a lower bound of 0.15 on mid-visible AOD for accepting
213 MISR-retrieved particle size distributions. We assume that the aerosol components follow log-normal size
214 distributions, and extract the size distribution of the MISR aerosol components at diameters ranging over the MISR
215 size-detection range of about 0.1-3 μm .

216

217 For more details of the MISR data over the OPC-N2s in Nairobi refer to section S1.2.1 in Supplementary
218 Information.

219 **2.2.2 MODIS MAIAC AOD**

220 MODIS samples every location on the globe about twice a day, but lacks particle size information (e.g., Levy et al.,
221 2013). As aerosol type appears to be fairly constant on monthly timescales, we scale the MODIS-MAIAC
222 (MultiAngle Implementation of Atmospheric Correction) AOD retrieval product (Lyapustin et al., 2011a; Lyapustin
223 et al., 2011b), with available, particle-size-resolved AOD from MISR over each month.

224

225 MODIS has 36 spectral channels, designed to provide a wide variety of biogeophysical information. Unlike MISR,
226 which uses near-simultaneous, multiangle observations for aerosol-surface retrievals, MODIS offers single-view,
227 broad-swath, multi-spectral data. The MAIAC algorithm applies image-based processing techniques to analyze
228 MODIS time-series, i.e., multiple views of each surface location, in different parts within the MODIS swath (and
229 therefore different view-angles), acquired over a sliding, 16-day orbit-repeat cycle. This non-coincident multi-angle
230 approach produces cloud detection, AOD and atmospheric correction over both dark vegetated land and a range of



231 brighter surfaces, at 1 km x 1 km resolution (Lyapustin et al., 2012). Compared to operational MODIS retrievals,
232 MAIAC AOD has similar accuracy over dark and vegetated surfaces, and higher accuracy over brighter surfaces
233 (Lyapustin et al., 2011a; Lyapustin et al., 2011b).

234

235 For details about MAIAC AOD over Nairobi during the study period, refer to Supplementary Information section
236 S1.2.2

237 **2.3 GEOS-Chem Aerosol Vertical Scaling**

238 GEOS-Chem simulations were used in our study to provide a constraint on the vertical distribution of the aerosols,
239 because AOD from the satellites is a column-integrated quantity, whereas $PM_{2.5}$ is assessed near-surface. The
240 GEOS-Chem model is driven with GEOS-5 assimilated meteorology from the NASA Global Modelling and
241 Assimilation Office (GMAO) at $0.5^\circ \times 0.667^\circ$ horizontal resolution (Bey et al., 2001). The model is nested over the
242 African continent and boundary conditions are from a global simulation at $2^\circ \times 2.5^\circ$. Natural emissions are from
243 MEGANv2.1 for biogenic volatile organic compounds (VOCs) (Guenther et al., 2012), for soil NO_x (Hudman et al.,
244 2012), and for lightning NO_x (Murray et al., 2012). Biogenic isoprene emissions are updated using the improved
245 model developed by (Marais et al., 2014). Open fire (biomass burning) emissions are from GFED4 (van der Werf et
246 al., 2010). Inventories of anthropogenic emissions in Africa include DICE-Africa for cars, motorcycles, traditional
247 biofuel use (fuelwood, charcoal, crop residue), charcoal production, ad hoc oil refining, backup generators, kerosene
248 use, and gas flares (Marais and Wiedinmyer, 2016). Pollution from industrial and on-grid power generation are from
249 EDGARv4.2 for SO_2 , NO_x , and CO (EC-JRC/PBL, 2011), RETROv2 for VOCs (Schultz et al., 2007), and (Bond et
250 al., 2007) for black carbon (BC) and organic carbon (OC). Detailed gas and aerosol chemistry are described by (Mao
251 et al., 2013, 2010).

252

253 Details about the model simulations we used for the Nairobi case, as well as our attempts to validate the vertical
254 distribution of aerosol obtained from the GEOS-Chem model, are provided in section S1.3 in Supplementary
255 Information.

256

257 **3 Methodology**

258

259 Our approach uses the size distribution of the aerosol components from MISR retrievals to constrain the size
260 distribution derived from low-cost OPCs. The satellite size distribution data is encoded in the fractional contribution
261 of each MISR component AOD to the total MISR AOD. We use the ‘monthly’ effective fraction of each MISR
262 component AOD to scale the more frequent MAIAC AODs, yielding AOD values parsed out for the individual
263 MISR components on a more frequent basis. In particular, the constraint on the aerosol size distribution from MISR
264 remote-sensing data is especially important for particles with diameters $< 0.54 \mu m$, which the OPC cannot detect.



265 Obtaining an understanding of the size distribution between 0.1 and 0.54 μm allows for better estimation of $\text{PM}_{2.5}$
266 from the combined MISR and OPC measurements. We assess the assumptions required for this analysis in Section 5.

267 **3.1 Step 1: Estimate the ground-based size distribution of aerosols at each site from the** 268 **Alphasense-OPC N2 monitors**

269 We obtain the lognormal size distribution: $dN/d(\ln(d))$, from the Alphasense OPC-N2 ground-based data, at the time
270 of the Terra overpass, for the diameter at the mid-point of each OPC bin using Equation 1.

271

$$272 \frac{dN}{d\ln(d)} = \frac{\Delta n}{\ln(D_{upper}) - \ln(D_{lower})} \times \frac{1}{\text{flow rate} \left(\frac{\text{m}}{\text{s}}\right) \times 10^{-6} \times \left(\frac{\text{m}^3}{\text{ml}}\right) \times \text{sampling time}} \quad (1)$$

273

274 Here D_{upper} and D_{lower} are the upper and lower diameters of each OPC bin. Δn is the number of particle-counts in each
275 bin. N is the averaged number concentration of particles (units: #/volume of air) over the seven-minute Terra
276 overpass. The number concentration units derived from Equation 1 are #/ml. We thus multiply the result by 10^6 to
277 convert the number concentration from our surface monitors to Number of particles (#) / m^3 .

278

279 Equation 1 uses only the raw particle counts from the OPC. We do not include the first bin (0.38-0.54 μm) in this
280 analysis, as the error in the number concentration measurement for this bin is the highest (Sousan et al., 2016). Note
281 that the mode diameter of urban aerosol tends to be $\sim 0.2 \mu\text{m}$. Unfortunately, the Alphasense OPC-N2 only ‘sees’
282 larger aerosols. This is a key reason for combining the OPC data with the satellite retrievals. In future deployments,
283 other instruments that can see the smaller particles can be used.

