The authors thank the reviewers for their helpful comments. Reviewer comments are reproduced here in red, while our responses are indicated in blue. Where applicable, passages from the manuscript have been reproduced.

We would also like to note a slight change in methodology compared with the initial version of this paper. In the revision, we use AOD at either 470nm or 550nm as independent variables in the regression, whereas before both were used. Because of the high correlation of these two variables, there was little added value to including both, and in fact this led to worse performance for certain datasets with minimal initialization data. By instead using only one of the two variables, the results are generally more robust.

Reviewer 1

The goal of this paper is to assess the conversion of satellite AOD values (not measurements)…

References to satellite AOD "measurements" have been modified throughout the paper; we refer to these instead as AOD data or AOD retrievals.

Most of my comments are for PA since the paper focuses on this region.

The study region is very small 0.7 degrees by 0.7 degrees. The paper definitely needs a map of some sort showing the location of the regulation grade monitors and the location of the low cost sensors since I have no idea how close are far away these sensors are!

Additional maps for the ground calibration sites have been included in the supplemental information as Figures S4 through S9, with background maps including local landmark and scale information.

The paper never discusses as to how space-time collocation was done for the ground versus satellite data. The results vary depending upon the width of the time and space windows. The paper also does not provide the slope/intercept values for these linear correlations.

This discussion has been included in Section 2.4 (lines 216-218):

> "Satellite AOD data are considered to be collocated in space with data from a ground site when the center of the AOD pixel is within 1 km of the ground site. Data are considered concurrent if the satellite overpass occurs within the hour interval over which ground site data have been averaged to arrive at the hourly-average $PM_{2.5}$ concentration value used."

Slope and intercept values have been included in the supplemental information, Section S3.1.

The range of annual values in PA was low and the satellite data and the low cost sensors have larger uncertainties in this range and therefore the results may not be robust. Given this backdrop I am not sure how meaningful the PA results are. This is probably the main reason that the correlations are low – Page 11 (Line 325+). Not sure about the usefulness of an offline approach where only a single conversion factor is used. Why report these values when we know that this is not relevant?

In the Pittsburgh area, we are able to analyze the effect of ground monitoring network density, which is not possible with the currently sparsely-monitored African locations. Section 3.2 shows that the satellite AOD to surface PM conversion uncertainty reduces meaningfully for up to about ten low-cost sensors over the 600 square kilometer area, which is useful guidance for future low-cost sensor deployments, including those planned for African cities. Further, the results for Pittsburgh are presented to provide a baseline and contrast for the results obtained for Sub-Saharan Africa, where the low-cost sensor and satellite data combination is thus seen to be quite valuable. A single conversion factor is used as it represents the simplest and most robust calibration method, while more sophisticated calibrations might be subject to over-fitting to the calibration data sets. Results are presented for the offline approach as a baseline to compare with an online approach, to assess what benefit if any the online approach provides.

Page 11, Line 319. What is the cloud cover for each site and how does it affect annual average AOD? Given some of the issues mentioned above I am not sure that page 12 (line 24-244) conclusion is acceptable. Also given that the linear correlation has so many problems, using satellite data and ground monitors to assess the linear relationship is fraught with uncertainties.

Information on satellite data coverage is included in the supplemental information, Tables S2 and S3. However, since we do not consider long-term average values in this work, we only compare cloud-free AOD to surface PM measurements taken at approximately the same time (i.e. as the hourly average value for the period in which the satellite overpass occurs). Therefore, there will be no issues related to sampling bias for only using data from cloud-free days in these comparisons, as would be the case if we were looking at longer averaging periods.

Although we agree that the methods presented have numerous inherent uncertainties, a major goal of this paper is to assess whether, even with such uncertainties, useful results can be obtained by combining low-cost sensor and satellite data. We find that this is the case, at least in the context of Sub-Saharan Africa where signal-to-noise ratios can be higher and there is very little ground-based monitoring.

In summary, I believe that low cost sensors play an important role for $PM_{2.5}$ research but unless calibration issues and comparisons with ground monitors of regulation grade are made carefully as a function of space, time, meteorology we cannot be sure how useful the data can be for quantitative monitoring, assessment, and research (e.g. epidemiology). It is also not fair to state that (Page 16, line 482) that using the nearest monitor is better than using satellite data because none of the meteorological factors have been taken into account for estimating $PM_{2.5}$ from satellite data.

Careful corrections by collocation-based comparison of low-cost PM sensors with regulatory-grade monitors and different methodological approaches in the Pittsburgh context have been the subject of a previous paper (Malings et al. 2019b as cited in the paper, DOI 10.1080/02786826.2019.1623863). We have included, where possible, performance assessments for the low-cost monitors in other contexts, but this is a subject of ongoing work and beyond the scope of this paper. Rather, this paper represents a preliminary attempt to quantify the usefulness of simple linear relationships between AOD and ground PM from low-cost sensors, even taking into account any inherent uncertainties these instruments may have.

We did not mean to assert that the use of nearby sensors was always better than using satellite data in all contexts, but merely within the current high-spatial-density monitoring network in Pittsburgh and the confines of the linear conversion method applied. This statement has been clarified in the text (lines 501-504):

> "However, it was found that for Pittsburgh, with a relatively dense low-cost sensor network (median inter-site distance of about 1 km) and low $PM_{2.5}$ concentrations, use of the nearest

> ground measurement sites outperformed the use of satellite AOD data to estimate surface $PM_{2.5}$ using linear conversions."

Minor comments

Wang and Christopher, 2003 – Not Wang, 2003

We apologize for the oversight. This has been corrected.

Some of the references are outdated. E.g. Zhang et al 2009 for correlation coefficients.

This particular reference has been removed in Section 3.1, but has been retained in the Introduction for its value in providing general background information on AOD to surface PM correlations.

Page 3 : What spatial/temporal scales did Murray et al used

This paper made use of 12-km spatial scale data at daily temporal resolution. This has been noted in the text (lines 86-88):

> "Methods incorporating the outputs of chemical transport models (in this case at lower spatial resolutions of 12 km compared to the 1 km AOD resolution, and at daily temporal resolution) can further improve these results (e.g. Murray et al., 2019)."

Page 3 : Not all studies find 'anti-correlation' in India.

Thank you for pointing this out. Since our present work does not cover India, this information is not strictly relevant, and so we no longer reference it in the paper.

Page 3: Last sentence needs a reference

Low-cost sensor and reference monitor typical prices are based on manufacturer prices in our experience from the past several years. This has been stated (lines 103-107):

> "Low-cost air quality monitors have much lower purchase and operational costs in contrast to traditional or regulatory-grade monitors (Snyder et al., 2013; Mead et al., 2013). For example, a lower-cost multi-pollutant monitor (measuring gases and PM) costs a few thousand US dollars; single-pollutant PM sensors can cost just a few hundred US dollars. A comparable multi-pollutant suite of traditional air quality monitoring instruments would cost a hundred thousand US dollars or more; a regulatory-grade PM monitor can cost tens of thousands of US dollar (based on recent manufacturer quotations)."

Page 3: The cloud cover problems needs to be addressed and referenced. Christopher & Gupta (2010) Satellite Remote Sensing of Particulate Matter Air Quality: The Cloud-Cover Problem, Journal of the Air & Waste Management Association, 60:5, 596-602, DOI: 10.3155/1047-3289.60.5.596

This reference has been added to the introduction section (lines 67-70):

> "Cloud cover also makes AOD retrievals impossible; the frequency of cloudy days in an area can therefore make it difficult to establish reliable relationships between AOD and surface PM, although this is not likely to be a concern for the continental US (Christopher and Gupta, 2010; Belle et al., 2017)."

The cloud cover problem can be important for long-term averages. As noted previously, cloud cover is not an issue in our comparisons because we focus on hourly data during cloud-free periods (lines 218-223):

> "As we compare data from individual satellite passes directly to temporally collocated ground site data, we do not need to consider (as would be essential for long-term averages) the potential impact of the fraction of time where satellite measures are missing (due to cloud cover or other factors). Likewise, we do not consider the biases associated with the fact that satellite passes occur at certain times of day (required when comparing with daily-averaged ground monitoring data) since here we only compare AOD to surface $PM_{2.5}$ during the same hour when the satellite pass occurs."

Page 4: Errors cannot average out and it depends on the range of PM2.5 values and a host of other factors.

This was a conjecture as to possible future applications of satellite and low-cost sensor data. The sentence has been removed.

Section 2.1.1 to 2.1.3 belongs in a Table rather than a few sentences of text

We thank the reviewer for this suggestion. The information presented in these sections, as well as basic details of the study areas, have been presented in Tables 1 and 2.

Page 5: Line 1 : Here not hare

This has been corrected.

Page 7 says 'as summarized in 2.1.4' but 2.1.4 does not describe calibration in any detail. Erroneous data screening for negative values is easy but doing this manually for the entire low cost network is not possible.

A full presentation of the calibration methods is beyond the scope of this work, and is more fully covered in the cited publication (Malings et al., 2019b). While it is true that manual error detection and elimination for a large network of sensors is difficult, it can be aided through the use of certain automatic processes. While we seek to present data that has been calibrated and validated to the best of our abilities, we acknowledge that fool-proof error detection and correction is not possible. Such errors are a source of uncertainty in the present work, and one of our major goals with this paper is to demonstrate and quantify the extent to which low-cost sensor data, even with these uncertainties, can provide additional information to support the conversion of AOD to surface $PM_{2.5}$.

Additional details have been provided in the text (Section 2.1, lines 160-170):

> "Collected data are down-averaged from their device-specific collection frequencies to a common hourly timescale. Erroneous data identified either automatically (e.g. negative concentration values or unrealistically high or low values) or manually (e.g. devices exhibiting abnormal performance characteristics identified during periodic inspections) are removed. To correct for particle hygroscopic growth effects (i.e. the impact of ambient humidity on the PM mass as measured by the low-cost sensors), previously developed calibration methods (Malings et al., 2019b) were implemented for the NPM and PA-II sensors. Briefly, first, a hygroscopic growth factor is computed using the local humidity and temperature as measured by the low-cost monitor itself, along with an average or typical particle composition. Then, a linear correction is

applied to the data based on past collocations with regulatory-grade monitoring instruments. Utilizing these methods, the uncertainties on hourly average $PM_{2.5}$ concentration are about 4 $\mu g/m^3$ (Malings et al., 2019b). For the Alphasense OPC sensors, raw bin count numbers were integrated to produce a new concentration estimate for $PM_{2.5}$, and a similar relative humidity correction was applied (Di Antonio et al., 2018)."

Page 6: Line 180-183 says the data are scaled for workdays and non work days. This type of scaling may work for this study but how about other regions?

Indeed, different scaling factors may be necessary in other regions, and this is the subject of ongoing research on the generalizability of low-cost sensor calibration approaches across the vast continent of Africa. For the purposes of this paper, we seek to use data from low-cost sensors which represent the best available practices in each instance. Therefore, we have included scaling factors in Rwanda based on applicable local comparisons and calibration. Since we are using linear methods, the presence or absence of linear scaling factors that are equally applied to both training and testing sets of low-cost sensor data should not influence the assessment of the methodology.

Page 8: The satellite data needs some description with a proper journal reference. Briefly, how was AOD retrieved, what are the uncertainties, how much cloud cover for the analysis, what quality flags were used, etc.

A more complete description of the satellite data has been provided in Section 2.4 (lines 205-223):

"The satellite data product used in this paper is the MODIS MCD19A2v006 dataset (Lyapustin and Wang, 2018) available through NASA's Earth Data Portal (earthdata.nasa.gov). This dataset consists of AOD information for the 470nm and 550nm wavelengths from the MODIS system, processed using the Multi-angle Implementation of Atmospheric Correction (MAIAC) algorithm, and presented at 1 km pixel resolution for every overpass of either the Aqua or Terra satellites (Lyapustin et al., 2011a, 2011b, 2012, 2018). This represents a Level 2 data product, meaning that it includes geophysical variables derived from raw satellite data, but has not yet been transformed to a new temporal or spatial resolution, as is the case for data derived from multiple satellite passes, e.g. monthly average AOD data. Data from identified cloudy pixels are masked as part of the data product; possible misidentification of cloudy pixels is one source of error in relating surface $PM_{2.5}$ and AOD. As per recommendations in the User Guide for this dataset, only data matching "best quality" quality assurance criteria are used. This dataset was chosen as it represents the highest possible spatial and temporal resolution for AOD, thus providing the most points for comparison with the high spatio-temporal resolution low-cost monitor data.

Satellite AOD data are considered to be collocated in space with data from a ground site when the center of the AOD pixel is within 1 km of the ground site. Data are considered concurrent if the satellite overpass occurs within the hour interval over which ground site data have been averaged to arrive at the hourly-average $PM_{2.5}$ concentration value used. As we compare data from individual satellite passes directly to temporally collocated ground site data, we do not need to consider (as would be essential for long-term averages) the potential impact of the fraction of time where satellite measures are missing (due to cloud cover or other factors). Likewise, we do not consider the biases associated with the fact that satellite passes occur at certain times of day

> (required when comparing with daily-averaged ground monitoring data) since here we only compare AOD to surface $PM_{2.5}$ during the same hour when the satellite pass occurs."

Additional details on the cloud cover and uncertainty analysis are included in the supplemental information, Tables S2 and S3.

Reviewer 2

General Comments

The majority of the results section focuses on the analysis for the Pittsburgh region. The goal of the paper is to assess the utility of low-cost sensors in deriving satellite AOD conversion factors, however, the results for Pittsburgh seem to suggest that ground monitor data overall performs poorly as a data source for the conversions over the region, at least in terms of correlations. As the authors note, this is likely due to the low concentrations being within the range of signal-to-noise in the sensors. This makes the results less meaningful, because it is difficult to determine whether the results are reflecting the ability of the low-cost sensors to be data sources for the satellite AOD conversion, or whether the results are just overwhelmed by the uncertainties in the measurements, and undermines the authors' conclusions that low-cost sensors perform just as well if not slightly better than the regulatory grade monitors in this region.

One of the major motivations for including the results from Pittsburgh is to present a baseline case for a densely monitored (with both regulatory and low-cost monitors) region in order to contrast with results from more sparsely monitored locations in Rwanda and elsewhere. In particular, although we agree that overall performance of the satellite AOD to ground $PM_{2.5}$ conversion is rather poor in the conditions of Pittsburgh, it is at least consistent for both ground data sources (regulatory reference instruments and low-cost monitors). Note that the typical $PM_{2.5}$ concentrations in Pittsburgh (an inter-quartile range of 6 to 12 μg/m^3) are still above the hourly-average measurement uncertainty (3 to 4 μg/m^3) of the low-cost sensors. Considering the reasonable agreement between low-cost and regulatory-grade monitors identified in previous work, together with the observation from this work that performance is not noticeably disadvantaged by the substitution of regulatory-grade for low-cost monitors, we believe it is reasonable to assume that most of the poor performance of the satellite AOD to ground $PM_{2.5}$ conversion is due to the inherent difficulties of this problem and the low-concentration regime of Pittsburgh, rather than the data quality of the ground source. We have restated the conclusion based on our comparative analysis of low-cost and regulatory-grade instruments in Pittsburgh to better emphasize this (lines 389-396):

> "In all cases, performances using low-cost sensor data are comparable to that of the same conversion approaches utilizing the regulatory-grade instruments. Note that the low-cost monitors used here have been carefully corrected by collocation with regulatory-grade monitors (Malings et al., 2019b) which accounts for known artefacts with low-cost sensors. Thus, there is no evidence from this analysis of any inherent disadvantage to the use of carefully corrected low-cost sensors to provide ground data as compared to more traditional instruments. Rather, based on these results, any additional uncertainty due to data quality differences between low-cost sensors and regulatory-grade instruments are seen to be negligible compared to the difficulties associated with relating satellite AOD to surface-level $PM_{2.5}$, and therefore have had no systematic impact on the performance of the assessed linear conversion method, at least for this study area."