284 **3.2 Step 2: Estimate stable and consistent aerosol size-resolved information from satellite data**

285 We estimate the corresponding size distribution of surface particulate matter from MISR and MAIAC AOD
286 information by calculating the monthly effective near-surface AOD for each of the eight MISR aerosol components.

287

288 We denote the column fractional AOD for each aerosol component (listed in Table S3 in Supplementary
289 Information), as $\text{AOD}_{i,k}$: the mid-visible AOD fraction of component i in the k th MISR atmospheric column
290 retrieval. It is calculated as the mixture-AOD-weighted AOD from all passing mixtures for component i in the MISR
291 RA aerosol climatology.

292

293 **Step 2a. Estimate the near-surface fraction of the satellite AOD.** We estimate the fractional AOD for each aerosol
294 component residing in the lowest atmospheric layer of the GEOS-Chem model (up to ~ 130 meters above the
295 surface), by scaling the total-column fractional AOD with the simulated aerosol vertical profiles from GEOS-Chem
296 using Equation 2.



297

$$298 \text{ AOD}_{\text{N-S}i} = \frac{\text{GEOS Chem lower AOD}}{\text{GEOS Chem column AOD}} \times \text{MISR AOD}i \quad (2)$$

299

300 Here N-S denotes Near-Surface.

301

302 **Step 2b. Associate the near-surface AOD with particular aerosol species in the model.** Given the difference
303 between the MISR aerosol components and the GEOS-Chem aerosol species, we use an approach similar to Liu et
304 al. (2007) to connect the two. Specifically, we sum GEOS-Chem AOD values for spherical species, SO₄-NH₄-NO₃,
305 OC and BC. We then calculate the ratio of the AOD for these species in the lowest GEOS-Chem atmospheric layer
306 to the total columnar spherical-species AOD as the scaling factor for the MISR spherical components. For the very
307 large spherical (MISR aerosol component 6) and non-spherical components (MISR aerosol components 19 and 21),
308 we use the ratio of GEOS-Chem dust AOD in the lowest layer to the total column dust AOD (Kahn and Gaitley,
309 2015). Henceforth, we refer to MISR component-specific, *near-surface* fractional AODs as MISR fractional
310 AODs.

311

312 **Step 2c. Derive the satellite-component size distribution contributions to specific sizes.** We now obtain the particle
313 properties from the MISR RA needed to constrain the OPC aerosol size distribution for sizes smaller than 0.54 μm.
314 Depending on retrieval conditions, if the aerosol retrieval is successful, MISR is able to distinguish aerosols in about
315 3-5 size bins (section 2.2.1). The MISR RA uses these data to constrain a universe of possible aerosol mixtures to a
316 subset of components that fit the data best. Although there is uncertainty in the details of the size distribution, the
317 instrument provides consistent and stable retrievals over large areas and for a long period of time. Similarly, the
318 process of constraining the universe of MISR aerosol types present is also consistent and stable over time. The
319 corresponding lognormal size distribution: dN/d(ln(d)) of all the aerosol components from the satellite data is
320 obtained from Equations 3 and 4a.

321

$$322 Si(d) = \frac{e^{\frac{-(\ln(d) - \ln(dc_i))^2}{2(\ln(\sigma_i))^2}}}{\ln(\sigma_i) \times \sqrt{2\pi}} \quad (3)$$

323

$$324 \frac{dN}{d\ln(d)} = \sum_{i=1}^8 N_{\text{N-S}i} \times Si(d) \quad (4a)$$

325

326 In Equation 3, S_i(d) is the normalized size distribution of MISR aerosol component i. The representative size
327 parameters are, specifically, the characteristic diameter (d_{c_i}) and the distribution width (σ_i) for each of the eight



328 MISR aerosol components. Note that the upper and lower diameters of each aerosol component are considered in
329 this analysis. Based on the retrieval algorithm assumptions, the size distribution of an aerosol component for
330 diameters outside the range of each component is 0. For the Nairobi cases, only small, spherical particles and
331 medium-coarse particles contribute significantly to the MISR-retrieved AOD (Table 2). N_{N-Si} is the total number
332 concentration of each MISR aerosol component present near-surface for each observation.

333

334 The size distributions $Si(D)$ for MISR aerosol components 2, 8 and 14 are the same (Table S3). MISR aerosol
335 components 2, 8, and 14 represent optical analogs of typical urban pollution with different light-absorption
336 properties. We rewrite Equation 4a, grouping these three components into one aggregate term in Equation 4b. Here
337 $N_{N-S\{2,8,14\}}$ is the total near-surface number concentration of components 2, 8 and 14. The index i here runs only
338 over the remaining MISR aerosol components: 1,3,6,19,21.

339

$$340 \quad \frac{dN}{dn(d)} = \sum_{i=(1,3,6,19,21)} N_{N-Si} \times Si(d) + N_{N-S\{2,8,14\}} \times S_{\{2 \text{ or } 8 \text{ or } 14\}}(d) \quad (4b)$$

341

342 Importantly, the column-effective size distribution from Equation. 4b, derived from the MISR retrievals,
343 corresponds to the surface-measured value from Equation 1 only if the near-surface aerosol properties are
344 representative of the entire atmospheric column. Due to a lack of additional observational constraints, we must
345 accept this as an assumption, along with the corresponding uncertainty. The assumption will be favored in places
346 where the aerosol load is concentrated near-surface, which is common when the aerosol column is dominated by
347 local sources. This is likely the case for many urban regions and is supported by the high correlation between MISR
348 or MAIAC AOD_{N-S} and OPC $PM_{2.5}$ in Nairobi when $AOD > 0.15$ (see section S2 in the Supplementary Information).
349 The size distribution of the total aerosol derived from a MISR retrieval is a sum of the size distributions of
350 individual aerosol components, as represented in Equation 4.

351

352 **Step 2d. Formulate the satellite constraint on size-specific surface concentration so it can be regressed against**
353 **the OPC data.** By definition, AOD_{558} is proportional to [the number concentration of aerosols] x [the extinction area
354 of each particle at 558 nm wavelength] x [the path over which AOD is assessed (which here is 130 meters
355 vertically)]. In order to obtain near-surface number concentration of each aerosol component using this physical
356 definition of AOD, we assume a uniformly mixed, near-surface aerosol, with the AOD measured in all cases over a
357 vertical path through the first 130 m of the GEOS-Chem model. As shown in Equation 5, for each aerosol
358 component, a dimensionless proportionality constant multiplied by the $AOD_{N-S}/$ path length (130 meters) x spectral
359 extinction coefficient is the number concentration of particles, summed over the path, per unit area. The spectral



360 extinction coefficients of each aerosol component can be found in Table S3. The near-surface number concentration
 361 of each aerosol group is thus represented as:

362

363 For MISR aerosol components: 1,3,6,19,21:

364

$$365 \quad N_{N-S\{1,3,6,19,21\}} = \Gamma_{i=\{1,3,6,19,21\}} \times \frac{AOD_{N-Si}}{130 \text{ m} \times 10^{-12} \times \frac{(m)^2}{(\mu\text{m})^2} \times \text{optical extinction coefficient at } 558 \text{ nm } (\mu\text{m})^2}$$

366 (5a)

367

368 For the aggregate MISR aerosol group comprising of MISR aerosol components: 2, 8 and 14:

$$369 \quad N_{N-S\{2,8,14\}} = \Gamma_{\{2,8,14\}} \times \sum_{i=\{2,8,14\}} \frac{AOD_{N-Si}}{130 \text{ m} \times 10^{-12} \times \frac{(m)^2}{(\mu\text{m})^2} \times \text{optical extinction coefficient at } 558 \text{ nm } (\mu\text{m})^2}$$

370 (5b)

371

372 The spectral extinction coefficients obtained from Table S3 are in units of $(\mu\text{m})^2$. To convert this to m^2 , we multiply
 373 these coefficients by 10^{-12} . The number concentration N_{N-Si} in Equations 5a and 5b has units $\#/\text{m}^3$. Γ_i is a
 374 dimensionless scaling parameter, needed to relate the modeled aerosol number concentration of each component to
 375 the actual number concentration present from the OPC measurements. We expect this value to be a constant, because
 376 the MISR retrievals are stable and consistent over time. We derive this parameter using the ground-based size
 377 distribution from the OPC-N2s, in the size range where the surface instruments have sensitivity.

378

379 **Step 2e. Increase the number of satellite data points by scaling MODIS AOD with MISR sizes.** To increase the
 380 satellite dataset, we use the average fractional AOD of each MISR aerosol component for a given month over a
 381 specific site to parse the total AOD from the more frequently sampled MAIC product, using Equation 6 to represent
 382 the MISR component fraction, and Equation 7 to calculate the corresponding MAIAC value.

$$383 \quad \text{MISR AOD}_{N-S, \text{month}, i} = \frac{\sum_{j=1}^n \text{MISR}_{N-Sj}}{n} \quad (6)$$

384

$$385 \quad \text{MAIAC}_{N-Si} = \text{MAIAC} \times \frac{\text{MISR AOD}_{N-S, \text{month}, i}}{\sum_{i=1}^8 \text{MISR AOD}_{\text{month}, i}} \quad (7)$$

386 Here $\text{MISR AOD}_{N-S, \text{month}, i}$ is the effective MISR near-surface AOD for component i over a given surface site for a
 387 specific MISR month of the year (obtained by averaging the available data, with the assumption of negligible change in



388 particle properties over the month, as discussed in Section 2.2.1), and n is the number of MISR AOD_i retrievals for
389 that month. The AOD assigned to each MISR component i , based on scaling a given MAIAC AOD retrieval, is
390 denoted $MAIAC_i$. For the remaining analysis, we use the scaled $MAIAC_{N-S,i}$ instead of $MISR_{N-S,i}$ in Equations 5a and
391 5b.

392

393 **Step 2f. Regress the satellite near-surface, size-constrained particle concentration constraints against the OPC**
394 **data to obtain a more complete near-surface aerosol size-concentration distribution.** To appropriately link the
395 size-distribution from the OPCs with the MISR retrievals, we would ideally aggregate the OPC size bins in a similar
396 way MISR does: very small, small, medium and large, calculate the OPC size distribution at the mid-point of these
397 bins, and fit these size distributions with the size distribution derived from MISR. However, as the OPC has
398 predefined bins, we assume that for favorable retrievals, each aerosol component follows a log-normal size
399 distribution, consistent with the MISR algorithm assumptions. We use Equation 4 to extract the size distribution of
400 the total aerosol from MISR measurements that corresponds to the mid-point of each pre-existing OPC bin within its
401 range of sensitivity. Although the OPC counts particles for 16 diameter bins between 0.38 and 17 μm (Table S1), we
402 perform the OPC-MISR regression analysis only within the diameter range 0.54-2.55 μm for which both MISR and
403 the OPCs have adequate sensitivity. This corresponds to six of 16 OPC size bins, Bin 2-Bin 7 (Table S1). When we
404 use the MAIAC data, we still rely on the size information obtained from the MISR retrievals to represent aerosol
405 size distribution.

406

407 We perform the regression analysis, substituting the right side of Equation 1 into the left side of Equation 4b, and
408 substituting the right side of Equations 5a and 5b for the two $N_{N-S,i}$ terms on the right side of Equation 4b. We can
409 then evaluate the Γ_i , based on the relationship between the surface-monitor size distribution on the left side of this
410 equation (obtained from Equation 1), and the satellite values represented on the right side, for each coincident
411 observation. The Γ_i are essentially the aerosol-group-specific adjustment factors required to equate the near-surface
412 aerosol number concentration measured by the surface monitor with that derived from the satellite. After calculating
413 Γ_i , we can calculate $N_{N-S,i}$ using Equations 5a and 5b.

414 **3.3 Step 3: Calculate $PM_{2.5}$ from the number concentration of the different MISR Aerosol Groups**

415 In the final step, we calculate $PM_{2.5}$ using the ‘OPC-calibrated’ aerosol size distribution from MISR. As is already
416 evident from the discussion above, it is not straightforward to obtain quantitative $PM_{2.5}$ values from the particle size
417 distribution information derived from satellite passive remote sensing. Further, Alphasense uses a proprietary
418 algorithm to convert particle counts to dry mass. Particle counts in each of the 16 bins are multiplied by the volume
419 of particles under ambient conditions in each bin assuming spherical particle shape, an assumed particle density, and
420 a factor corresponding to the ISO respirable convention for $PM_{2.5}$. Assumptions are made about the efficiency of the
421 instrument inlet as a function of particle size, and about the size distribution functional form, to obtain the volume of