The analysis over Africa appears to be more promising, but much less time is spent discussing those results. The authors may be better suited by more prominently presenting the analysis over Africa. Low-cost sensor data would provide more benefit over regions such as Africa where the regulatory grade monitors are sparse; there already exist dense regulatory grade monitors over North America, so focusing more on the analysis over Africa would be of greater interest. Describing in detail the comparison of low-cost sensors and regulatory grade monitors in Pittsburgh would make sense if the results were meaningful, as they would provide a meaningful evaluation of the ability of the low-cost sensors to be used to convert satellite AOD in general, but in this case the results seem to suggest the method just doesn't work over Pittsburgh, and does little to provide confidence in the low-cost sensor only analysis over Africa.

We thank the reviewer for recognizing the potential benefit of low-cost sensors for Africa. This is a point we seek to make and support quantitatively through the results presented in this paper. We have expanded our discussion of results in Africa to increase the relative emphasis placed on these results. We have also reorganized the paper somewhat and restructured the discussion of the results, including a new figure related to this discussion (Figure 6) to better emphasize the relative significance and importance of the results for Africa. However, we feel it is also important to present the "weaker" results for Pittsburgh as a basis of comparison for the more promising results for sub-Saharan Africa. Furthermore, the analysis of the potential benefits of high spatial density low-cost sensor networks (the "how many sensors are needed" question) can only be performed using the Pittsburgh data, where such a network has been operational since 2016.

Specific Comments

- Several of the figures are difficult to decipher. Figure 2 is difficult to read because the labels on the y-axis are clustered so close together. Figure 7 is extremely difficult to interpret, because it is hard to see the shades of red. Supplemental figures S6-S9 are very hard to follow and do not help to clarify the methods.

The vertical spacing of Figure 2 has been increased. The color scale of Figure 7 has been changed to improve interpretability. Numerical values corresponding to these colors have also been provided in the supplemental information (Table S8). Supplemental Figures S6 to S9 were augmented with a more detailed narrative description of the methods (including new figures, with all figures now numbered S11 to S18), which we believe makes these points more clearly.

- In addition to Figure S5, the authors should have map plots for each region with the monitor locations over-laid, with a better indicator for the distance between monitors than just latitude and longitude. It is very difficult from Fig S5 to discern where the monitors are positioned throughout the cities, which would provide insight into the results. It is very difficult to tell which monitors are low-cost and which are regulatory without looking extremely closely.

Map plots depicting the locations of the monitors have been included in the supplemental information as Figures S4 through S9. The markers are much larger and are overlaid on geographical maps which should help better illustrate the monitor locations.

- It is unclear how the satellite AOD and ground monitor data are being sampled; are the authors using pixels co-located to the ground monitor sites, or are they comparing a broader area of AOD to the ground monitor points? Also at which time-scales are the data points being sampled? At satellite-overpass time? This information would have important implications for the results.

A more complete description of the sampling method has been provided in Section 2.4 (lines 205-223):

> "The satellite data product used in this paper is the MODIS MCD19A2v006 dataset (Lyapustin and Wang, 2018) available through NASA's Earth Data Portal (earthdata.nasa.gov). This dataset consists of AOD information for the 470nm and 550nm wavelengths from the MODIS system, processed using the Multi-angle Implementation of Atmospheric Correction (MAIAC) algorithm, and presented at 1 km pixel resolution for every overpass of either the Aqua or Terra satellites (Lyapustin et al., 2011a, 2011b, 2012, 2018). This represents a Level 2 data product, meaning that it includes geophysical variables derived from raw satellite data, but has not yet been transformed to a new temporal or spatial resolution, as is the case for data derived from multiple satellite passes, e.g. monthly average AOD data. Data from identified cloudy pixels are masked as part of the data product; possible misidentification of cloudy pixels is one source of error in relating surface $PM_{2.5}$ and AOD. As per recommendations in the User Guide for this dataset, only data matching "best quality" quality assurance criteria are used. This dataset was chosen as it represents the highest possible spatial and temporal resolution for AOD, thus providing the most points for comparison with the high spatio-temporal resolution low-cost monitor data.
>
> Satellite AOD data are considered to be collocated in space with data from a ground site when the center of the AOD pixel is within 1 km of the ground site. Data are considered concurrent if the satellite overpass occurs within the hour interval over which ground site data have been averaged to arrive at the hourly-average $PM_{2.5}$ concentration value used. As we compare data from individual satellite passes directly to temporally collocated ground site data, we do not need to consider (as would be essential for long-term averages) the potential impact of the fraction of time where satellite measures are missing (due to cloud cover or other factors). Likewise, we do not consider the biases associated with the fact that satellite passes occur at certain times of day (required when comparing with daily-averaged ground monitoring data) since here we only compare AOD to surface $PM_{2.5}$ during the same hour when the satellite pass occurs."

- In several instances more "methods" type descriptions are mixed in with the results. Having all methods descriptions in the methods section would make the presentation of the results clearer.

We thank the reviewer for this suggestion. These descriptions have been moved into their own subsection (2.6) within the "Methods" section.

Minor comments:

- Line 70: what is a "good" correlation? No range of values from the studies is given.

A representative value from the reference has been provided (lines 72-75):

> "Nevertheless, early examinations of AOD data from the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument, launched aboard the Terra and Aqua satellites in 1999 and 2002, showed good correlation (e.g. correlation coefficient r about 0.7 for Jefferson County, Alabama in 2002) with surface PM2.5 concentrations in the United States, although these relationships varied from region to region (Wang and Christopher, 2003; Engel-Cox et al., 2004)."

- Throughout the manuscript the authors refer to “satellite AOD measurements”, when technically they are retrievals and not direct measurements.

References to satellite AOD “measurements” have been modified throughout the paper. We now refer to these as AOD data or AOD retrievals.

- In the introduction the second paragraph on page 3 is confusing. It is structured as though they are discussing studies that use models combing satellite AOD with CTMs to estimate PM2.5, but then all of a sudden they are discussing satellite AOD and ground monitor PM2.5 agreement over Africa.

This paragraph has been split into two to better present these different topics.

- When discussing the yearly/monthly conversion factors on page 11, it is unclear whether the monthly conversion factors are applied on a monthly basis, or if they are calculated on a monthly basis then applied on an annual basis: “the ‘monthly’ case, data from the previous month are used to develop conversion factors used in the current month; the median performance across months is presented”.

These factors are applied on a monthly basis. This has been clarified in the text (lines 295-299):

> “For a “yearly” conversion, data from the entire calendar year are used to develop the conversion factors, while in the “monthly” case, data from the previous month are used to develop conversion factors that are then assessed in the current month (e.g. January data are used to develop conversion factors that are applied in February, then the February data are used to develop conversion factors that are applied in March, etc.). For the “monthly” case, the median performance across months is presented.”

Application of Low-Cost Fine Particulate Mass Monitors to Convert Satellite Aerosol Optical Depth ~~Measurements~~ to Surface Concentrations in North America and Africa

Carl Malings[1,2,~~3~~], Daniel M. ~~Westervelt[3]~~Westervelt[4], Aliaksei ~~Hauryliuk[4]~~Hauryliuk[5], Albert A. ~~Presto[4]~~Presto[5], Andrew ~~Grieshop[5]~~Grieshop[6], Ashley ~~Bittner[5]~~Bittner[6], Matthias Beekmann[1,2], R Subramanian[1,2]

[1]OSU-EFLUVE - Observatoire Sciences de l'Univers-Enveloppes Fluides de la Ville à l'Exobiologie, Université Paris-Est-Créteil, CNRS UMS 3563, Ecole Nationale des Ponts et Chaussés, Université de Paris, France
[2]Laboratoire Interuniversitaire des Systèmes Atmosphériques (LISA), UMR 7583, CNRS, Université Paris-Est-Créteil, Université de Paris, Institut Pierre Simon Laplace, Créteil, France
[3]Currently a NASA Postdoctoral Program Fellow, Goddard Space Flight Center, Greenbelt, MD 20771, USA
~~[3]Lamont~~[4]Lamont-Doherty Earth Observatory, Columbia University, New York, NY, USA
~~[4]Center~~ [5]Center for Atmospheric Particle Studies, Carnegie Mellon University, 5000 Forbes Avenue, Pittsburgh, PA 15213, USA
~~[5]Department~~ [6]Department of Civil, Construction and Environmental Engineering, North Carolina State University, Raleigh, NC, USA

Correspondence to: Carl Malings, R Subramanian (cmalings@alumni.cmu.edu, subu@cmu.edu)

Abstract. Low-cost particulate mass sensors provide opportunities to assess air quality at unprecedented spatial and temporal resolutions. Established traditional monitoring networks have limited spatial resolution and are ~~frequently~~ simply absent in ~~less-developed countries (e.g.~~many major cities across ~~in~~ sub-Saharan Africa (SSA)~~)~~. Satellites provide snapshots of regional air pollution~~,~~ but require ground-truthing. Low-cost monitors can supplement and extend data coverage from these sources worldwide, providing a better overall air quality picture. We ~~demonstrate~~ investigate ~~such~~ the utility of such a multi-source data integration approach using two case studies. First, in Pittsburgh, Pennsylvania, both traditional monitoring and dense low-cost sensor networks are ~~present, and are~~ compared with satellite aerosol optical depth (AOD) data from NASA's MODIS system and a linear conversion factor is developed to convert AOD to surface fine particulate matter mass concentration (as $PM_{2.5}$). ~~We assess the performance of linear conversion factors for AOD to surface $PM_{2.5}$ using both networks, and identify relative benefits provided by the denser low-cost sensor network. In particular,~~With ~~with~~ 10 or more ground monitors in ~~the city~~Pittsburgh,~~,~~ there is a two-fold reduction in ~~worst-case~~ surface $PM_{2.5}$ estimation mean absolute error compared to using only a single ground monitor. Second, ~~in Rwanda, Malawi, and the Democratic Republic of the Congo, traditional ground-based monitoring is lacking and must be substituted with low-cost sensor data. Here, w~~we assess the ability of combined regional-scale satellite retrievals and local-scale low-cost sensor measurements to ~~complement each other.~~ improve surface $PM_{2.5}$ estimation at several urban sites in SSA. In Rwanda, we find that combining local ground monitoring information with satellite data provides a 40% improvement ~~(~~in ~~terms of~~ surface $PM_{2.5}$ estimation accuracy~~)~~ with respect to using low-cost ground monitoring data alone. A linear AOD to surface $PM_{2.5}$ conversion factor developed in

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Kigali, Rwanda did not generalize well to other parts of SSA, and varied seasonally for the same location, emphasizing the need for ongoing and localized ground-based monitoring, which can be facilitated by low-cost sensors. Overall, we find that combining ground-based low-cost sensor and satellite data, even without including additional meteorological or land use information, can improve and expand spatio-temporal air quality data coverage especially in ~~in both well-monitored and~~ data-sparse regions.

1 Introduction

Air quality is the single largest environmental risk factor for human health; o~~. O~~utdoor air pollution exposure is estimated to have caused about four million premature deaths annually in recent years (WHO, 2016, 2018a). Particulate matter (PM), which represents a mixture of solid and liquid substances suspended in the air, is one of the most commonly tracked and regulated atmospheric pollutants globally (WHO, 2006). ~~Not only does it have a~~Exposure to fine PM is known to have major adverse health impacts ~~by itself~~ (e.g. Schwartz et al., 1996; Pope et al., 2002; Brook et al., 2010). In addition, PM mass concentration ~~, but its concentration~~ is ~~also~~ often used as a proxy for overall air quality (WHO, 2018a). PM mass concentration is typically tracked as PM_{10} (total PM mass with diameter below 10 micrometers) and/or $PM_{2.5}$ (total PM mass with diameter below 2.5 micrometers). Even at low concentrations, PM can have significant health impacts (Bell et al., 2007; Apte et al., 2015). These health impacts are especially notable in low-income communities and countries, where they can interact with other socio-economic risk factors (Di et al., 2017; Ren et al., 2018).

Sub-Saharan Africa (SSA) in particular is affected by poor air quality, with less than 10% of communities assessed by the WHO meeting recommended air quality guidelines, compared with 18% globally, and 40 to 80% in Europe and North America (WHO, 2018b). This poor air quality manifests in terms of high infant mortality (Heft-Neal et al., 2018), increased risk of chronic respiratory and cardiovascular diseases (Matshidiso Moeti, 2018), and reduced gross domestic product (World Bank, 2016). Industrial development and climate trends will likely only exacerbate this problem in the future (Liousse et al., 2014; UNEP, 2016; Silva et al., 2017; Abel et al., 2018).

Many African countries have among the highest estimated annual average PM_{10} and $PM_{2.5}$ concentrations, yet are also among those with the lowest number of in situ ~~reference~~regulatory-grade PM monitoring sites per capita. Fig. 1 ~~Figure 1~~ shows estimated average annual $PM_{2.5}$ concentrations for various regions of the world versus the density of ~~reference~~regulatory-grade monitoring sites in these regions (note that low-cost monitors are not considered), based on information from the Global Health Observatory (GHO). The GHO~~, which~~ combines data from multiple sources, including data collected ~~in~~ during different years and ~~by~~ from sporadic field monitoring ~~from field~~ campaigns, and ~~so does~~it is not necessarily reflective of continuous routine monitoring for all regions (WHO, 2017). This lack of continuous surface monitoring data makes it difficult to answer basic scientific and policy questions related to air quality assessment and mitigation (Petkova et al., 2013; Martin et al., 2019). A major reason for this gap is the high capital and operational costs of traditional ground-based air quality monitoring equipment. Two emerging technologies have the capacity to close this gap: satellite-based air quality monitoring and ground-based low-cost sensor systems.

Satellites are much more expensive than traditional ground-based monitors, but their mobility and unique vantage point allow them to provide near-global coverage. Data from earth-observing satellites can be used to assess air quality in a variety of ways. In particular, aerosol optical depth (AOD) ~~represents a measurement~~retrievals quantify the~~ of the~~ absorption and scattering (extinction) of light by the atmosphere~~,~~ and can be related to the concentration of light-absorbing or light-scattering pollutants in the atmosphere. Several factors complicate the relationship between AOD and surface-level particulate matter mass concentrations (Paciorek and Liu, 2009). As a vertically-integrated quantity, AOD is related to total light extinction by a column of atmosphere. The spatial distribution of particulate matter, especially vertical stratification, the presence or absence of plumes aloft, humidity, and the size and optical properties of particles ~~drive~~ affect the relationship between AOD and surface concentrations (Kaufman and Fraser, 1983; Liu et al., 2005; Paciorek et al., 2008; Superczynski et al., 2017; Zeng et al., 2018). Cloud cover also makes AOD retrievals impossible; the frequency of cloudy days in an area can therefore make it difficult to establish reliable relationships between AOD and surface PM, although this is not likely to be a concern for the continental US (Christopher and Gupta, 2010; Belle et al., 2017)~~(Belle et al., 2017)~~. Changes in surface brightness can also confound this relationship, although this may be less of an issue in developing countries with higher aerosol levels (Paciorek et al., 2012).