422 particles within each size bin. The total is then divided by the sampling time and sample flow rate to calculate the
 423 mass obtained per unit volume of air. Given these assumptions, we have more confidence in observed *differences* in
 424 the measurements than in the reported absolute concentration values. Our interpretation of the results in the next
 425 section proceeds with this in mind. Assuming spherical particles, the normalized volume distribution per particle for
 426 MISR aerosol component i is:

$$427 \quad v_i(d) = \sum_{j=1}^n \frac{\pi d^3}{6} \times \frac{e^{-\frac{(\ln(d) - \ln(d_{c_j}))^2}{2(\ln(\sigma_j))^2}}}{d \times \ln(\sigma_j) \times \sqrt{2\pi}} \quad (8)$$

428 Note here the index i corresponds to MISR aerosol components: 1,3,6,19,21 or the aggregate group: 2, 8 and 14. In
 429 Equation 8, $v_i(d)$ is the total normalized volume distribution of each aerosol component or group per volume of air.
 430 The total volume of the aerosol group with diameters between d and $d+\Delta d$ per volume of air is provided by $V(d)$ in
 431 Equation 9. N_{N-Si} is the ambient value of the total near-surface aerosol number concentration for MISR
 432 component/group i . The N_{N-Si} value in Equation 9 will be the same as that derived directly from the MISR data in
 433 Equations 5a and 5b only to the extent that the near-surface aerosol type represents the total-column aerosol type, an
 434 assumption we make consistently in this analysis.

$$435 \quad V_i(d) = N_{N-Si} \times \int_d^{d+\Delta d} v_i(d) \times d(d) \quad (9)$$

436 The integration of $v_i(d)$ for each aerosol component/group from 0 to a finite diameter is nontrivial. We solve this
 437 integral numerically using Equation 10 to obtain the total volume contributed by each aerosol component per
 438 volume of air. When doing this integration, we are careful to take into consideration the lower and upper limits on
 439 the radius for each MISR aerosol component in each aerosol component/group.
 440

$$441 \quad V_i(D) = N_{N-Si} \times \sum_{d=1}^{d=D} (v_i(\frac{d}{10000}) \times 0.0001) \quad (10)$$

442 The unit of volume (V_i) here is $(\mu m)^3$, as the unit of the diameter we use here is in μm . To calculate $PM_{2.5}$ we need
 443 to multiply the total volume of each of the eight aerosol components for particles calculated using Equation 10, by
 444 the particle density, as shown in Equation 11.

$$445 \quad PM_{2.5} = density \times \sum_{i=1}^8 V_i(D_i) \quad (11)$$

446 In this analysis, we assume the same particle density that Alphasense uses in its algorithm. We compute $PM_{2.5}$ in
 447 units of $\mu g/m^3$ from the volume obtained:

$$448 \quad 1.65 \text{ g/cm}^3 \text{ or } 1.65 \times 10^{-6} \mu g/m^3 \left(\frac{\#}{m^3} \times (10^{-18} \times \frac{m^3}{(\mu m)^3}) \times (\mu m)^3 \times 1.65 \frac{g \times 10^6 \mu g}{cm^3 \times (\frac{10^{-6} m^3}{cm^3})} \right).$$



449 Note that the Alphasense algorithm to convert particle counts to mass is proprietary, and we do not have access to its
450 methodology.

451 **4. Size-Dependent Near-Surface Particle Concentrations, Constrained by** 452 **Regression Against Satellite Data for Nairobi, Kenya**

453 In this section we apply the method described in Section 3 above to the OPC and satellite data collected in Nairobi
454 from May 2016 through early March 2017. We present the results using the limited coincident MISR data and the
455 larger scaled-MODIS dataset, and then summarize the assumptions and mitigating factors in the current analysis,
456 which includes a discussion of possible improvements for future deployments.

457 **4.1 Application of the method to the 2016-2017 Nairobi OPC deployment**

458 Following Steps 1, 2a, and 2b of the methodology described in Section 3, Table 1 shows the near-surface AOD for
459 the Nairobi data obtained from the vertically scaled MISR Research Algorithm for aerosol components 1,3,6,19 and
460 21, as well as that for the aerosol group comprised of components 2,8 and 14, using the standard universe of 74
461 mixtures. Table S2 in Supplementary Information shows the lognormal size distribution ($dN/d(\ln D)$) from the OPCs
462 for the coincident surface observations that correspond to the 10 successful MISR retrievals where the total AOD_{558}
463 > 0.15 .

464

465 We obtain the group-specific particle-size data from MISR (Step 2c), and the associated number concentrations
466 ($N_{N,S}$) from Equations 5a and 5b (Step 2d). We then linked the size distribution of the MISR aerosol groups with that
467 of the OPCs (Step 2f). The regression analysis was conducted using the total $dN/d(\ln D)$ derived from the MISR
468 measurements as the predictor of the $dN/d(\ln D)$, with the ground-based measurements as the dependent variable,
469 assessed at six different diameters corresponding to the mid-points of the OPC size bins Bin 2 – Bin 7 (Equation 1),
470 where the datasets overlap. For each of the 10 high-AOD MISR cases, we have six $dN/d(\ln D)$ measurements (= 60
471 rows in our regression analyses).

472

473 For all regression analyses we excluded MISR component 21 as the AOD retrieved for this component is 0. In
474 Regression Analysis 1, we included the remaining MISR components. Not all of the coefficients in the regression
475 are significant, and some are negative. Each coefficient in the regression represents the total number concentration
476 of the respective aerosol group, which physically cannot be negative. However, it is possible for a statistical weight
477 to be negative, as the regression approach aims to formally match the retrieved values with available observations,
478 and there can be aerosol components and mixtures missing from the MISR algorithm climatology (Kahn et al.,
479 2010). As such, leveraging from the better-fitting components can skew the coefficients for other particles negative.
480 Provided the negative weights are small compared to the dominant retrieved components, the negative values



481 represent noise in the results. This can apply to components 1 and 8 that are often retrieved in relatively small
482 quantities, as well as to component 19, a dust optical analog, that very likely does not match actual dust in the
483 region. Moreover, MISR component 1, with $r_e=0.06 \mu\text{m}$, is well below the OPC lowest size sensitivity limit.
484 Regression Analysis 2 was run without component 1 and 19.
485

486 The results of regression Analyses 1 and 2 are given in Table 2. Figure 1 shows the particle size distributions
487 ($dN/d\ln D$) from the air quality monitors obtained for all relevant ground-based observations, superimposed on the
488 size distributions derived from the regression analysis results of Analysis 2. The derived size distributions from each
489 instrument are quite well matched in nearly all cases, despite the assumptions involved. For Analysis 2, the adjusted
490 R squared is 0.82.
491

492 To increase satellite sampling, we repeated the regression analysis by scaling MAIAC AODs using the monthly
493 effective MISR aerosol component AOD fractions (Steps 2e and 2f). We have 1712 MAIAC AOD retrievals that fall
494 within a radial distance of 1.6 km of a ground-station. However, there are only 10 favorable MISR particle property
495 retrievals, on three unique days. Using the MISR component AOD values to parse the MAIAC total-AOD, even on
496 a monthly basis, leaves 304 MAIAC retrievals on 20 unique days (Figure S6 in Supplementary Information). Yet
497 this provides about 30 times as much data as the MISR data alone. Like Analysis 1, Analysis 3 includes all MISR
498 aerosol components, but was run using the scaled MAIAC dataset. We also ran Analyses 4 and 5 the MAIAC data,
499 this time excluding MISR components 1 and 19. For Analysis 5, we also restricted the MAIAC retrievals to those
500 with the total AOD ≥ 0.15 (85 MAIAC AODs), to ensure that near-surface aerosols dominate in this analysis. The
501 adjusted R squared for Analysis 5 is 0.76. When we used MAIAC AODs at a radial distance of 1 km and 0.5 km
502 from each site (instead of 1.6 km), repeating Analysis 5, yielded adjusted R squared values of 0.77 in both cases.
503 This suggests that our results are robust to the radius considered.
504

505 The results for the five analyses are given in Table 2. All the coefficients for the remaining aerosol groups included
506 in Analyses 2, 4 and 5 are positive and statistically significant (p-value almost equal to, or less than 0.05). Figure 2a
507 shows $\text{PM}_{2.5}$ from the ground-based OPCs (scaled by a factor of 4 for the sake of comparison) and the corresponding
508 $\text{PM}_{2.5}$ calculated from MISR (Step 3), using the results of Analysis 2. The MISR-derived and OPC PM tend to show
509 similar peaks, with the exception of All Saints. Taking all points into consideration, the correlation between the two
510 PM datasets is 0.56. The OPC at All Saints is situated in a particularly clean area, surrounded by hotspots of
511 pollution due to informal settlements nearby. The average pollution in the coincident satellite grid cell is higher than
512 that observed by the OPC at this particular site, likely caused by the difference in spatial sampling. When we drop
513 measurement at All Saints from this analysis, the correlation between the derived $\text{PM}_{2.5}$ from MISR and that of the
514 OPC is 0.76 (Figure 2b).
515



516 Similarly, Figure S7 in Supplemental Information displays the derived $PM_{2.5}$ concentrations from MAIAC/MISR
517 AOD estimates using coefficients from Analysis 5 and the corresponding surface $PM_{2.5}$ from the OPCs. The
518 correlation between the two PM values is 0.47. When we drop All Saints, the correlation increased to 0.48.
519 However, the adjusted R squared is ~ 0.8 when working directly with size distribution information (Step 2f) rather
520 than the $PM_{2.5}$ values due to the additional assumptions involved (Step 3).

521

522 The satellite-derived PM values are very high relative to the OPCs in nearly all cases. An important contributing
523 factor is that a large fraction of aerosols in Nairobi are primary combustion aerosols with diameters $< 0.54 \mu m$ that
524 MISR detects (Figure S4 and Table S3), but that are not included in the OPC data due to lack of sensitivity. In
525 addition, any secondary aerosol formation from the many sources of gaseous precursors would produce small
526 particles, and any underestimate in the particle density assumed in the OPC retrieval might also play a role. A
527 further possible contributing factor, at least at one site (Kibera Girls Soccer Academy), is the frequent dominance of
528 coarse mode particles, which contribute to the total AOD observed by MISR. However, MISR does not retrieve
529 specific size information for particles larger than about 2-3 μm (Section 2.2.1 above), so the MISR total AOD is
530 ascribed to smaller-sized particles, where the retrieval is sensitive; this can inflate the number concentration of these
531 particles. Given these issues, our method focuses on the size range over which both the OPC and MISR
532 measurements are sensitive (Figure 1). As most of the particles retrieved over the urban Nairobi region are
533 components within the typical combustion-particle size distribution (see Section S1.2.1 Supplemental Material), the
534 method yields a high correlation despite the limitations of the data, and actually uses the satellite data to account for
535 smaller particles that the OPCs miss.

536

537 **4.2 Assumptions, and mitigating factors in the current analysis, with advice for future** 538 **deployments**

539 The data collected during the 2016-2017 Nairobi experiment are not ideal for the current application. However,
540 there were also mitigating factors, which we summarize here, along with the lessons learned for the benefit of future
541 deployments.

542

543 • *MISR sampling frequency.* Generally low AOD over Nairobi, combined with the relatively narrow MISR swath
544 width and low latitude of the target region, left just 10 cases meeting the criteria for good aerosol-type retrievals
545 from MISR during the OPC surface-network deployment. As such, we were forced to assume that single or pairs of
546 MISR particle-type retrievals in a given month represent the aerosol properties for the entire month. However, the
547 observation that the MISR-retrieved particles varied little among the available observations (Figure S3) and are
548 typical of urban pollution from the local sources expected in Nairobi favors this approach. Selecting cases having
549 mid-visible $AOD \geq 0.15$ also favors conditions where local sources dominate. The assumption is further supported
550 by GEOS-Chem model aerosol-type simulations (Section 2.3 above, and Figure S5). As AOD varies considerably
551 more than aerosol type at the Nairobi site, we addressed that aspect of limited MISR sampling by using MISR



552 monthly size-resolved information to scale the much more frequent MODIS-MAIAC AOD retrievals. In future
553 experiments, sites typically experiencing higher AOD, preferably also at higher latitude, as well as longer
554 deployments, could greatly improve the MISR sampling statistics for this application.