Nevertheless, early examinations of AOD data from the ~~m~~Moderate ~~r~~Resolution I~~i~~maging S~~s~~pectroradiometer (MODIS) instrument, launched aboard the Terra and Aqua satellites in 1999 and 2002, showed good correlation (e.g. correlation coefficient r about 0.7 for Jefferson County, Alabama in 2002) with ~~long-term average~~ surface $PM_{2.5}$ concentrations in the United States, although these relationships varied from region to region (Wang and Christopher, 2003; Engel-Cox et al., 2004)~~(Wang, 2003; Engel-Cox et al., 2004)~~. For ~~shorter timescales~~instance, correlations between AOD and hourly surface $PM_{2.5}$ were found to vary from an r^2 of 0.~~36~~ 6 in the southeastern United States to an r^2 of 0.2~~04~~ in the southwestern United States during 2005-2006, with root-mean-square errors (RMSE) of about 9 µg/m^3 for surface $PM_{2.5}$ reconstructed from AOD using linear relationships, with worse results over urban areas (Zhang et al., 2009). Additional studies show broadly similar relationships, with r ranging between about 0.5 and 0.8 in the northeastern United States (e.g. Paciorek and Liu, 2009), with changes in agreement depending on season (Chudnovsky et al., 2013a) and with better agreement at higher spatial AOD resolution (Chudnovsky et al., 2013b). Using additional covariates, such as land cover, land usage, and meteorological information, can further improve these relationships. In particular, surface $PM_{2.5}$ estimation models combining daily-averaged, 1~~-~~ km~~ilometer-~~ resolution AOD data with meteorological and land use regression variables ~~can~~ achieved an agreement (~~quantified as~~ r^2) with EPA ground-based monitors of up to about 0.95 in the northeastern and 0.~~8~~ 9 in the southeastern United States, with a mean absolute error of about 3 µg/m^3 (Chang et al., 2014; Chudnovsky et al., 2014; Kloog et al., 2014). Methods incorporating the outputs of chemical transport models (in this case at lower spatial resolutions of 12 km compared to the 1 km AOD resolution, and at daily temporal resolution) can further improve these results (e.g. Murray et al., 2019).

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Models combining satellite AOD data with vertical profiles derived from chemical transport models tend to underestimate surface-level $PM_{2.5}$ outside of Europe and North America, mainly in India and China where ground-based comparison data are available (van Donkelaar et al., 2010, 2015). In China, the r~~2~~ between surface $PM_{2.5}$ estimates derived from satellite AOD, meteorological, and land use information and measured surface $PM_{2.5}$ was found to be about 0.~~7~~8, corresponding to a ~~root mean square error (~~RMSE~~)~~ of about 30 μg/m^3 (roughly half the mean concentration) in resulting satellite-derived surface concentration estimates (Ma et al., 2014). A method that updates the relationships between AOD and surface $PM_{2.5}$ on a daily basis (Lee et al., 2011) was able to improve these results, increasing r~~2~~ above 0.~~8~~ 9 while reducing RMSE to about 20 μg/m^3 (Han et al., 2018). This method, however, relies on local ground-based measurements to provide the data necessary to perform this daily updating.

Satellites have the potential to provide broad data coverage to previously unmonitored areas such as in SSA. ~~In Africa, although s~~Satellite-based AOD and ground-based AOD ~~measurements~~ agreed well during a recent assessment in West Africa (Ogunjobi and Awoleye, 2019), but an assessment in South Africa found a poor relationship between satellite AOD and surface $PM_{2.5}$, with maxima in the surface concentrations coinciding with minima in the AOD (Hersey et al., 2015). ~~Similar results were found in India, with anticorrelation observed between satellite AOD and surface PM2.5 for some locations (see supplemental information, Fig. S1). Overall, while satellites have the potential to provide broad data coverage to previously unmonitored areas such as in SSA, r~~Relationships between AOD and surface $PM_{2.5}$ developed using ground monitoring data elsewhere in the world may not transfer well to SSA, leading to inaccurate quantification of surface air quality~~ quantification~~.

Low-cost air quality monitors~~, defined in contrast to traditional or regulatory-grade monitors,~~ have much lower purchase and operational costs in contrast to traditional or regulatory-grade monitors (Snyder et al., 2013; Mead et al., 2013).~~, e.g.~~ For example, a lower-cost ~~-~~multi-pollutant monitor (measuring gases and PM) costs a few thousand US dollars; single-pollutant PM sensors can cost just a few hundred US dollars. A ~~on the order of five thousand US dollars per multi-pollutant monitor (measuring gases and PM), while a~~ comparable multi-pollutant suite of traditional air quality monitoring instruments would cost a hundred ~~of~~ thousand US dollars or more; a regulatory-grade PM monitor can cost tens of thousands of US dollar (based on recent manufacturer quotations).~~.~~ This cost reduction is made possible by a combination of lower-cost measurement technologies (such as electrochemical sensors for gases and optical particle detectors for PM) and ~~recent~~ decreasing costs of battery, data storage, and communications technologies. Much recent research interest has been focused on assessing the performance of these technologies (e.g. AQ-SPEC, 2015, 2017), developing methods for accounting for cross-interference effects in gas sensors (e.g. Cross et al., 2017; Zikova et al., 2017; Kelly et al., 2017; Zimmerman et al., 2018; Crilley et al., 2018; Malings et al., 2019a) and humidity dependence in optical PM measurement methods (e.g. Malings et al., 2019b) to improve data quality, and demonstrating the utility of these low-cost monitors in various use cases (e.g. Subramanian et al., 2018; Tanzer et al., 2019; Bi et al., 2020). Because of their relatively low cost, these instruments can be deployed more widely than traditional monitoring technologies, enabling measurements in previously unmonitored areas. ~~The~~ A trade-off for this increased affordability~~ is~~ can be ~~a decrease in~~reduced accuracy compared to traditional air

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quality monitoring instruments. While there are currently no agreed-upon criteria for assessing low-cost monitor performance (Williams et al., 2019), several schemes suggest tiered rankings ranging from, for example, 20% relative uncertainty for reasonable quantitative measurements to 100% uncertainty for indicative measurements (Allen, 2018); this gives a general sense of the expected performance characteristics of such instruments. In particular, recent testing of two types of such low-cost monitors (which are the types used in this paper) found relative uncertainties on the order of 40% and correlation coefficient r of 0.7 ~~(r^2 of 0.5)~~ with regulatory-grade instruments for hourly $PM_{2.5}$ measurements (Malings et al., 2019b). These results are generally consistent with similar studies conducted in a variety of environments and concentration regimes, although relative performance tends to improve at higher concentrations (Kelly et al., 2017; Zheng et al., 2018).

The potential exists to use both satellite and low-cost sensor data together ~~in order~~ to address the shortcomings of each data source individually and ~~thereby~~ to fill existing data gaps globally. Satellite data provides near-global coverage, but relationships between AOD and surface $PM_{2.5}$ do not generalize well across regions, and so local ground-based data are needed for establishing conversion factors. Low-cost sensors can provide these local data in areas where existing monitoring networks are sparse or data are ~~if reference-grade data are only~~ sporadically available. ~~Although individual low-cost sensors are subject to noise and drift, if a large number of such sensors is covered with a single satellite pass these errors may be averaged out. This paper~~The current work examines the use of low-cost PM sensors as ground data sources for ~~converting~~ estimating surface concentrations from satellite AOD retrievals ~~measurements into surface information for~~via two case studies. Specifically, we seek to quantify to what extent, even with the inherent uncertainties of low-cost sensors, their data might still be useful in estimating surface $PM_{2.5}$ from AOD.

First, using a dense network of low-cost monitors in Pittsburgh, Pennsylvania, USA, where a regulatory-grade monitoring network already exists, we assess the utility of low-cost sensors as compared to these traditional instruments. Second, using low-cost monitors deployed ~~in SSA in various locations~~ in Rwanda, Malawi, and the Democratic Republic of the Congo, we explore the utility of these low-cost sensors in previously unmonitored areas. ~~Although we have no overlapped networks of regulatory-grade and low-cost monitors in SSA to refer to, w~~We use US State Department data (~~freely~~ publicly available from US government websites as well as ~~various sources, including the US State Department and~~ the OpenAQ Platform at openaq.org~~openaq.org~~) from regulatory monitors at the US Embassies in Kampala, Uganda and Addis Ababa, Ethiopia to supplement our analysis of the relationship between converted satellite AOD data and surface-level $PM_{2.5}$ across SSA. In this work, we focus on high spatial and temporal resolution satellite data, which best aligns with the capacity of low-cost sensors to provide local air quality information in near-real-time. We do not incorporate meteorological or land use information, as such additional information may not be available in sparsely monitored areas. Further, keeping the model as simple as possible avoids over-fitting a more sophisticated model to its calibration data set, which can limit its generalizability. Instead, we use simple linear AOD to surface $PM_{2.5}$ conversion factors to indicate how low-cost sensors alone may provide additional information to inform conversion of AOD to surface $PM_{2.5}$, particularly in data-sparse domains. The techniques presented ~~hare~~ here are likely to translate to other data sources (e.g. new ~~reference~~regeulatory-grade monitors, new geostationary satellites) as they become available in the future.

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2 Methods

2.1 Low-cost PM$_{2.5}$ sensor data

Surface PM$_{2.5}$ data were collected with three types of low-cost sensors ~~systems~~(MetOne NPM, PurpleAir PA-II, and Alphasense OPC), as described ~~below~~in Table 1.

~~**2.1.1** MetOne Neighborhood Particulate Monitor (NPM)~~

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~~The Met-One Neighborhood Particulate Monitor (NPM) sensor uses a forward light scattering laser to provide estimates of PM mass. It is equipped with an inlet heater and PM$_{2.5}$ cyclone. The performance of these instruments has been assessed in previous studies (AQ-SPEC, 2015; Malings et al., 2019b) and they have been shown to have moderate correlation to regulatory-grade instruments. The cost of an NPM unit is about $2000, or about one-tenth that of a regulatory-grade instrument. It is recommended that these units be cleaned and re-calibrated regularly between field deployments; such maintenance activities are not always possible in certain remote deployment locations, however, and so long-term calibration drift and accumulation of debris in the cyclone is a potential source of error for these devices.~~

~~**2.1.2** PurpleAir II (PA-II)~~

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~~The PurpleAir PA-II monitor uses a pair of Plantower PMS 5003 laser sensors to detect particles. Estimates of PM$_1$, PM$_{2.5}$, and PM$_{10}$ mass concentrations are provided by these sensors. The units also have internal temperature and humidity sensors and wireless communications capability, allowing them to transmit data over local networks. Several units were also modified to interface with an external device for data collection (see Sect. 2.1.4). Previous tests have shown high correlation between these units and regulatory instruments, although this can vary, especially at high humidity (AQ-SPEC, 2017; Malings et al., 2019b). Individual Plantower sensors are also subject to malfunctions and performance degradation; a comparison between the Plantower sensors within the PA-II can be useful in detecting when these errors occur. These sensors are sold for about $250, or roughly one hundredth of the price of a regulatory-grade monitor.~~

~~**2.1.3** Alphasense Optical Particle Counter (OPC)~~

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~~The Alphasense OPC-N2 optical particle counter measures particles in the 0.38 to 17 μm range, and converts particle counts to PM$_1$, PM$_{2.5}$, and PM$_{10}$ mass concentrations using proprietary internal calibrations. Previous tests of these sensors showed moderate correlation with regulatory-grade instruments in field conditions (AQ-SPEC, 2016; Crilley et al., 2018). The Alphasense OPC sensors used in this paper were integrated into ARISense low-cost monitor nodes (see Sect. 2.1.4), which provided temperature and humidity information along with data collection and transmission services. The sensors themselves cost about $350, but this does not include the cost of the necessary electronics for logging and transmitting data nor of a weatherproof housing.~~

~~**2.1.4** Data collection and processing~~

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For data collection, all NPM and most PA-II units were paired with RAMP lower-cost monitoring packages. The RAMP (Real-time Affordable Multi-Pollutant) monitor is produced by SENSIT Technologies (Valparaiso, IN; formerly Sensevere), and has internal gas, temperature, and humidity sensors, along with the capability to interface with external PM monitors (newer models also have internal PM sensors). This allows data collected by these PM monitors to be stored and transmitted over cellular networks by the RAMP. The characteristics and operation of the RAMP are described elsewhere (Zimmerman et al., 2018; Malings et al., 2019a). The ARISense node, manufactured by Quant-AQ (Somerville, MA; formerly manufactured by Aerodyne Research), is a lower-cost sensor package ~~which~~ that combines internal gas, humidity, temperature, wind, and noise sensors, together with the Alphasense OPC-N2 PM sensor, and provides internet connectivity for data transmission (Cross et al., 2017). Most low-cost $PM_{2.5}$ data are collected via one of these two systems; the exception is a single independently-deployed PA-II unit in Kinshasa, DRC (see Sect. 1.1.1~~2.2.4~~).

Collected data are down-averaged from their device-specific collection frequencies to a common hourly timescale. Erroneous data identified either automatically (e.g. negative concentration values or unrealistically high or low values) or manually (e.g. devices exhibiting abnormal performance characteristics identified during periodic inspections) are removed. To correct for particle hygroscopic growth effects (i.e. the impact of ambient humidity on the PM mass as measured by the low-cost sensors), previously developed calibration methods (Malings et al., 2019b) were implemented for the NPM and PA-II sensors. Briefly, first, a hygroscopic growth factor is computed using the local humidity and temperature as measured by the low-cost monitor itself, along with an average or typical particle composition. Then, a linear correction is applied to the data based on past collocations with regulatory-grade monitoring instruments. ~~(these are described in detail by Malings et al., 2019b).~~ Utilizing these methods, the uncertainties on~~, based on previous assessments~~ ~~(Malings et al., 2019b),~~ hourly average $PM_{2.5}$ concentration ~~measures from both sensors (after calibration) differed from those of co-located regulatory-grade instruments by~~are about 4 µg/m^3~~, on average, with low long-term biases~~(Malings et al., 2019b). ~~(on the order of 1 µg/m^3 for annual averages).~~ For the Alphasense OPC sensors, raw bin count numbers were integrated to produce a new concentration estimate for $PM_{2.5}$, and a similar relative humidity correction was applied (Di Antonio et al., 2018). ~~Finally, a~~An additional correction factor of 1.69 (for workdays) or 1.39 (for non-work-days) was applied to data collected by NPM sensors in Rwanda, based on previous results showing that current calibration methods tended to underestimate $PM_{2.5}$ there (R Subramanian et al., under review)~~(R Subramanian et al., in preparation)~~. While we seek to use low-cost sensor data that have been calibrated and validated in accordance with best practices, there remain uncertainties associated with these instruments and inaccuracies compared to regulatory-grade instruments. A major goal of this paper is to assess to what extent, even with these uncertainties, low-cost sensor data might still be useful in the context of conversion of AOD to surface $PM_{2.5}$.

2.2 Ground-based sampling locations

Surface $PM_{2.5}$ data analyzed in this paper ~~are~~ were collected in ~~six~~ seven different areas, as ~~described~~ listed in Table 2, where approximate locations, number of sites in each area, and durations of data collection are also listed~~below~~. Maps of these sites are also provided in the supplemental information (Fig. S4-S9). The Pittsburgh area includes sites in the surrounding Allegheny county, although most sites are concentrated within the city. Similarly, the Rwanda area has most sites located in the capital city of Kigali, with one rural monitoring site collocated with the Mount Mugogo Climate Observatory in Musanze. In the Pittsburgh and Rwanda areas, low-cost sensors are connected with RAMP low-cost monitors. In Malawi,

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data are collected by three ARISense monitors using Alphasense OPC sensors, deployed to three locations in the vicinities of Lilongwe and Mulanje. The two locations in the vicinity of Mulanje are village-center sites, and so may be influenced by nearby combustion activities. In Kinshasa, a single PurpleAir PA-II was deployed independently (i.e. without an associated RAMP unit, as was the case in Pittsburgh) at the US Embassy. Temperature and humidity data were therefore obtained from the internal sensors within the devices ~~itself~~themselves, and data connectivity was achieved using the local wireless internet network. At Kampala and Addis Ababa, regulatory-grade monitoring data collected at US Embassies are used to provide ground comparison data for concentration estimates derived from satellite AOD data. Additional information about all of these areas are also provided in the supplemental information (Sect. S1).

~~2.4.0 Pittsburgh, United States of America~~

~~This area represents the city of Pittsburgh, Pennsylvania, USA, as well as the surrounding Allegheny County. Data from this area were collected during the calendar year of 2018 (i.e. January 1, 2018 to December 31, 2018). All ground measurement locations for this area were contained within a rectangular region ranging from 40.1ºN, 80.5ºW to 40.8 ºN, 79.7ºW. Low-cost monitoring data for this area were collected by a mixture of NPM and PA-II sensors, all of which were connected to RAMP monitors. During the data collection period, the number of active instruments in this area at any given time varied from 10 to 46. Calibration of these measures are performed according to the methods described by Malings et al. (2019b) as summarized in Sect. 2.1.4.~~

~~In the Pittsburgh area, ground-level $PM_{2.5}$ data were also available from a local regulatory-grade monitoring network operated by the Allegheny County Health Department (ACHD). These data are collected at five sites in Allegheny county, with Beta Attenuation Monitors (BAMs), a federal equivalent monitoring method, providing hourly concentration measurements for air quality index calculation purposes (Hacker, 2017; McDonnell, 2017). Nominally, such federal equivalent methods are required to be accurate within 10% of federal reference methods (Watson et al., 1998; US EPA, 2016). Since BAM data have been used to establish the calibration methods for low-cost PM sensor data, the data from the BAM instruments are used as provided for uniformity, without any additional corrections being applied.~~

~~2.7.0 Rwanda~~

~~Data collection in Rwanda occurred mainly in the capital city of Kigali, along with a single rural monitoring site co-located with the Mount Mugogo Climate Observatory in Musanze. Data in this area were collected between April 1, 2017 and May 27, 2018. The sites were located in a rectangle ranging from 2.2ºS, 29.4ºE to 1.4ºS, 30.5ºE. In this area, NPM sensors paired with RAMP monitors were used exclusively. A total of four ground sites were active in this area, with a maximum of three sites being active simultaneously.~~

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~~**2.9.0** Malawi~~

~~Data in Malawi were collected by three ARISense monitors using Alphasense OPC sensors, deployed to three locations in the vicinities of Lilongwe and Mulanje between June 25, 2017 and July 30, 2018. These sites were contained within a rectangular region spanning from 16.2ºS, 33.6ºE to 14.0ºS, 35.7ºE. The two locations in the vicinity of Mulanje are village center sites, and so may be influenced by nearby combustion activities.~~

~~**2.11.0** Kinshasa, Democratic Republic of the Congo~~

~~Data in Kinshasa, Democratic Republic of the Congo were collected by a single PurpleAir PA-II sensor deployed at the US Embassy, at approximately 4.3ºS, 15.3ºE. This sensor was deployed independently, i.e. without an associated RAMP unit as in Pittsburgh. Temperature and humidity data were therefore obtained from the internal sensors within the device itself, and data connectivity was achieved using the local wireless internet network. Data from this device collected between March 20, 2018 and October 31, 2019 are used in this paper.~~

~~**2.13.0** Kampala, Uganda~~

~~In Kampala, Uganda, regulatory-grade monitoring data collected at the US Embassy are used to provide ground comparison data for concentration estimates derived from satellite AOD data. The embassy is located at approximately 0.3ºN, 32.6ºE, and hourly data collected from January 1, 2019 to December 31, 2019 are used in this paper. These data are collected by BAM monitors, and no additional corrections have been applied.~~

~~**2.15.0** Addis Ababa, Ethiopia~~

2.3 ~~**In Addis Ababa, Ethiopia, a regulatory-grade monitor deployed at the US Embassy is also used as a ground comparison data source, with data collected from January 1, 2019 to December 31, 2019 being used in this paper. The embassy is located at approximately 9.0ºN, 38.8ºE. These data are also collected by BAM monitors, and no additional corrections have been applied.**~~ **Regulatory-grade instrument data**

At several locations in the Pittsburgh area, as well as at the US Embassy locations in Kampala and Addis Ababa, hourly-averaged ground-level $PM_{2.5}$ data are also available from regulatory-grade monitoring instruments. In Pittsburgh, these monitors are operated by the Allegheny County Health Department (ACHD). At the US Embassies, these instruments are operated by the US State Department and US EPA and data are made available by these agencies (https://www.airnow.gov/international/us-embassies-and-consulates), as well as by the OpenAQ Platform (openaq.org). In all cases, regulatory-grade monitoring data are collected with Beta Attenuation Monitors (BAMs), a federal equivalent monitoring method, that provide hourly $PM_{2.5}$ concentration measurements for air quality index calculation purposes (Hacker, 2017; McDonnell, 2017). Nominally, such federal equivalent methods are required to be accurate within 10% of federal reference methods (Watson et al., 1998; US EPA, 2016). Since BAM data have been used to establish the calibration

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methods for low-cost PM sensor data (Malings et al., 2019b), the data from the BAM instruments are used as provided for uniformity, without any additional corrections being applied.

~~2.17~~2.4 Satellite data

The satellite data product used in this paper is the MODIS MCD19A2v006 dataset (Lyapustin and Wang, 2018) available through NASA's Earth Data Portal (earthdata.nasa.gov). This dataset consists of AOD information for the 470nm and 550nm wavelengths from the MODIS system, processed using the Multi-angle Implementation of Atmospheric Correction (MAIAC) algorithm, and presented at 1 km ~~kilometer~~ pixel resolution for every overpass of either the Aqua or Terra satellites (Lyapustin et al., 2011a, 2011b, 2012, 2018). This represents a Level 2 data product, meaning that it includes geophysical variables derived from raw satellite data, but has not yet been transformed to a new temporal or spatial resolution, as is the case for data derived from multiple satellite passes, e.g. monthly average AOD data. Data from identified cloudy pixels ~~is~~ are masked as part of the data product; possible misidentification of cloudy pixels is one source of error in relating surface $PM_{2.5}$ and AOD. As per recommendations in the User Guide for this dataset, only data matching "best quality" quality assurance criteria are used. This dataset was chosen as it represents the highest possible spatial and temporal resolution for AOD, thus providing the most points for comparison with the high spatio-temporal resolution low-cost monitor data.

Satellite AOD data are considered to be collocated in space with data from a ground site when the center of the AOD pixel is within 1 km of the ground site. Data are considered concurrent if the satellite overpass occurs within the hour interval over which ground site data have been averaged to arrive at the hourly-average $PM_{2.5}$ concentration value used. As we compare data from individual satellite passes directly to temporally collocated ground site data, we do not need to consider (as would be essential for long-term averages) the potential impact of the fraction of time where satellite measures are missing (due to cloud cover or other factors). Likewise, we do not consider the biases associated with the fact that satellite passes occur at certain times of day (required when comparing with daily-averaged ground monitoring data) since here we only compare AOD to surface $PM_{2.5}$ during the same hour when the satellite pass occurs.

~~2.18~~2.5 Conversion Methods for satellite AOD ~~data~~

A linear regression approach is used to establish relationships between satellite AOD and surface-level $PM_{2.5}$. Let $y_{i,t}$ denote the ground-level $PM_{2.5}$ measurement at location i and time t, and let $x_{i,t}$ represent the ~~vector of~~ satellite AOD ~~measurements~~ (i.e., a vector combining the AOD ~~measurements~~ at 470nm ~~and~~ or 550nm wavelength~~s,~~ ~~together~~ with a "placeholder" constant of one to allow fitting of affine functions) corresponding to location i and time t. For this paper we present results using AOD at 550nm; results for AOD at 470nm are similar and are included in the supplemental information (Sect. S3.2). The total set of ground measurement sites in an area, S, is partitioned into two disjoint sub-sets. Subset S_{in} represents the

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sites used to establish the linear relationship between AOD and surface $PM_{2.5}$ concentrations. The remainder of sites, in the subset S_{ap}, are used for the application, i.e., to serve as an independent set to evaluate the performance of the linear relationship established from the S_{in} sites. Likewise, the time domain T is partitioned into initialization phase T_{in}, during which linear relationships are established, and application phase T_{ap}, during which these relationships are applied and evaluated.

Linear relationships are determined as follows. First, satellite AOD data and surface $PM_{2.5}$ monitor data from the S_{in} sites during the T_{in} phase ~~were~~ are collected together:

$$X_{\mathrm{in}} = \{x_{i,t}\} \quad Y_{\mathrm{in}} = \{y_{i,t}\} \quad \forall\ i \in S_{\mathrm{in}}\,,\ t \in T_{\mathrm{in}}, \tag{1}$$

A linear relationship is established between these, defined by parameters β_{in}, using classical least-squares linear regression (e.g., Goldberger, 1980):

$$\beta_{\mathrm{in}} = \left(X_{\mathrm{in}}^{\mathrm{T}} X_{\mathrm{in}}\right)^{-1} X_{\mathrm{in}}^{\mathrm{T}} Y_{\mathrm{in}}, \tag{2}$$

The covariance matrix of the parameters, $\Sigma_{\beta_{\mathrm{in}}}$, is also obtained:

$$\Sigma_{\beta_{\mathrm{in}}} = \frac{(Y_{\mathrm{in}} - X_{\mathrm{in}}\beta_{\mathrm{in}})^{\mathrm{T}} (Y_{\mathrm{in}} - X_{\mathrm{in}}\beta_{\mathrm{in}})}{\mathrm{length}(Y_{\mathrm{in}}) - \mathrm{length}(\beta_{\mathrm{in}})} \left(X_{\mathrm{in}}^{\mathrm{T}} X_{\mathrm{in}}\right)^{-1}, \tag{3}$$

where $\mathrm{length}(\cdot)$ is a function returning the number of elements in the input. During the application phase, the linear relationship can be used to estimate the surface $PM_{2.5}$ concentration at location i and time t, $\hat{y}_{i,t,\mathrm{prior}}$, from the satellite AOD data corresponding to that location and time:

$$\hat{y}_{i,t,\mathrm{prior}} = x_{i,t}\ \beta_{\mathrm{in}}, \tag{4}$$

The above procedure constitutes an offline or (in Bayesian terminology) prior conversion, i.e., it uses data collected during the initialization phase to define a single conversion factor ~~which~~ that is applied throughout the application phase. An online, dynamic, or (in Bayesian terminology) posterior approach can also be adopted, in which this relationship is modified as additional data are available. This approach has been proposed by Lee et al. (2011) and evaluated by Han et al. (2018), and allows for the potentially time-varying relationship between satellite AOD and surface $PM_{2.5}$ concentration to be accounted for. In the online approach, for a time t during the application phase, a new data set consisting of $Y_{\mathrm{in},t}$ and $X_{\mathrm{in},t}$ is created by combining all data available from the S_{in} ground sites together with satellite AOD data for that time:

$$X_{\mathrm{in},t} = \{x_{i,t}\} \quad Y_{\mathrm{in},t} = \{y_{i,t}\} \quad \forall\ i \in S_{\mathrm{in}}, \tag{5}$$

Based on these new data, a linear relationship is established for that time, as above:

$$\beta_t = \left(X_{\mathrm{in},t}^{\mathrm{T}} X_{\mathrm{in},t}\right)^{-1} X_{\mathrm{in},t}^{\mathrm{T}} Y_{\mathrm{in},t}, \tag{6}$$

This relationship is combined with the prior relationship established during the initialization phase (using a Bayesian approach and assuming normally-distributed parameter values) to establish a new posterior relationship specific to that time, $\beta_{t,\text{post}}$:

$$\beta_{t,\text{post}} = \beta_{\text{in}} + \Sigma_{\beta_{\text{in}}}\left(\Sigma_{\beta_{\text{in}}} + \eta^2 \text{diag}\left(\Sigma_{\beta_{\text{in}}}\right)\right)^{-1}\left(\beta_t - \beta_{\text{in}}\right) \approx \frac{1}{1+\eta^2}\left(\eta^2 \beta_{\text{in}} + \beta_t\right), \tag{7}$$

where $\text{diag}(\cdot)$ denotes a matrix diagonalization and η is a relative error scale parameter, used to define how much "weight" is given to the time-specific relationship parameters β_t versus the prior relationship parameters β_{in} in the updating process (with values of η near zero placing more weight on the time-specific relationships, while high values of η place more weight on the prior). The posterior relationship is then used to estimate surface $PM_{2.5}$ concentrations from the satellite AOD data for that time:

$$\hat{y}_{i,t,\text{post}} = x_{i,t}\, \beta_{t,\text{post}}, \tag{8}$$

Both the offline and online approaches are used in this paper, and their performance is compared (see Sect. 3.1).

This simple linear correction factor method does not explicitly account for vertical distribution profiles, cloud cover, or any other variables ~~which~~ that affect the relationship of AOD to surface $PM_{2.5}$. Instead, the aggregate ~~affect~~effect of these variables is accounted for implicitly in an empirical relationship. The offline approach uses fixed relationships, which cannot account for time-varying effects such as changes in vertical distribution profiles. The online approach can account for these time-varying effects ~~to some degree,~~by assuming their observed impact on the AOD to surface $PM_{2.5}$ relationship at the S_{in} sites is representative of their short-term impact throughout the region where the corresponding correction factors are applied. Finally, note that all parameters described above can be solved for analytically using the equations presented in this section (i.e. no iterative or approximate solution methods are necessary).

2.6 Analyses conducted in this paper

This section provides details of how the various analyses and comparisons to be discussed in Sect. 3 are performed. Additional details are also provided in the supplemental information (Sect. S2.2 to S2.4).

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2.6.1 Comparison of regulatory and low-cost monitors as ground stations to develop conversion factors for AOD

Here, we seek to compare the performance of AOD conversion to surface $PM_{2.5}$ using either low-cost or regulatory-grade monitors as the ground-level data source for initialization. As only Pittsburgh has networks of both types of sensors in place, we focus our analysis in this area. The surface $PM_{2.5}$ data collected at the five ACHD regulatory monitoring locations are used to assess the performance of the satellite AOD conversion, regardless of how the conversion factors are initialized. First, we use four of five ACHD locations to develop a conversion factor and apply it to the fifth. All ACHD sites are rotated through in this manner, providing a performance metric assessed for AOD conversion applied to each site. Second, we use

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low-cost sensors for developing the conversion factor; in this case, we select a subset of four locations in Pittsburgh where RAMP low-cost monitors are deployed, so that the number of ground sites used matches the number of ACHD sites used in the first case. These low-cost monitor locations are chosen to provide a similar spatial coverage over Allegheny county as the ACHD sites. Low-cost monitors collocated with ACHD sites were specifically not chosen to allow for a fairer comparison when performance is assessed against these ACHD site (since, if this were not done, it would be possible to have initialization sites which are collocated with the application sites, which was not possible when the ACHD sites alone were used). In this case, a conversion factor developed using the four low-cost sensor sites is applied at all five ACHD sites, with performance assessed at each site.