555

556 • *Aerosol vertical distribution.* We also use the GEOS-Chem AOD vertical distribution to obtain the near-surface
557 component of the MISR total-column AOD and assume that MISR-retrieved total-column particle properties are
558 dominated by near-surface particles in the study region. As expected, our analysis works best on days when the
559 satellite-derived AOD was ≥ 0.15 , and near-surface urban aerosols dominate the column (Figure S5). The
560 observation that the MISR-retrieved particles are typical of urban pollution from local sources in Nairobi (Table 1
561 and Section 1.2.1 in Supplemental Material) also favors this assumption. Further, dust is the most likely transported
562 species, and it is distinguished from pollution particles in MISR retrievals based on large size and non-spherical
563 shape. AOD is derived from satellite instruments under ambient RH conditions. If the particles were hygroscopic,
564 however, they could adsorb water vapor and appear larger than they would be under dry conditions, which is how
565 $PM_{2.5}$ is usually assessed. Yet, the RH at the Nairobi site was generally low during the study period (Table S2),
566 pollution particles are not very hygroscopic, and the OPC measurements were also obtained at ambient RH (section
567 2.1 above), all mitigating the RH issue. Unfortunately, there were no local lidar observations to validate the model
568 vertical aerosol distribution, and neither the CALIPSO nor the CATS space-based lidars acquired data useful for this
569 purpose, as discussed in section S1.3 in Supplementary Information. In future deployments, a single, well-placed
570 surface lidar in the region could test the assumptions about aerosol vertical distribution and determine whether any
571 aerosol layers aloft contribute significantly to the satellite, column-effective particle property retrievals.

572

573 • *OPC small-particle sampling.* Pollution particles typically have diameters in the range $0.1 - 0.3 \mu\text{m}$, and the
574 pollution particles MISR retrieved had effective radii $0.12 \mu\text{m}$ (effective diameter $0.24 \mu\text{m}$). Yet, the Alphasense
575 OPC-N2 instruments used in the current study do not register particles $< 0.38 \mu\text{m}$ in diameter, and the smallest size
576 bin is noisy, effectively limiting the OPC size sensitivity to particles $> 0.54 \mu\text{m}$. As such, particle-size regressions in
577 this study were performed over six size bins spanning $0.54 - 3 \mu\text{m}$, capturing the range over which both satellite and
578 surface instruments are sensitive. The small-particle-observation limitations represent a significant uncertainty in
579 the results. However, the particle-size comparisons shown in Figure 1 demonstrate very good agreement over the
580 six-bin range, and further, we obtained $\sim 0.8 R^2$ model fits for the aerosol size distribution formally, when
581 considering either the MISR retrievals alone or the better-sampled MAIAC AODs parsed to the MISR component
582 fractions. As MISR sensitivity extends to particles $\sim 0.1 \mu\text{m}$, the satellite data help account for fine aerosols having
583 diameters $< 0.54 \mu\text{m}$ in our analysis. For future deployments where the dominant particle type is urban pollution,
584 including surface instruments that have sensitivity to particles down to $\sim 0.1 - 0.2 \mu\text{m}$ in diameter would make the
585 surface-station dataset substantially more robust. Further, at least one coincident, strategically located reference air
586 quality monitor would make it possible to quantify retrieval sensitivity with greater confidence.



587 **5. Conclusions**

588 For many locations around the world, the alternative to deploying low-cost air-quality monitors is having no
589 ground-monitoring at all. Surface monitors are essential to help characterize the near-surface aerosol components
590 within total-column satellite observations, but they offer only limited coverage, and the PM measurements from
591 low-cost monitors in themselves are generally not well calibrated.

592

593 This paper develops and presents a novel method that moves away from the conventional approach of linking
594 remotely sensed, total-column AOD from satellites with directly sampled particulate mass per volume of air from
595 surface monitors. Instead, it combines satellite, component-specific AOD retrievals with particle counts from
596 low-cost monitors, to constrain the size distribution of surface aerosol and $PM_{2.5}$. Retrieving some particle-size
597 information is possible with data from the space-based MISR instrument under favorable retrieval conditions.
598 MISR-retrieved particle effective cross-sectional area is linked with the size distribution of particulates as observed
599 by the low-cost OPC-N2 observations. As far as we know, size-resolved particle counts have not previously been
600 used to associate remote-sensing and direct-surface aerosol data, as most standard reference monitors provide
601 particulate mass measurements and not particle counts partitioned by particle size.

602

603 We applied the method presented in Section 3 to data from a 2016-2017 10-month Nairobi experiment, due to the
604 relative longevity of that data record. Limitations in the experiment design and implementation included relatively
605 infrequent MISR sampling and low AOD, as well as the lack of a lidar or high-quality reference particle sampler in
606 the field to validate assumptions about aerosol vertical distribution and satellite-retrieved small-particle surface
607 concentration, respectively. However, the dominance of locally generated urban pollution particles concentrated near
608 the surface, low relative humidity, and an effective approach for scaling more frequent MODIS data with the
609 MISR-retrieved size distributions were mitigating factors. The method produced high correlations (~ 0.8) between
610 satellite-derived and surface-station-measured $PM_{2.5}$, and most importantly, the satellite data helped significantly to
611 account for smaller particles that tend to dominate urban aerosol pollution but are below the detection size limit of
612 the OPCs.

613

614 Our analysis also led to specific suggestions for performing future deployments with fewer assumptions, such as
615 including at least one carefully sited, surface-based lidar and reference air quality monitor. Applying the technique
616 under conditions more favorable for this approach could help assess air quality in rapidly urbanizing cities in
617 developing countries, where pollution increases are having dramatic public health consequences, and where
618 monitoring is limited or entirely absent. We hope with the increasing focus on air quality (e.g., the expansion of the
619 SPARTAN network, Weagle et al., 2018), broader application of low-cost monitoring can occur.

620



621

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631 **Competing Interests**

632 The authors declare that they have no conflict of interest

633



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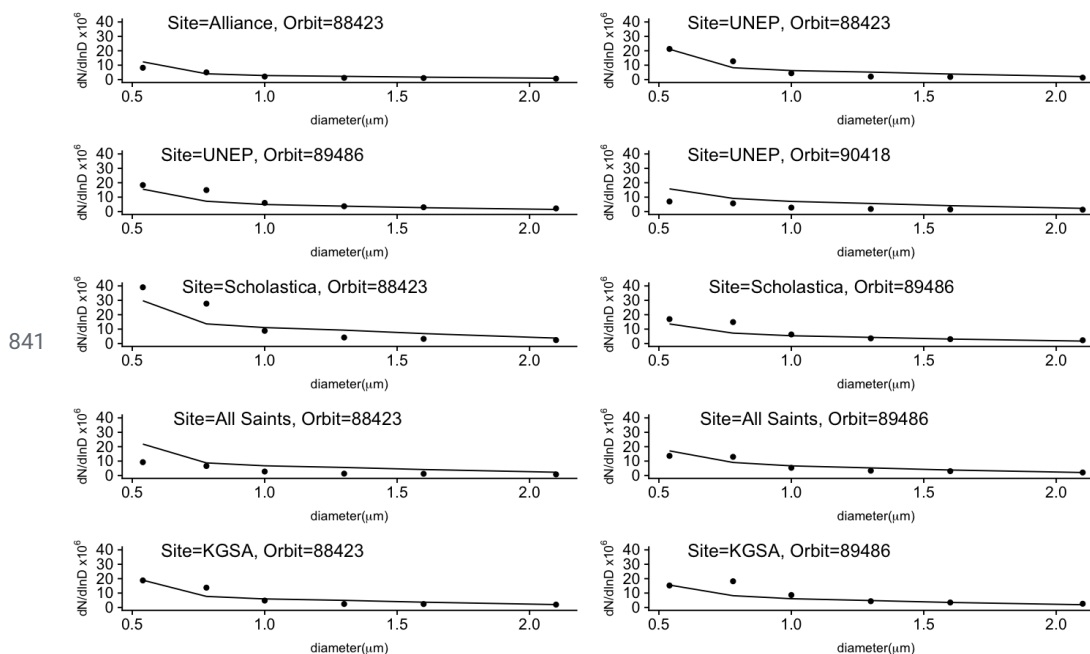
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838 Figures

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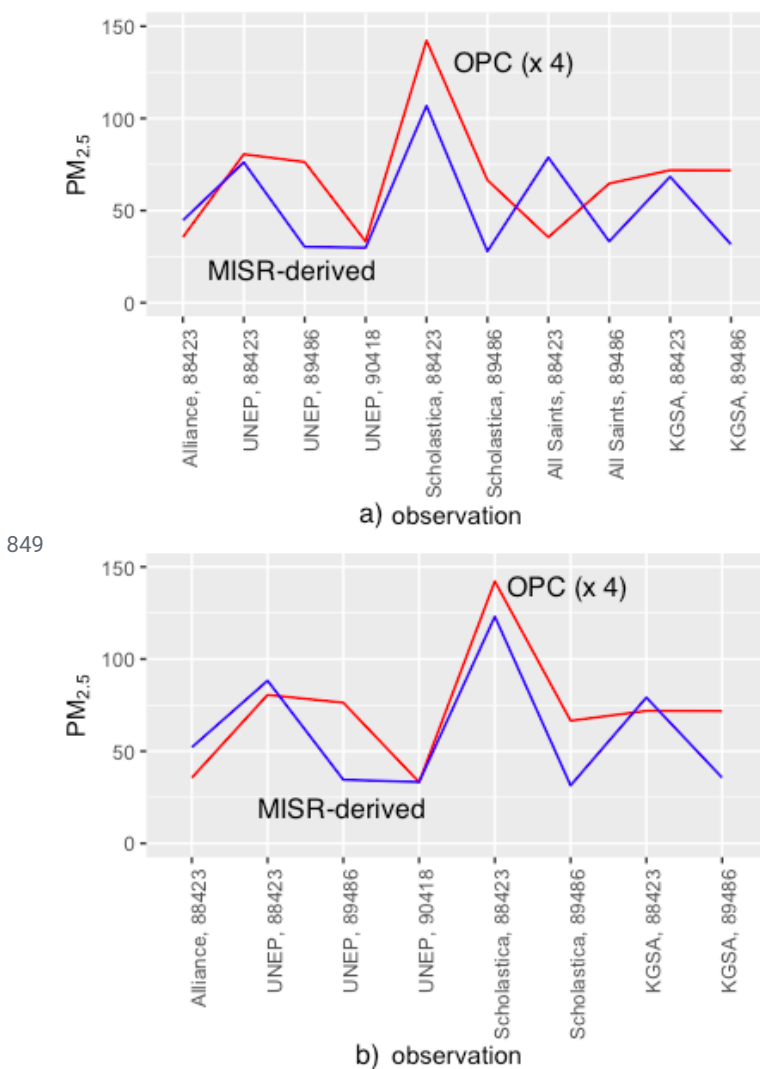
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844 **Figure 1:** Ground-based size distributions ($\#/m^3$) obtained from the low-cost air quality monitors, represented by
845 points at the bin-center diameters (μm) for each of OPC bins 2-7, and the corresponding size distribution derived
846 from the 10 favorable MISR retrievals (represented by lines). The orbit number of the satellite observation is
847 provided along with which ground-based monitor location with which the satellite pixel overlapped.

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 851 **Figure 2:** (Red) PM_{2.5} (μg/m³) measured from the OPC-N2 (scaled up by a factor of 4 to make comparable with the
 852 PM derived from MISR), and (Blue) PM_{2.5} calculated from coincident MISR observations for the (a) 10 cases
 853 where MISR AOD > 0.15 (identified by the MISR orbit number and the coincident site name along the horizontal
 854 axis), and (b) Coincident MISR observations at all sites, but All Saints, using model coefficients from Analysis 2 in
 855 Table 2. The regression analysis yields a correlation of 0.56 for the data in panel (a), whereas the correlation is 0.76
 856 for panel (b). A major factor contributing to the quantitative difference is probably the lack of OPC sensitivity to
 857 particles < 0.54 μm in diameter

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861 Tables

862 **Table 1:** Successful near-surface MISR aerosol optical depth retrievals for each MISR aerosol component (including
 863 the aggregate scaled AOD from components 2, 8 and 14), the total near-surface MISR AOD and the total MISR
 864 AOD, averaged over a radial distance of 1.6 km² from each surface monitoring site. These values were obtained for
 865 each of the 28 coincident observations from the MISR research algorithm, run with the standard universe of 74
 866 mixtures. The AOD is set to zero for aerosol components not present among the MISR-retrieved aerosol types. The
 867 retrieved amounts of Components 19 and 21 were negligible or zero in all the retrievals. Near-surface values were
 868 obtained by scaling total-column AOD based on GEOS-Chem simulated aerosol vertical distributions. The 10
 869 highlighted rows correspond to observations that have a MISR total AOD (sum of the AOD of the eight MISR
 870 aerosol components) > 0.15. The corresponding surface PM_{2.5} from the ground-based OPC for the 10 favorable
 871 MISR retrievals is also presented. Note we have rounded the PM_{2.5} values to the nearest integer to acknowledge the
 872 uncertainties in the OPC PM_{2.5} measurements.