Different application cases of the satellite AOD conversion method are also tested. Note that in either case, we use all the collocated ground and satellite data across the entire time period without averaging these data in time. For a "yearly" conversion, data from the entire calendar year are used to develop the conversion factors, while in the "monthly" case, data from the previous month are used to develop conversion factors that are then assessed in the current month (e.g. January data are used to develop conversion factors that are applied in February, then the February data are used to develop conversion factors that are applied in March, etc.). For the "monthly" case, the median performance across months is presented. Although the "yearly" case would technically require having access to data that have not yet been collected (assuming this method is being applied for data collected in the current year), we use this to represent a case where data from a previous year are used to develop conversions applied in the current year, as we assume that the annual average AOD to surface $PM_{2.5}$ concentration relationship for a given area will not significantly change from one year to the next. In addition, we also assess the relative performance of the offline (prior) conversion factors, where the same relationship parameters determined during the initialization period are applied to the entire application period, and the online (posterior, dynamic) conversion, where these initial parameters are modified based on the AOD to surface $PM_{2.5}$ relationships specific to each individual satellite pass. The results of this analysis are discussed in Sect. 3.1.

2.6.2 Analysis of AOD conversion factor performance versus number of ground sites

A significant advantage of low-cost monitors compared to traditional instruments is ~~the ability to~~that we can deploy ~~dense networks of the former for the same cost as a sparse network of the latter~~tens to hundreds of low-cost sensors for the price of a single regulatory-grade monitor. To assess the potential benefits of this in terms of conversion of satellite AOD data to surface $PM_{2.5}$, we analyze the ~~effect~~influence of the number of surface sites used on the performance of the surface $PM_{2.5}$ estimates from AOD conversion. We again examine the Pittsburgh region, vary the number of ground sites used for initialization to generate the AOD conversion factor, and ~~take~~evaluate the performance using the ACHD regulatory monitoring network as the "ground truth. ~~" against which performance is assessed. Here, the number of ground sites is varied, with sites being chosen from the set of possible sites.~~ For the ACHD network, the possible sites are the ACHD sites minus the one site against which performance is assessed (all ACHD sites are rotated through)~~; this is schematically shown in Fig. S7~~. For the low-cost sensors, the possible sites are all RAMP deployment locations in the area, excluding RAMPs that are collocated with ACHD sites, and performance is assessed against all ACHD sites. ~~,~~Subsets of varying size are randomly selected (10 different random set selections are used in this example); the mean of the performance metric across these 10 randomly selected sets is used as the assessed performance~~ (as depicted in Fig. S8)~~. In this case, a ~~monthly offline~~yearly online conversion factor is used (based on the performance of that method as described in Sect. 3.1)~~ (with the factor developed in one month being applied in the following month without modification). Figure 3 shows results of this assessment in terms of the CvMAE metric.~~

The results of this analysis are discussed in Sect. 3.2.

2.6.3 Comparison of converted AOD and nearest ground monitors as proxies for surface $PM_{2.5}$

~~In this section, w~~Here, we seek to assess the benefits of combining satellite AOD and ground-based sensor data, as compared to using ground-based sensor data alone. For this assessment, we compare estimates of surface $PM_{2.5}$ derived from satellite AOD data, using the methods presented previously in this paper, with estimates based on the surface $PM_{2.5}$ measurements alone, which we denote as "nearest monitor" estimates. For this estimation, we make use of a locally constant or naïve interpolation, in which the surface $PM_{2.5}$ estimate for a given time and location is the same as the measurement of the nearest available ground monitor (i.e., one of the ground monitors used for establishing conversion factors for the satellite AOD data) at that time:

$$\hat{y}_{i,t,\text{nearest}} = y_{j,t} \ \text{ s.t. } \ j = \text{argmin}_{k\in S_{\text{cal}}} \text{dist}(i,k), \qquad (9)$$

where $\text{dist}(i,k)$ indicates the distance between locations i and k, and argmin denotes the input ~~which~~that minimizes this objective.

~~Performance of both this nearest monitor method and the satellite AOD conversion method are assessed for Pittsburgh in Fig. 4.~~ In this case, ~~the~~ low-cost sensor data are used to represent the "ground truth" against which performance is assessed; this is done so that a comparable analysis can be made in Pittsburgh and Rwanda, since no regulatory-grade instruments were present in the latter area. Prior ~~Again, c~~conversion factors are developed for the entire time period and are ~~applied~~updated to posterior factors with time-specific data for their application~~ on a monthly basis~~. All but one low-cost sensor sites in a given area are used for development of these factors, with application and assessment on the final site.~~; it should be noted that this represents a greater number of ground sites than was evaluated in Sect. 3.1, leading to improved performance following the trend noted in Sect. 3.2.~~ These sites are then cycled through, to provide performance metrics across all sites. To allow for comparability between the nearest monitor approach and surface $PM_{2.5}$ estimation from satellite AOD, we make use of the same set of ground sites for both, i.e., for each site, data from the closest available sites are used as inputs to the nearest monitor method, and all sites are cycled through in this manner, providing performance metrics for each site as above.~~ A diagram of this procedure is provided in the supplemental information, Fig. S9.~~

The results of this analysis are discussed in Sect. 3.3 (for Pittsburgh) and 3.4 (for Rwanda).

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2.6.4 Analysis of inter-seasonal generalization of AOD conversion factors

Changing seasons can affect the relationship between satellite AOD and surface $PM_{2.5}$ due to changes in confounding factors like surface reflectance, aerosol vertical profiles, and particle composition. ~~Many of these seasonally varying factors are not accounted for in current AOD retrievals (Lyapustin et al., 2018).~~ Here, we assess the utility of developing seasonal AOD conversion factors for Pittsburgh and Rwanda. For this assessment, conversions are developed and applied in specific seasons (information on these seasons are presented in the supplemental information, Table S1 and Fig. S1). For Pittsburgh, these approximately correspond to a winter, spring, summer, and fall season, while in Rwanda, these represent alternating wet and dry seasons. For Pittsburgh, the major differences between seasons are related to temperature, with humidity varying to a lesser degree~~, as depicted in Fig. S2~~. In Rwanda, temperatures are relatively stable year-round, with seasons mainly differentiated by humidity changes (although the second dry season appears to have been unusually wet, comparable to the previous wet season).

RAMP data are used to represent “ground truth” concentrations for both areas. An offline or “prior” approach is used here, i.e., calibrations are not modified based on data collected within the application period, in order to investigate the effect of generalizing a calibration developed in one season to a different season. Metrics are assessed for each individual site in each area, with all other sites being used to establish AOD conversion factors as in the previous section. ~~The median results across all sites are presented in Fig. 6 for each combination of initialization and application season.~~

The results of this analysis are discussed in Sect. 3.5.

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2.6.5 Analysis of inter-regional generalization of AOD conversion factors

Finally, given the lack of ground-based monitoring in many parts of SSA, we assess whether a conversion factor developed in one city of this region can be generalized to other cities ~~and towns~~or locations across SSA. Here, a single AOD conversion factor is developed using one site in Kigali, Rwanda and this factor is applied without modification to other sites across SSA. These include a second site in Kigali, a site in Musanze in rural Rwanda, a site in Kinshasa (DR Congo), and three sites in Malawi (one near the urban area of Lilongwe and two other sites in more rural areas to the south, near Mulanje) where low-cost sensor systems are deployed. There are also two sites (Kampala, Uganda and Addis Ababa, Ethiopia) where hourly-resolution long-term regulatory-grade monitoring data are available; data from these sites are included for comparative purposes. An offline approach is used here, with a single factor being initialized over the entire study period. The results of this analysis are discussed in Sect. 3.6.

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3 Results

In this section, we apply the proposed method for satellite AOD to surface $PM_{2.5}$ concentration conversion in several use cases. In Sect. 3.1, 3.2, and 3.3, we assess the performance in Pittsburgh, comparing the use of regulatory-grade monitors and low-cost monitors as ground sites for establishing conversion factors. In Sect. 3.4 and 3.5, we extend the comparison to

Rwanda, examining the impact of using the relatively sparser low-cost sensor network there, and examining seasonal variations in the conversions. Finally, in Sect. 3.6, we examine the generalization of~~ a~~ Rwanda-based conversion factors to other locations across SSA. Assessment metrics used in this section, including correlation ($r^{\cancel{2}}$), coefficient of variation of the mean absolute error (CvMAE), and mean-normalized bias (MNB) are described in the supplemental information (Sect. S2.1).

3.1 Comparing the use of regulatory and low-cost monitors as ground stations to develop conversion factors for AOD

We first evaluate the utility of low-cost sensors as substitutes for regulatory-grade monitors when developing factors to convert satellite AOD data to surface $PM_{2.5}$ estimates, using the Pittsburgh area as our case study. ~~The five ACHD regulatory monitoring locations are used to assess the performance of the satellite AOD conversion in all cases. First, we use these same locations to develop the conversion factors; in this case, we use four of five locations to develop a conversion factor, and apply it to the fifth. All sites are rotated through in this manner, providing a performance metric assessed for each site. Second, we use low-cost sensors for developing the conversion factor; in this case, we select a subset of four locations where RAMP low-cost monitors are deployed, so that the number of ground sites used matches the number of ACHD sites used in the other case. These low-cost monitor locations are chosen to provide a similar spatial coverage over Allegheny county as the ACHD sites, although monitors co-located with ACHD sites were specifically not chosen, to allow for a fairer comparison when performance is assessed against the ACHD network (as a measurement will never be available at the exact location where the concentration is to be estimated, as was the case when the ACHD sites alone were used). In this case, a conversion factor developed using the four low-cost sensor sites is applied across all five ACHD sites, with performance assessed at each site. A diagram of this procedure is provided in the supplemental information Fig. S6.~~

~~Different application cases of the satellite AOD conversion method were also tested. For a "yearly" conversion, data from the entire calendar year were used to develop the conversion factors, while in the "monthly" case, data from the previous month are used to develop conversion factors used in the current month; the median performance across months is presented. Although the "yearly" case would technically require having access to data which have not yet been collected (assuming this method is being applied for data collected in the current year), we use this to represent a case where data from a previous year are used to develop conversions applied on the current year, as we assume that the annual average AOD to surface $PM_{2.5}$ concentration relationship for a given area will not significantly change from one year to the next. In addition, we also assess the relative performance of the offline (prior) conversion factors, where the same relationship parameters determined during the initialization period are applied to the entire application period, and the online (posterior) conversion, where these initial parameters are modified based on the AOD to surface $PM_{2.5}$ relationships specific to each individual satellite pass.~~ Results for all eight combinations of ground initialization site monitor type ("ACHD" v. "RAMP"), initialization period length ("yearly" vs. "monthly"), and ~~processing method~~application mode ("prior" vs. "post.") are presented in Fig. 2.

Overall, these results indicate relatively weak relationships between satellite AOD and surface $PM_{2.5}$ for Pittsburgh, regardless of the method used. Correlations are weak ($r^{\cancel{2}} < 0.$~~3~~5)~~,~~ and mean absolute errors are on the order of half to threequarters the concentration values (annual average concentrations ~~range from~~are about 10~~ to 12~~ μg/m^3 across most of Pittsburgh). ~~However, these results are consistent with similar comparisons conducted between hourly AOD and surface PM$_{2.5}$ in the eastern United States, which found r^2 between 0.04 and 0.36 depending on season and location (Zhang et al., 2009).~~ Biases are low on averag~~e,~~e but can vary across locations. In comparing the different application modes, ~~it seems that~~ the “~~posterior~~posterior” method provides ~~slightly worse~~better performance~~, especially~~ ~~on ACHD data~~in terms of correlation~~,~~ than the “~~prior~~prior” method. This suggests that variability in AOD to surface PM$_{2.5}$ relationships between satellite passes (e.g., due ~~for example~~ to differences in the vertical profile of PM$_{2.5}$ over the area, and/or to differences between “point” measurements of the ground monitors and “area” AOD~~ measurements~~) is ~~not being well captured through the “posterior” method, i.e., that the additional uncertainty incurred by calibrating relationships using satellite data from a single pass (versus relying only on the more robust calibration from multiple passes as in the “prior” method) tends to degrade performance~~better captured by updating prior relationships with new information from each new satellite pass. In terms of other performance metrics, there is little difference between these application modes, with slight improvements observed in the “posterior” method for the RAMP data, but slight decreases for the ACHD data. Comparing the use of annual to monthly initializations, performance metrics are slightly worse in the monthly case, indicating that the additional initialization data used in the yearly case generally leads to a more robust conversion. ~~This may be due to the~~It should be noted, however, that these conclusions may be specific to relatively low PM$_{2.5}$ concentrations as found in ~~conditions of~~ Pittsburgh~~, however; the comparatively low PM$_{2.5}$ concentrations in this area (averaging less than 10 μg/m^3 during the study period) may reduce the signal-to-noise ratio to the point where the noise is dominant~~.

In all cases, performances using low-cost sensor data are comparable ~~or superior~~ to that of the same conversion approaches utilizing the regulatory-grade instruments. Note that the low-cost monitors used here have been carefully corrected by collocation with regulatory-grade monitors (Malings et al., 2019b) which accounts for known artefacts with low-cost sensors. Thus, there is no evidence from this analysis of any inherent disadvantage to the use of carefully corrected low-cost sensors to provide ground data as compared to more traditional instruments. Rather, based on these results, any additional uncertainty due to ~~D~~data quality differences between low-cost sensors and regulatory-grade instruments ~~seem~~ are seen to be negligible compared to the difficulties associated with relating satellite AOD to surface-level PM$_{2.5}$, and therefore have had ~~little to~~ no systematic impact on the performance of the assessed linear conversion method~~s~~, at least for this study area.

3.2 How many ground stations are needed to improve surface PM$_{2.5}$ estimates from AOD ~~data~~retrievals?

Fig. 3 sh~~A significant advantage of low-cost monitors compared to traditional instruments is the ability to deploy dense networks of the former for the same cost as a sparse network of the latter. To assess the potential benefits of this in terms of conversion of satellite AOD data to surface PM$_{2.5}$, we analyze the effect of the number of surface sites used on the performance of the surface PM$_{2.5}$ estimates from AOD conversion. We again examine the Pittsburgh region, and take the ACHD regulatory monitoring network as the “ground truth” against which performance is assessed. Here, the number of ground sites is varied, with sites being chosen from the set of possible sites. For the ACHD network, the possible sites are~~

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~~the ACHD sites minus the one site against which performance is assessed (all ACHD sites are rotated through); this is schematically shown in Fig. S7. For the low-cost sensors, the possible sites are all RAMP deployment locations in the area. Subsets of varying size are randomly selected (10 different random set selections are used in this example); the mean of the performance metric across these 10 randomly selected sets is used as the assessed performance (as depicted in Fig. S8). In this case, a monthly offline conversion factor is used (with the factor developed in one month being applied in the following month without modification). Figure 3 shows results of this assessment in terms of the CvMAE metric.~~ows results of the assessment conducted as described in Sect. 2.6.2 in terms of the CvMAE metric.