Date	Orbit #	Location (1.6 km radial average)	MISR Near-Surface AOD by component						Total near-surface AOD ₅₅₈	Total AOD	30 minute-averaged OPC PM _{2.5} (µg/m ³)
			1	2+8+1 4	3	6	19	21			
8/2/16	88423	UNEP	0.00	0.13	0.00	0.03	0.00	0.00	0.156	0.340	20
8/2/16	88423	Alliance	0.00	0.08	0.00	0.01	0.00	0.00	0.090	0.192	9
8/2/16	88423	Scholastica	0.00	0.17	0.00	0.05	0.00	0.00	0.219	0.463	36
8/2/16	88423	KGSA	0.00	0.11	0.00	0.03	0.00	0.00	0.139	0.301	18
8/2/16	88423	All Saints	0.00	0.13	0.00	0.03	0.00	0.00	0.162	0.348	9
10/14/16	89486	UNEP	0.02	0.04	0.01	0.02	0.00	0.00	0.085	0.201	19
10/14/16	89486	Alliance	0.01	0.03	0.01	0.02	0.00	0.00	0.062	0.146	
10/14/16	89486	Scholastica	0.01	0.03	0.01	0.02	0.00	0.00	0.076	0.179	17
10/14/16	89486	KGSA	0.02	0.03	0.01	0.02	0.00	0.00	0.086	0.203	18



10/14/16	89486	All Saints	0.01	0.03	0.01	0.03	0.00	0.00	0.089	0.211	16
12/17/16	90418	UNEP	0.01	0.03	0.01	0.03	0.00	0.00	0.075	0.179	8
12/17/16	90418	Alliance	0.01	0.02	0.01	0.02	0.00	0.00	0.055	0.130	
12/17/16	90418	Scholastica	0.01	0.02	0.01	0.02	0.00	0.00	0.055	0.131	
12/17/16	90418	KGSA	0.01	0.01	0.01	0.01	0.00	0.00	0.041	0.102	
12/17/16	90418	All Saints	0.01	0.01	0.01	0.01	0.00	0.00	0.041	0.105	
1/2/17	90651	KGSA	0.01	0.02	0.01	0.02	0.00	0.00	0.048	0.124	
1/18/17	90884	UNEP	0.00	0.02	0.01	0.02	0.00	0.00	0.052	0.132	
1/18/17	90884	Alliance	0.00	0.02	0.01	0.01	0.00	0.00	0.041	0.106	
1/18/17	90884	Scholastica	0.00	0.02	0.01	0.02	0.00	0.00	0.047	0.118	
1/18/17	90884	All Saints	0.00	0.02	0.01	0.02	0.00	0.00	0.046	0.119	
1/25/17	90986	UNEP	0.01	0.02	0.01	0.02	0.00	0.00	0.049	0.123	
1/25/17	90986	Scholastica	0.01	0.02	0.01	0.02	0.00	0.00	0.046	0.113	
1/25/17	90986	All Saints	0.01	0.02	0.01	0.02	0.00	0.00	0.053	0.129	
2/3/17	91117	UNEP	0.00	0.00	0.00	0.00	0.00	0.00	0.010	0.028	
2/3/17	91117	Alliance	0.00	0.00	0.00	0.00	0.00	0.00	0.004	0.012	
2/3/17	91117	Scholastica	0.00	0.00	0.00	0.00	0.00	0.00	0.011	0.030	
2/3/17	91117	All Saints	0.00	0.01	0.00	0.01	0.00	0.00	0.018	0.049	
2/26/17	91452	Alliance	0.01	0.02	0.01	0.02	0.00	0.00	0.058	0.134	

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875 **Table 2:** Results from multiple linear regression analyses using the size distribution of MISR aerosol components as
 876 the independent variable, and the size distribution from the OPC as the dependent variable. In Analyses 1 and 2, the
 877 size distribution of components for MISR observations with a total AOD > 0.15 is used. In Analyses 3, 4 and 5



878 MISR component AODs were obtained by scaling MAIAC AODs using the monthly effective MISR aerosol
 879 component AOD fractions. Equations 5a and 5b are used to derive the total number concentration of each MISR
 880 aerosol group (N_{N-Si}). Because the AOD retrieved for MISR aerosol component 21 is 0, we do not consider this
 881 component in the regression analysis. Analysis 1 and 3 includes MISR aerosol component 1 and 19, while Analysis
 882 2, 4 and 5 do not. In Analysis 5, we restricted the MAIAC retrievals considered to those where the total AOD \geq
 883 0.15.
 884

	Analysis 1 (MISR only)		Analysis 2 (MISR only)		Analysis 3 (MAIAC)		Analysis 4 (MAIAC)		Analysis 5 (total MAIAC AOD \geq 0.15)	
	Coef ficient nts	95% CI	Coeff icient s	95% CI	Coefficie nts	95% CI	Coefficie nts	95% CI	Coefficie nts	95% CI
Compo nent1	-1.7 x 10^{10}	-5.1 x 10^{10} , 1.9 x 10^{10}	-		-3.3 x 10^{10} (***)	(-4.0, -2.6) x 10^{10}	-	-		
Compo nent 2,8,14	4.3 x $10^{8(***)}$)	3.2 x 10^8 , 5.4 x 10^8	4.2 x $10^{+8(***)}$)	3.1 x 10^8 , 5.3 x 10^8	5.8 x 10^8 (***)	(5.4, 6.2) x 10^8	5.3 x $10^{8(***)}$	(4.9, 5.7) x 10^8	6.0 x $10^{8(***)}$	(5.3, 6.6) x 10^8
Compo nent 3	1.4 x 10^9 ()	0.1 x 10^9 , 2.6 x 10^9	8.2 x $10^{+8(***)}$)	0.4 x 10^9 , 1.3 x 10^9	1.7 x 10^9 (***)	(1.5, 2.0) x 10^9	6.0 x $10^{8(***)}$	(5.0, 6.9) x 10^8	3.4 x $10^{8(***)}$	(1.6, 5.2) x 10^8
Compo	6.2	3.9 x 10^9 ,	5.7 x	4.2 x	7.1	(6.4, 7.8)	6.8 x	(6.4, 7.2)	6.8 x	(6.1,



ment 6	$\times 10^9$ (^{***})	8.4×10^9	10^9 (^{***}))	10^{10} , 7.3 $\times 10^{10}$	$\times 10^9$ (^{***})	$\times 10^9$	10^9 (^{***})	$\times 10^9$	10^9 (^{***})	$7.5) \times 10^9$
Component 19	-9.0 $\times 10^9$	-3.1 \times 10^{10} , 1.2 \times 10^{10}	--	--	-1.5 \times 10^{10} (^{***})	(-2.2, -0.8) \times 10^{10}			-	-
Adjusted R squared	0.82		0.82		0.75		0.74		0.76	

885 *p-values of coefficients: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*