For small numbers of ground sites, results for the ACHD network and the low-cost sensor network are similar in terms of mean performance across different randomly selected subsets of the network, with slightly better performance using the RAMP network sites. ~~The spread in performance across selected sites is lower for the ACHD network; this~~This may be ~~is~~ related to the smaller number of possible combinations of ACHD sites to be randomly selected compared to the RAMP sites; with more RAMP sites to choose from, the likelihood of selecting more generally representative (rather than more source-impacted) sites is higher, whereas with the ACHD network there is a high likelihood of choosing a heavily source-impacted site (especially since several ACHD locations are specifically chosen to monitor such local sources; see supplemental information Fig. S4). ~~s, which would lead to lower variability in the results.~~ The limited number of ACHD sites prevents this analysis ~~to be carried forward~~ from being expanded to larger numbers of locations; at four chosen locations, there is only one possible combination to be selected, and so the spread in performance collapses to match the mean. With the low-cost sensor network, as more ground sites are included, mean ~~performance~~ CvMAE decreases until about 10 sites are chosen, but afterwards remains relatively constant as more sites are included. ~~stays roughly constant, but p~~Performance variability decreases as more site are added, indicating that by adding additional ground sites, even sites positioned at random throughout the domain, the conversion relationship becomes increasingly robust. ~~In particular, while~~ While for a single ground monitor, worst-case CvMAE is on the order of 1.5 to 2, with 10 or more monitors, worst-case performance is improved below 0.~~8~~6, a more than two-fold improvement in worst-case performance. ~~This performance increase slows beyond about 15 ground stations, indicating that this may be an optimal density (at least in the Pittsburgh area) for ground sites for establishing conversion relationships to satellite AOD data.~~ Overall, this demonstrates the potential benefits of dense low-cost sensor networks for conversion of satellite AOD data, even over a limited spatial domain (covering about 600 ~~square kilometers~~km^2). Furthermore, it shows that even with quasi-random placement of the ground sites, such as might be achieved by citizens making personal decisions to deploy low-cost monitors on their own properties, increasingly robust conversion results can be achieved as more sensors are included, although these benefits diminish beyond (at least in th~~e~~is case of Pittsburgh) about ~~15~~ 1 monitor~~s~~ ~~across~~ per 6~~0~~0 ~~square kilometers~~km^2.

3.3 Comparison of AOD-based surface $PM_{2.5}$ to measurements from a dense ground network

Performance of both the nearest monitor method and the satellite AOD conversion method are assessed for Pittsburgh in Fig. 4. It should be noted that all available ground sites have been used for conversion factor initialization in this section, versus a

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limited subset of these in Sect. 3.1, leading to improved performance of this method following the trend noted in Sect. 3.2. ~~In this section, we assess the benefits of combining satellite AOD and ground-based sensor data, as compared to using ground-based sensor data alone. For this assessment, we compare estimates of surface $PM_{2.5}$ derived from satellite AOD data, using the methods presented previously in this paper, with estimates based on the surface $PM_{2.5}$ measurements alone, which we denote as "nearest monitor" estimates. For this estimation, we make use of a locally constant or naïve interpolation, in which the surface $PM_{2.5}$ estimate for a given time and location is the same as the measurement of the nearest available ground monitor (i.e., one of the ground monitors used for establishing conversion factors for the satellite AOD data) at that time:~~

$$\cancel{\hat{y}_{i,t,\mathrm{nearest}} = y_{j,t} \ \text{ s.t. } j = \operatorname{argmin}_{k \in S_{\mathrm{cal}}} \mathrm{dist}(i,k),} \qquad \cancel{(9)}$$

~~where $\mathrm{dist}(i,k)$ indicates the distance between locations i and k, and argmin denotes the input which minimizes this objective.~~

~~Performance of both this nearest monitor method and the satellite AOD conversion method are assessed for Pittsburgh in Fig. 4. In this case, the low-cost sensor data are used to represent the "ground truth" against which performance is assessed. Again, conversion factors are developed and applied on a monthly basis. All but one low-cost sensor sites are used for development of these factors, with application and assessment on the final site; it should be noted that this represents a greater number of ground sites than was evaluated in Sect. 3.1, leading to improved performance following the trend noted in Sect. 3.2. These sites are then cycled through, to provide performance metrics across all sites. To allow for comparability between the nearest monitor approach and surface $PM_{2.5}$ estimation from satellite AOD, we make use of the same set of ground sites for both, i.e., for each site, data from the closest available sites are used as inputs to the nearest monitor method, and all sites are cycled through in this manner, providing performance metrics for each site as above. A diagram of this procedure is provided in the supplemental information, Fig. S9.~~

~~In~~In Pittsburgh, we see reduced performance (lower correlation, larger CvMAE~~, larger spread in the bias~~) when using converted satellite data as compared to nearest monitor data. This is likely a result of the quite dense network of low-cost sensors present in Pittsburgh, where the median distance between sensors in the network is about 1 km. With this dense network, there is a good chance that the nearest ground monitor will be quite close to the location at which concentrations are to be estimated, and the resulting "nearest monitor" estimate is therefore likely to be quite good, as PM concentrations tend to be homogenous at this spatial scale ~~have~~ in Pittsburgh (Li et al., 2019). When $PM_{2.5}$ is instead estimated from satellite data using a simple linear relationship, spatial and temporal variability in surface $PM_{2.5}$ to AOD relationships ~~is introduced, which~~ can confound the assessment. This is especially important considering the relatively low levels of surface $PM_{2.5}$ concentration and AOD in and above Pittsburgh, meaning that any introduced noise will be relatively large in proportion to the signal being assessed. These results indicate that dense ground-based monitoring (if available) will likely outperform AOD-derived surface $PM_{2.5}$ at least for the simple conversion method used here.

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~~3.5~~3.4 The utility of AOD-based surface PM$_{2.5}$ in regions with a sparse ground monitoring network

Performance of the nearest monitor method and the satellite AOD conversion method are assessed for Rwanda in Fig. 5, in a similar manner as was done for Pittsburgh in Fig. 4. In Rwanda, we see an improvement across all metrics (~~slightly~~ higher and more consistent correlation, ~~much~~ smaller and more consistent CvMAE, and less spread in the bias) as satellite data are combined with surface PM$_{2.5}$ monitor data. ~~In particular, m~~Median CvMAE is reduced from about 0.5 to 0.3, a 40% improvement. Because of the relative sparsity of the low-cost monitor network in Rwanda (4 measurement sites, not all of which were simultaneously operational) compared to that in Pittsburgh, the assumption of spatial homogeneity of concentrations between monitoring sites is less valid, and so the inclusion of satellite data is beneficial in resolving these spatial differences. Furthermore, the relatively high levels of PM$_{2.5}$ concentration in Rwanda (average of about 40 μg/m^3 over the study period) allows for a higher signal-to-noise ratio relative to Pittsburgh. Together, these results indicate the high utility of low-cost sensors, used in conjunction with satellite data, when these are deployed even in relatively sparse networks to previously unmonitored areas with high surface PM$_{2.5}$ concentrations.

This point is further explored in Fig. 6, which compares the correlations between ground measurements in Pittsburgh and Rwanda with the AOD-to-surface-PM correlations in these areas. In Pittsburgh, the high density of available monitors leads to relatively high inter-site correlations, above the typical range of the AOD-to-surface-PM correlations. It is therefore difficult to extract meaningful patterns from the AOD information that would not also be present in available surface-level measurements, suggesting that AOD data provide little additional value in this densely monitored area (at least in terms of what can be derived without including additional information sources like atmospheric modelling and land use characteristics). Meanwhile, in sparsely monitored Rwanda, inter-site correlations are lower, overlapping the typical range of AOD-to-surface-PM correlations. This means that AOD data can still provide useful information for spatial heterogeneities in this region.

~~Together, these results indicate the high utility of low-cost sensors, used in conjunction with satellite data, when these are deployed even in relatively sparse networks to previously unmonitored areas with high surface PM$_{2.5}$ concentrations.~~

~~3.7~~3.5 Seasonal effects on satellite AOD conversion to surface PM$_{2.5}$

Fig. 7 presents the median performance metrics across all sites in either Pittsburgh or Rwanda for each combination of initialization and application season. ~~Changing seasons can affect the relationship between satellite AOD and surface PM$_{2.5}$ due to changes in confounding factors like surface reflectance, aerosol vertical profiles, and particle composition. Many of these seasonally varying factors are not accounted for in current AOD retrievals (Lyapustin et al., 2018). Here, we assess the utility of developing seasonal AOD conversion factors for Pittsburgh and Rwanda. For this assessment, conversions are developed and applied in specific seasons (information on these seasons are presented in the supplemental information). For Pittsburgh, these approximately correspond to a winter, spring, summer, and fall season, while in Rwanda, these represent alternating wet and dry seasons. For Pittsburgh, the major differences between seasons are related to temperature, with~~

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~~humidity varying to a lesser degree, as depicted in Fig. S2. In Rwanda, temperatures are relatively stable year-round, with seasons mainly differentiated by humidity changes (although the second dry season appears to have been unusually wet, comparable to the previous wet season).~~

~~RAMP data are used to represent "ground truth" concentrations for both areas. An offline or "prior" approach is used here, i.e., calibrations are not modified based on data collected within the application period, in order to investigate the effect of generalizing a calibration developed in one season to a different season. Metrics are assessed for each individual site in each area, with all other sites being used to establish AOD conversion factors as in the previous section. The median results across all sites are presented in Fig. 6 for each combination of initialization and application season.~~

For Pittsburgh, spring conversion factors seem to generalize best when applied to other seasons, with the lowest biases and highest precisions. Low correlations are observed in the summer and winter regardless of initialization period, and clear seasonality is observed with summer initializations being biased high in winter and winter initializations being biased low in summer.~~the summertime conversion factors perform best across all seasons, while the wintertime conversion factor performs worst (except when applied to winter). Thus, while there are some seasonal differences, a conversion factor developed during summer (or a conversion factor developed over the course of spring through fall) might generalize reasonably well to the entire year.~~

In Rwanda, an alternating pattern is revealed, with wet season conversion factors applying well to other wet seasons, and dry season conversion factors applying to other dry seasons. Many factors could contribute to this pattern, including changes in humidity and the resulting impact on extinction, as well as seasonal burning patterns affecting particle sizes and compositions. Conversion factors appear to generalize better between wet seasons than between dry seasons. Correlations are highest during the first dry season (DS1), regardless of ~~when~~ whether the conversion factor is developed during this season or during the surrounding wet seasons; this was also the driest season and the season with the highest $PM_{2.5}$ concentrations ~~of the seasons measured~~. Applications of conversion factors developed in other seasons to DS1 underestimate $PM_{2.5}$ in this season, especially applications of factors developed during the wet seasons (when $PM_{2.5}$ levels were much lower). This indicates that there is seasonality to $PM_{2.5}$ concentrations ~~which~~ that is not being reflected in the AOD data ~~alone~~, and ~~would~~ requires local monitoring to identify. Overall, these results indicate that conversion factors should be developed or updated at least on a seasonal basis, especially in Rwanda; a conversion factor developed during a limited monitoring campaign occurring in one specific season may fail to generalize well to other seasons.

~~3.8~~3.6 Regional generalization of AOD conversion factors developed in Rwanda

~~Finally, given the lack of ground-based monitoring in many parts of SSA, we assess whether a conversion factor developed in one city can be generalized to other cities and towns across SSA. Here, a single AOD conversion factor is developed using one site in Kigali, Rwanda and this factor is applied without modification to other sites across SSA. These include a second site in Kigali, a site in Musanze in rural Rwanda, a site in Kinshasa (DR Congo), and three sites in Malawi (one near the urban area of Lilongwe and two other sites in more rural areas to the south, near Mulanje) where low-cost sensor systems are~~

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~~deployed. There are also two sites (Kampala, Uganda and Addis Ababa, Ethiopia) where hourly-resolution long-term regulatory-grade monitoring data are available; data from these sites are included for comparative purposes. An offline approach is used here, with a single factor being initialized over the entire study period.~~ Results of the analysis discussed in Sect. 2.6.5 are presented in Fig. 8~~7~~.

Correlation is relatively low across ~~all~~ most application areas, with a weak trend of decreasing correlation ~~trend~~ as distance from the initialization site increases (the exception to this is found at the rural Mugogo site). Best performance in terms of CvMAE and normalized bias is found in Kigali, Kampala, and Kinshasa; these urban zones are likely most similar to the initialization site in terms of land use and resulting source mix.~~;~~ R~~r~~elatively best performance is found at the spatially closest Kigali site ~~which is much closer spatially~~. The Kampala site, with data collected via a traditional monitoring instrument, shows similar results as obtained at these other urban sites ~~where~~ with low-cost monitors ~~are used~~. The other, more rural locations show poorer performance regardless of distance from the initialization site. However, the Addis Ababa site also shows much poorer performance, despite also being an urban area, although the Embassy is located on the outskirts of the city. This may be due to climate differences between Addis Ababa and the other cities considered, as well as differences in particle composition and size distributions, especially higher contribution to AOD from coarse (larger than $PM_{2.5}$) Saharan dust (De Longueville et al., 2010) ~~which~~ that would not be accounted for in the Kigali-based AOD conversion factor.
These results indicate that, while conversion factors may generalize to sites with similar land use and climate characteristics, physical distance alone is not as significant in determining AOD-PM relationship generalizability. Also, the overall low correlation values indicate the importance of local data, as spatial heterogeneity in satellite AOD to surface $PM_{2.5}$ relationships can be a concern even for nearby sites. Finally, it should be noted that a single annual conversion factor, as is assessed here, could fail to take into account seasonal variabilities (Sect. 3.5) and so can correlate poorly with surface $PM_{2.5}$ even in or near the area where it is developed (as seen for the Kigali site here). A conversion factor ~~which~~ that varies on at least a seasonal basis is therefore preferred; however, determining how to generalize such a time-varying conversion factor to other regions where seasonal definitions and characteristics can be quite different is a challenging problem. Overall, it does not appear from this analysis that AOD to surface $PM_{2.5}$ conversion factors can be broadly generalized across global regions with consistent results. Therefore, continuous localized monitoring, such as might be facilitated with local low-cost monitor networks, seems to be the most robust way to establish applicable AOD to surface $PM_{2.5}$ conversion factors.

4 Discussion

We have examined the feasibility of using low-cost sensors as a data source in developing relationships between surface $PM_{2.5}$ concentrations and satellite AOD ~~measurements~~. In a case study in Pittsburgh, there was no decrease in performance associated with the use of low-cost sensors for this purpose rather than more traditional regulatory-grade monitors, although performance was rather poor in both cases. ~~Furthermore, t~~The ~~increased~~ higher density ~~of~~ ground ~~sites~~ networks possible ~~using~~with low-cost sensors did provide~~d~~ benefits in terms of more robust conversion factors compared to the more sparsely

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deployed traditional monitoring network. However, it was found that for Pittsburgh, with a relatively dense low-cost sensor network (median inter-site distance of about 1 km) and low $PM_{2.5}$ concentrations, use of the nearest ground measurement sites outperformed the use of satellite AOD data to estimate surface $PM_{2.5}$~~.~~ using linear conversions. Partly, this could be because AOD is rather low over this area (average of about 0.2) leading to lower signal-to-noise ratios ~~which~~that reduce AOD to surface PM correlation. Conversely, in Rwanda, a relatively sparse low-cost sensor network combined with satellite data~~ with~~ in an environment with higher and more variable $PM_{2.5}$ concentrations provided better estimates of surface $PM_{2.5}$ concentrations than was available using only the nearest surface monitor alone. This result is highly relevant to SSA, as sparse local monitoring and high average $PM_{2.5}$ concentrations (as measured by the few available ground-based monitors) are common features, ~~D~~Differences in seasonal characteristics (especially at the Rwanda locations) show the added value of season-specific conversion factors (which are facilitated by continuous local monitoring), while differences in characteristics between areas, especially urban and rural locations with highly variable particle types, limit the generalizability of conversion factors across regions (again emphasizing the importance of local monitoring).

~~It should be noted that the results of this paper pertain to local and instantaneous relationships, using the highest spatial and temporal resolution of satellite data currently available. Results may differ for spatially or temporally aggregated satellite and ground site data. In particular, such spatial and temporal aggregation is likely to reduce the impact of noise (but not bias) both from low-cost instruments and from satellite retrievals. However, such aggregate information does not take advantage of the potential inherent in low-cost sensors to provide near-real-time information on local air pollution. On a related point, satellite data (at least, for most of the world using current platforms) cannot provide diurnal concentration profiles, instead presenting a "snapshot" of concentrations for a wide spatial domain but only for a specific time of day. Ground-based monitoring, including monitoring with low-cost sensors, will still be essential for this function, at least until new geostationary platforms with truly global coverage are available (Judd et al., 2018; She et al., 2020). Such satellites are planned for coverage of North America (the TEMPO satellite mission), Europe (Sentinel-4), and East Asia (GEMS); unfortunately, there are no current plans for coverage of Africa by similar satellites.~~

The results presented here continue to highlight the need for ground-based $PM_{2.5}$ monitoring in previously unmonitored areas such as SSA, especially in light of the benefits observed in Rwanda from having even a sparse ground monitoring network combined with satellite data on local spatial heterogeneity. Efforts to expand ground-based monitoring ~~These efforts~~ should make use of traditional regulatory-grade instruments wherever possible, supplemented with low-cost monitors to increase network density and ~~extend~~ expand spatial coverage. Findings in Pittsburgh indicate that denser monitoring networks, such as those made possible by low-cost sensors, improve accuracy and robustness of surface $PM_{2.5}$ estimates from satellites~~ (up to a certain point of diminishing returns)~~. Verification that the same trend will hold in other regions, especially in SSA, requires further dense deployments of low-cost sensors, and is the subject of ongoing work.

It should be noted that the results of this paper pertain to local and instantaneous relationships, using the highest spatial and temporal resolution of satellite data currently available. Results may differ for spatially or temporally aggregated satellite and ground site data. In ~~particular~~fact, such spatial and temporal aggregation is likely to reduce the impact of noise (but not

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bias) both from low-cost instruments and from satellite retrievals. However, such aggregate information does not take full advantage of the potential inherent in low-cost sensors to provide near-real-time information on local air pollution. On a related point, satellite data (at least, for most of the world using current platforms) cannot provide diurnal concentration profiles, instead presenting a "snapshot" of concentrations for a wide spatial domain but only for a specific time of day. Ground-based continuous monitoring, ~~including monitoring~~even, with low-cost sensors, will still be essential ~~for this function~~, at least until new geostationary platforms with truly global coverage are available (Judd et al., 2018; She et al., 2020). Such satellites are planned for coverage of North America (the TEMPO satellite mission), Europe (Sentinel 4), and East Asia (GEMS); unfortunately, there are no current plans for coverage of Africa by similar satellites.

Further technical and research developments in this area have enormous promise for improving ~~the~~ our understanding of local air quality worldwide. A functioning system for converting satellite to ground-level air pollution data, relying on a group of "trusted" ground data sources, could potentially be a valuable resource for assessing and correcting low-cost sensor data, allowing for in-field recalibration of drifting instruments, and better identification of malfunctioning sensors. Low-cost systems combining PM mass measurement and ground-up AOD data can help to establish AOD to surface PM relationships at finer spatio-temporal resolution (Ford et al., 2019). Open questions related to this research area include finding appropriate timescales over which conversion factors can be considered constant within regions as well as continuing to examine the question of conversion factor generalizability between regions separated by spatial distances and across different climates and land use characteristics. More sophisticated conversion methods incorporating meteorological and land use information and outputs of chemical transport models can also be considered, albeit with the recognition that some of these inputs may not yet be readily available or well validated for SSA.

Code and data availability

Data related to the results and figures presented in this paper are available online at https://doi.org/~~10.5281/zenodo.3691833~~10.5281/zenodo.3858063. Codes related to the analysis of data and generation of figures are also provided at the same site.

Author contribution

Conceptualization: RS, MB~~, RS~~; Funding acquisition: RS, AP, MB~~, RS~~; Methodology: CM, DW, AG, AB; Resources, DW, AG, AB; Software: CM, AH; Supervision: RS, AP, MB~~, RS~~; Writing – original draft: CM; Writing – review & editing: CM, DW, AP, AG, AB, MB, RS.

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Competing Interests

The authors declare that they have no conflict of interest.

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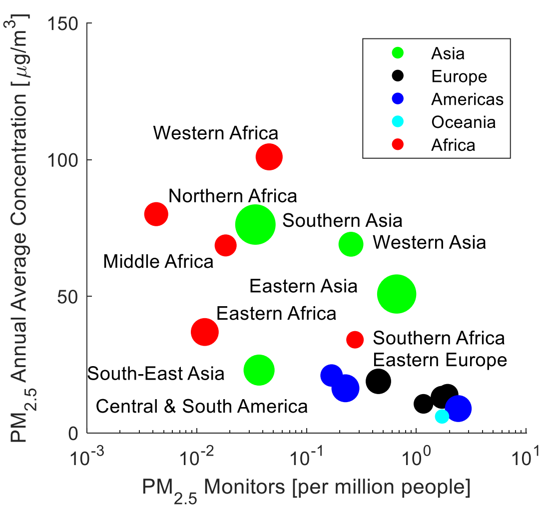
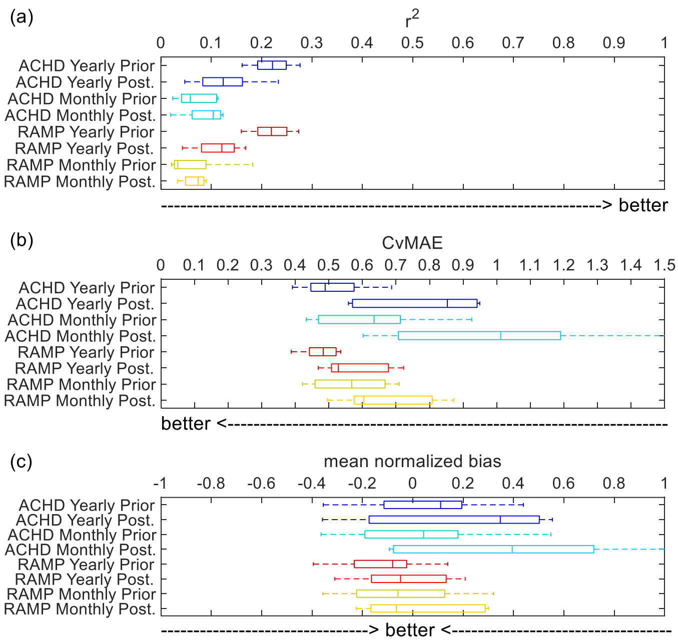


Figure 1: Estimated annual average $PM_{2.5}$ concentration versus density of ~~reference~~regulatory-grade monitoring stations across several global regions. Colors correspond to continents, and sizes roughly correspond to total regional population. This graphic is based on information available from the Global Health Observatory (WHO, 2017).


(a)
r²
0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1
ACHD Yearly Prior
ACHD Yearly Post.
ACHD Monthly Prior
ACHD Monthly Post.
RAMP Yearly Prior
RAMP Yearly Post.
RAMP Monthly Prior
RAMP Monthly Post.
-----> better
(b)
CvMAE
0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1 1.1 1.2 1.3 1.4 1.5
ACHD Yearly Prior
ACHD Yearly Post.
ACHD Monthly Prior
ACHD Monthly Post.
RAMP Yearly Prior
RAMP Yearly Post.
RAMP Monthly Prior
RAMP Monthly Post.
better <-----
(c)
mean normalized bias
-1 -0.8 -0.6 -0.4 -0.2 0 0.2 0.4 0.6 0.8 1
ACHD Yearly Prior
ACHD Yearly Post.
ACHD Monthly Prior
ACHD Monthly Post.
RAMP Yearly Prior
RAMP Yearly Post.
RAMP Monthly Prior
RAMP Monthly Post.
-----> better <-----

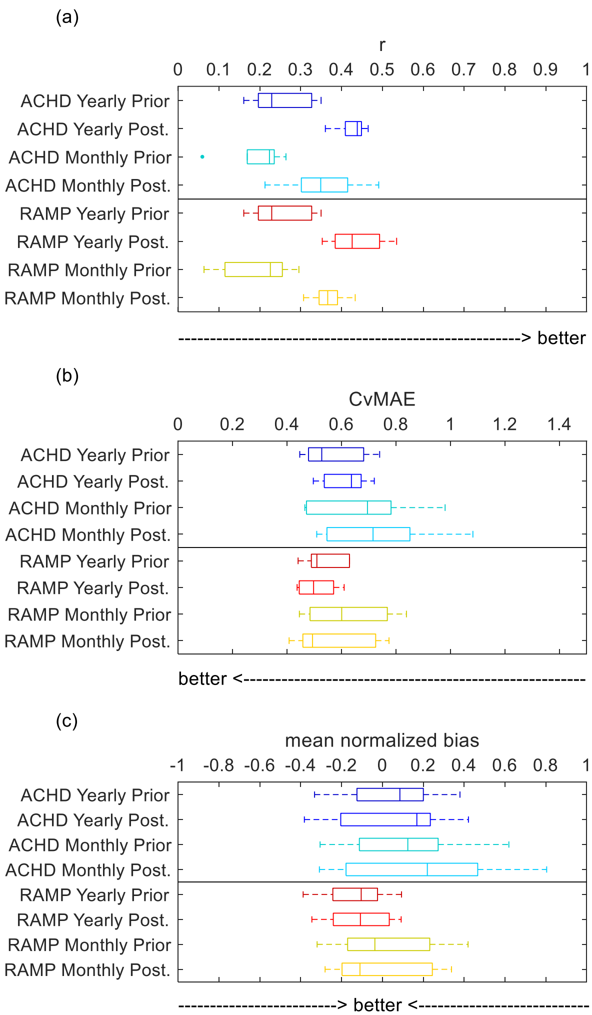


Figure 2: Comparison of performance metrics (a: correlation, b: CvMAE, and c: MNB) for surface $PM_{2.5}$ estimated from satellite AOD data in the Pittsburgh area. Performance is assessed at the ACHD regulatory-grade monitoring sites. Ground sites used for factor development are either four of the ACHD monitors (ACHD) or four low-cost sensors associated with RAMP monitors (RAMP). Conversion factors are established either on a Yearly or Monthly basis. Finally, either an offline (Prior) or online (Post.) approach is used.

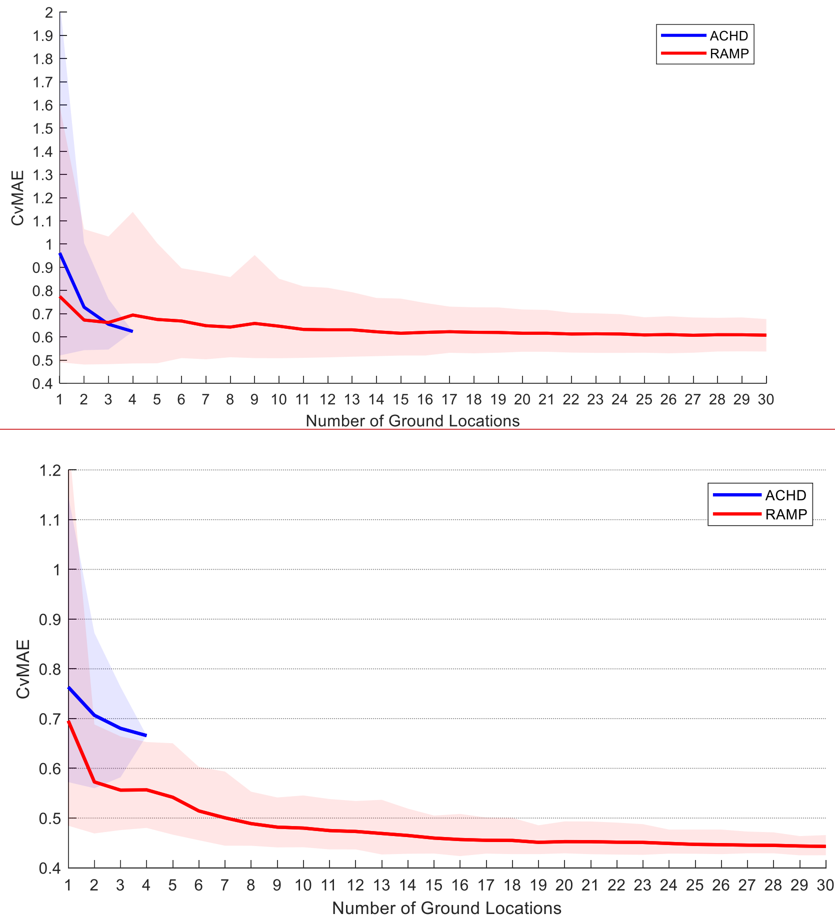
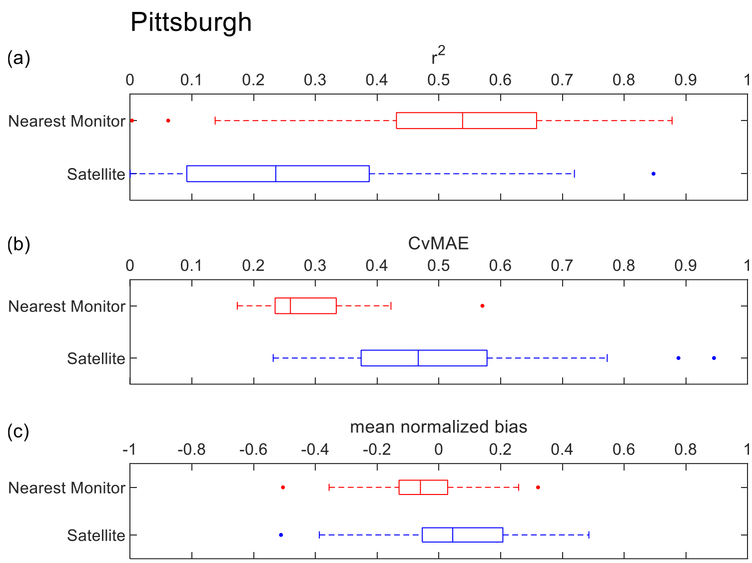


Figure 3: Performance (assessed in terms of CvMAE) for surface $PM_{2.5}$ estimated from satellite AOD data in the Pittsburgh area, plotted as a function of the number of ground sites used. Performance is assessed against the ACHD regulatory-grade monitors. Solid lines indicate mean performance across sites using either ACHD or low-cost sensor (RAMP) sites to establish conversion factors. Shaded regions indicate the range of variability ~~for different selected groups of~~across application sites.


Pittsburgh
(a)
r^2
Nearest Monitor
Satellite
(b)
CvMAE
Nearest Monitor
Satellite
(c)
mean normalized bias
Nearest Monitor
Satellite

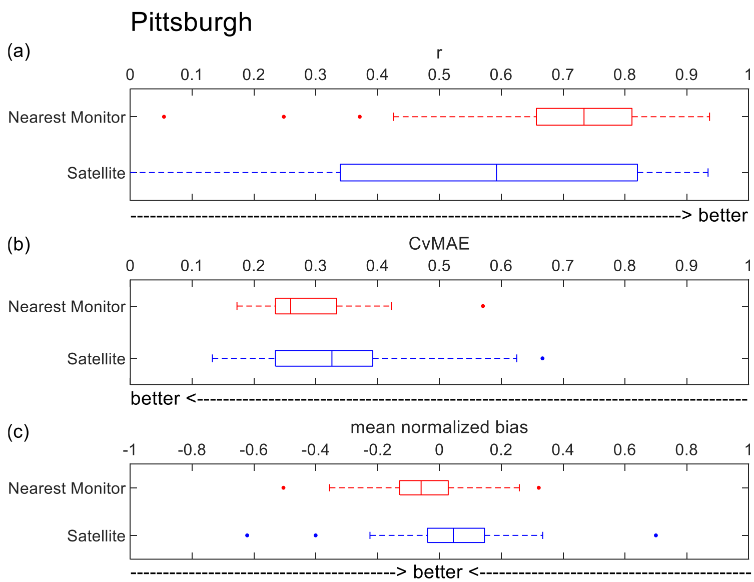
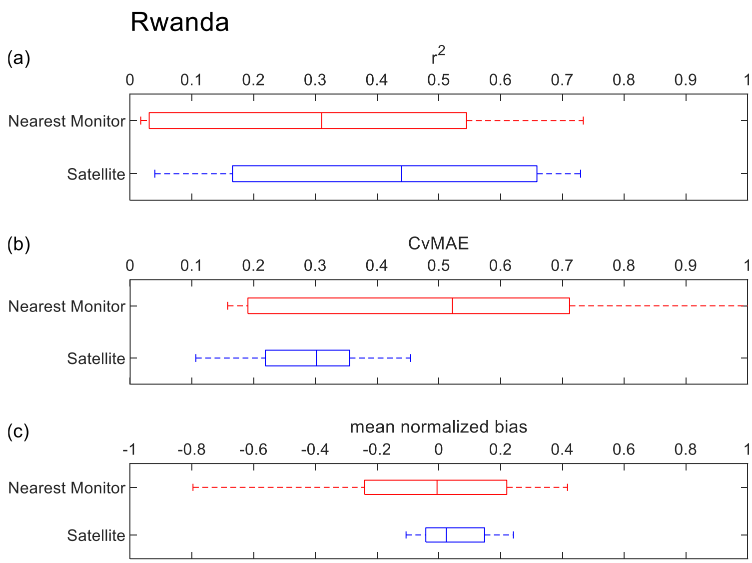
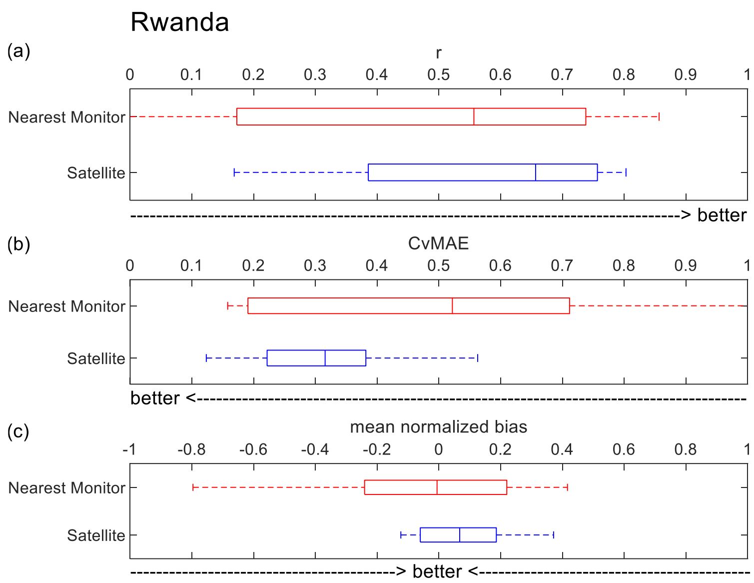


Figure 4: Comparison of performance metrics (a: correlation, b: CvMAE, c: MNB) for either surface $PM_{2.5}$ estimated from satellite AOD data (Satellite) or from the nearest ground-level $PM_{2.5}$ monitor (Nearest Monitor) in the Pittsburgh area. Note that these performance metrics are not directly comparable to those presented in Fig. 2, as in this case a larger number of ground initialization sites (9 to 45, depending on the number of active sites in Pittsburgh at any particular time) ~~is~~ are considered. Further, ~~, and~~ performance is now~~t~~ being assessed against the RAMP rather than the ACHD network (i.e., performance is assessed at the held-out active RAMP site); this is done to allow for comparability with the results from Rwanda, presented in Fig. 5, where only RAMP data are available.~~.~~


Rwanda
(a)
r^2
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Nearest Monitor
Satellite
(b)
CvMAE
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Nearest Monitor
Satellite
(c)
mean normalized bias
-1
-0.8
-0.6
-0.4
-0.2
0
0.2
0.4
0.6
0.8
1
Nearest Monitor
Satellite



1285 **Figure 5: Comparison of performance metrics (a: correlation, b: CvMAE, c: MNB) for either surface $PM_{2.5}$ estimated from satellite AOD data (Satellite) or from the nearest ground-level $PM_{2.5}$ monitor (Nearest Monitor) in the Rwanda area.**

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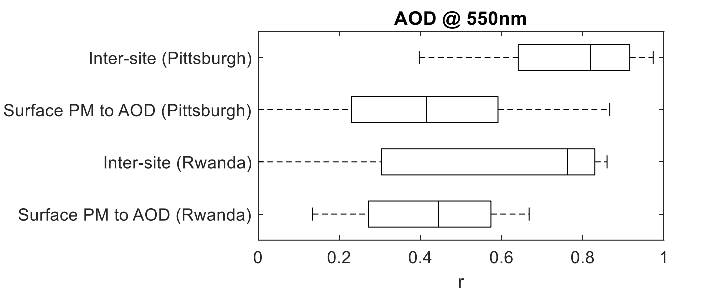
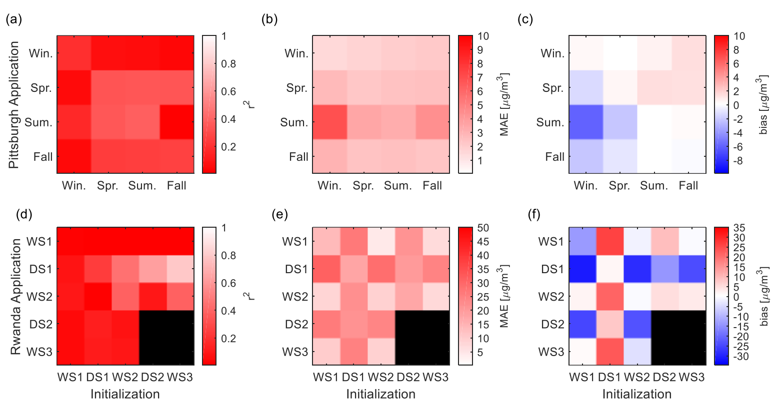


Figure 6: Comparison of inter-site correlations versus AOD-to-surface-$PM_{2.5}$ correlations in Pittsburgh and Rwanda



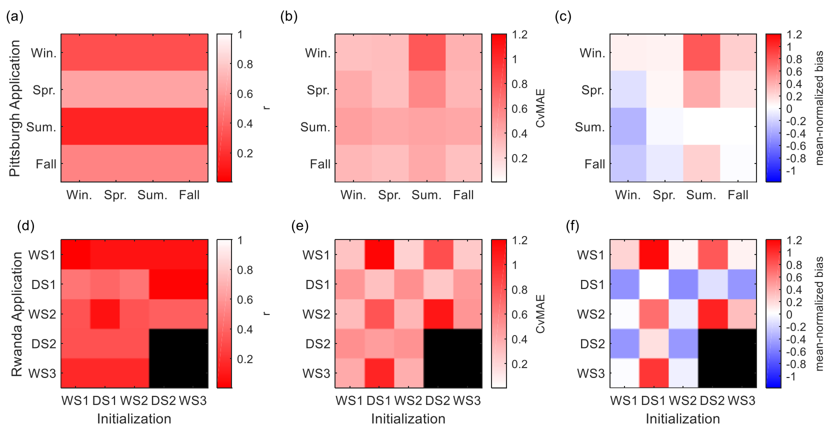


Figure 7~~6~~: Comparison of seasonal performance metrics (a, d: correlation; b, e: CvMAE; c, f: MNB~~bias~~) for surface $PM_{2.5}$ estimated from satellite AOD data across different seasons in the Pittsburgh (a, b, c) and Rwanda (d, e, f) areas. The horizontal axis differentiates the seasons during which initialization was performed, while the vertical axis denotes the seasons when the conversion was applied. Note that, in Rwanda, only one sensor was operational during Dry Season 2 (DS2) and Wet Season 3 (WS3), and so application of these conversions to an independent site was impossible; therefore, performance metrics are blacked out. In each figure diagonal (from top left to bottom right) elements correspond to the same season. Values are also listed in the supplemental information, Table S8.

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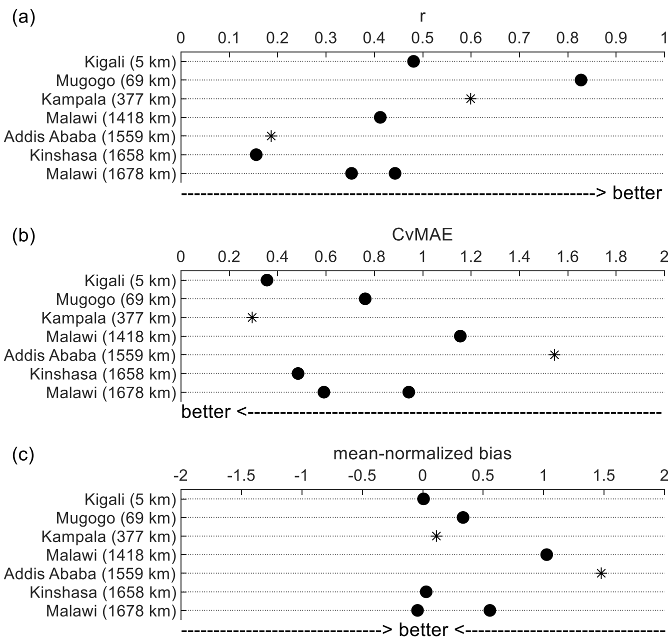

(a)
r
0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1
Kigali (5 km)
Mugogo (69 km)
Kampala (377 km)
Malawi (1418 km)
Addis Ababa (1559 km)
Kinshasa (1658 km)
Malawi (1678 km)
---> better
(b)
CvMAE
0 0.2 0.4 0.6 0.8 1 1.2 1.4 1.6 1.8 2
Kigali (5 km)
Mugogo (69 km)
Kampala (377 km)
Malawi (1418 km)
Addis Ababa (1559 km)
Kinshasa (1658 km)
Malawi (1678 km)
better <---
(c)
mean-normalized bias
-2 -1.5 -1 -0.5 0 0.5 1 1.5 2
Kigali (5 km)
Mugogo (69 km)
Kampala (377 km)
Malawi (1418 km)
Addis Ababa (1559 km)
Kinshasa (1658 km)
Malawi (1678 km)
------------------------------> better <------------------------------

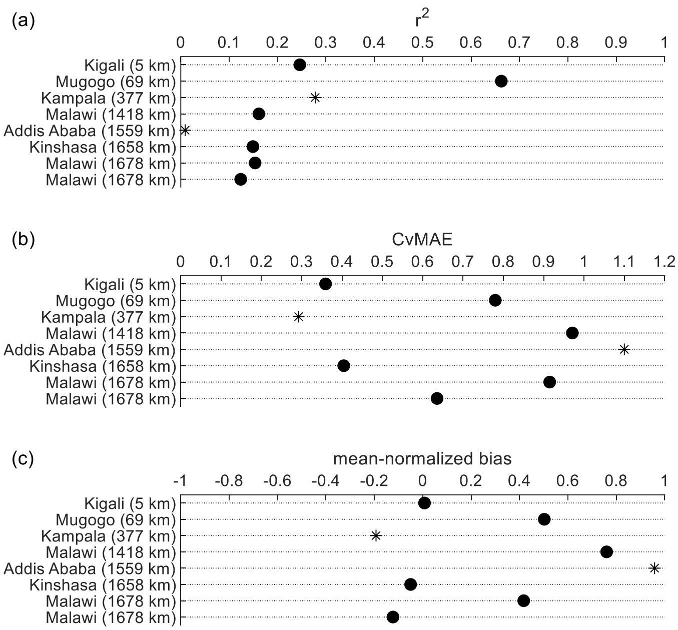

Figure 8~~7~~: Comparison of performance metrics (a: correlation, b: CvMAE, c: MNB) for surface $PM_{2.5}$ estimated from satellite AOD data across multiple sites in SSA. The conversion factor is developed at a central site in Kigali, Rwanda; the distances of each testing site to this central site are given. Performances are assessed for all data collected at the given sites, using the prior conversion factor only. Note that performance in Kampala and Addis Ababa is assessed using traditional reference monitors (indicated by ∗), while performance at the other sites reflects low-cost sensor data (indicated by ●).

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Table 1: Summary information for low-cost sensor systems utilized for this paper.

Manufacturer	MetOne	PurpleAir	Alphasense
Product	Neighborhood Particulate Monitor	PurpleAir II	OPC-N2
Abbreviation	NPM	PA-II	OPC
Measurement Method	forward light scattering laser	laser particle sensor	optical particle counting
Other Features	Includes $PM_{2.5}$ cyclone and inlet heater. Provides estimates of $PM_{2.5}$ mass concentrations using calibrations that are user-modifiable. Interfaced with RAMP low-cost monitor nodes.	Includes a pair of Plantower PMS 5003 units, along with temperature and humidity sensors. Provides estimates of PM_1, $PM_{2.5}$, and PM_{10} mass concentrations via proprietary calibrations. Interfaced with RAMP low-cost monitor nodes.	Detects particles in the 0.38 to 17 µm range, converts particle counts to PM_1, $PM_{2.5}$, and PM_{10} mass concentrations via proprietary calibrations. Integrated with ARISense low-cost monitor nodes.
Unit Cost (approx.)	$2000	$250	$350 (not including housing)
Performance Notes	Moderate correlation to regulatory-grade instruments in laboratory and field testing. Requires cleaning and re-calibration between deployments.	High correlation to regulatory-grade instruments, except at high humidity. Individual Plantower sensor malfunctions detectable via comparison between the two internal units.	Moderate correlation to regulatory-grade instruments in field conditions.
References	(AQ-SPEC, 2015; Malings et al., 2019b)	(AQ-SPEC, 2017; Malings et al., 2019b)	(AQ-SPEC, 2016; Crilley et al., 2018)

Table 2: Summary information for the ground sites presented in this paper.

Area Name	**Pittsburgh**	**Rwanda**	**Malawi**	**Kinshasa**	**Kampala**	**Addis Ababa**
Country	United States of America	Rwanda	Malawi	Democratic Republic of the Congo	Uganda	Ethiopia
Location (Approx.)	Between 40.1ºN, 80.5ºW and 40.8ºN, 79.7ºW	Between 2.2ºS, 29.4ºE and 1.4ºS, 30.5ºE	Between 16.2ºS, 33.6ºE and 14.0ºS, 35.7ºE	4.3ºS, 15.3ºE	0.3ºN, 32.6ºE	9.0ºN, 38.8ºE
Start	Jan. 1, 2018	April 1, 2017	June 25, 2017	Mar. 20, 2018	Jan. 1, 2019	Jan. 1, 2019
End	Dec. 31, 2018	May 27, 2018	July 30, 2018	Oct. 31, 2019	Dec. 31, 2019	Dec. 31, 2019
Low-Cost Sensors						
Total Sites	62	4	3	1		
Simultaneously Active Sites	10 to 46	1 to 3	1 to 3	1		
Sensor Type	NPM, PA-II	NPM	OPC	PA-II		
Regulatory-Grade Monitors						
Total Sites	5				1	1
Type	BAM				BAM	BAM

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