

# First Measurements of Ambient PM<sub>2.5</sub> in Kinshasa, Democratic Republic of Congo and Brazzaville, Republic of Congo Using Field-calibrated Low-cost Sensors

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## ABSTRACT

Estimates of air pollution mortality in sub-Saharan Africa are limited by a lack of surface observations of fine particulate matter (PM<sub>2.5</sub>). Despite being large metropolises, Kinshasa, Democratic Republic of the Congo (DRC), and Brazzaville, Republic of the Congo (ROC), which possess populations of 14.3 million and 2.4 million, respectively, use no reference air pollution monitors at the time of writing. However, a few reference monitors have recently been deployed in other parts of sub-Saharan Africa, including a Met One Beta Attenuation Monitor (BAM-1020) at the U.S. Embassy in Kampala, Uganda, next to which a low-cost PM<sub>2.5</sub> monitor, the PurpleAir, was collocated in August 2019. The raw PurpleAir data from September 2019 through February 2020 strongly correlated with the BAM-1020 measurements ( $R^2 = 0.88$ ) but also exhibited a mean absolute error (MAE) of approximately  $14 \mu\text{g m}^{-3}$ . Employing two calibration models, namely, multiple linear regression and random forests, decreased the MAE to  $3.4 \mu\text{g m}^{-3}$  and increased  $R^2$  to 0.96. Given the similarity in climate and emissions, we applied the collocated field correction factors for Kampala to four PurpleAir units in Kinshasa and one in neighboring Brazzaville, which were deployed in April 2018. We estimated an average annual PM<sub>2.5</sub> concentration of  $43.5 \mu\text{g m}^{-3}$  in Kinshasa for 2019, which exceeds the World Health Organization (WHO)'s Interim Target 1 ( $10 \mu\text{g m}^{-3}$ ) by 4 times. Finally, the surface PM<sub>2.5</sub> level and the aerosol optical depth were about 40% lower during the COVID-19 lockdown in 2020 than the corresponding period in 2019, which cannot be attributed solely to changes in meteorology or wildfire emission. Hence, our results highlight the need to implement clean air solutions in the Congo.

**Keywords:** Low-cost sensors, Particulate matter, Air quality, Africa

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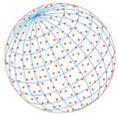
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## 1 INTRODUCTION

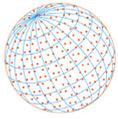
Ambient air pollution is a major global public health crisis that causes an estimated 4.9 million premature deaths per year around the world. Air pollution is the fifth leading risk factor for all mortality (Health Effects Institute, 2019), and on average reduces life span by 20 months worldwide, rivaling the global impact of cigarette smoking. According to one air quality modeling study, air pollution may cause at least an estimated 780,000 premature deaths annually in Africa (Bauer *et al.*, 2019), and a significant number of diseases (co-morbidities) are known to be worsened by chronic exposure to air pollution, like asthma, lung cancer, and chronic obstructive pulmonary disease (Burnett *et al.*, 2018). However, sparse air pollution monitoring imparts high uncertainty to estimates of exposure and impact. Most of these ambient air pollution deaths come from PM<sub>2.5</sub>, or particulate mass concentrations for particles with diameter less than 2.5  $\mu\text{m}$ .

There is currently no publicly available PM<sub>2.5</sub> monitoring in the city of Kinshasa, Democratic Republic of Congo, or Brazzaville, Republic of Congo, either as regulatory monitors or citizen-deployed low-cost sensors. Therefore, it is currently difficult to know the level of exposure and the potential health impacts of air pollution in Kinshasa and Brazzaville, an alarming gap in a pair of capital megacities containing more than 16 million people and experiencing rapid population growth. To address the lack of data in both cities, we deployed and calibrated a small network of 5 low-cost air quality sensors starting in 2018.

Almost no prior published work has considered PM<sub>2.5</sub> or air quality in Kinshasa or Brazzaville to this point. Mbelambela *et al.* (2017) used a portable sensor to calculate personal PM<sub>2.5</sub>, NO<sub>2</sub>, and SO<sub>2</sub> exposure in a cohort of 517 subjects, mostly bus drivers. Data were only collected between 20 April and 14 May of 2015 and are more representative of personal exposure rather than ambient concentrations. The authors reported PM<sub>2.5</sub> exposure over the 3-week period ranging from 64 to 129  $\mu\text{g m}^{-3}$ . The only other air quality study in the peer-reviewed literature in either city was a study of trace metals conducted in 1990 (Lobo *et al.*, 1990), before the Democratic Republic of the Congo was known as such, and has limited relevance to present-day exposures. No studies on air quality in neighboring Brazzaville were found in the literature. Additionally, to our knowledge, there are no national ambient air quality standards in either country.

Low-cost sensors (LCSs) have the potential to improve air quality data coverage throughout the world, especially in resource-limited areas (Amegah, 2018). For LCSs to provide high-quality data, understanding local conditions is vital. Calibration factors and sensor technical performance vary strongly with conditions such as temperature, relative humidity, particle size distribution, and particle loading (Levy Zamora *et al.*, 2019; Hagan and Kroll, 2020; Tryner *et al.*, 2020). Other factors such as sensor aging can also influence sensor performance and have been studied in both a laboratory and field setting (Malings *et al.*, 2019; Tryner *et al.*, 2020). Careful collocation, or side-by-side placement of LCSs with reference monitors, is an essential step to getting accurate data out of LCSs. Several recent studies have performed either a field calibration or a laboratory calibration for a variety of different sensors in a variety of different environmental conditions, paving the way for additional studies in diverse environments (Holstius *et al.*, 2014; Jiao *et al.*, 2016; Johnson *et al.*, 2016; Kelly *et al.*, 2017; Jayaratne *et al.*, 2018; Tryner *et al.*, 2019; Hagan and Kroll, 2020; Tryner *et al.*, 2020). However, to our knowledge, published LCS collocation and performance evaluation studies within sub-Saharan Africa are limited (Subramanian *et al.*, 2020).

Here we present the first-ever multi-year, field-calibrated ambient PM<sub>2.5</sub> dataset in Kinshasa and Brazzaville. We first build a multiple linear regression (MLR) model based on a collocation of sensors and reference (Federal Equivalence Method (FEM)) PM<sub>2.5</sub> monitors in Kampala, Uganda, and develop a correction factor for low-cost sensors. We then apply the correction to our network in Kinshasa and Brazzaville. We analyze PM<sub>2.5</sub> on monthly, weekly, daily, and hourly timescales. We interpret the data in the context of changing meteorology and changing human activity coinciding with COVID-19-related stay-at-home orders. Finally, we assess the air quality picture in Kinshasa as seen from satellite remote sensing.



## 2 METHODS

### 2.1 Description of PurpleAir Low-cost Sensors

We deploy five PurpleAir PA-II-SD low-cost PM<sub>2.5</sub> devices ([www.purpleair.com](http://www.purpleair.com)) in the Kinshasa-Brazzaville area and one PurpleAir device in Kampala for calibration purposes. PurpleAir uses dual Plantower PMS 5003 optical sensors to estimate PM<sub>2.5</sub> mass concentrations and a Bosch BME280 sensor to estimate temperature, relative humidity, and pressure. Data are transmitted via wireless connectivity in real time and recorded to an on-board 16 GB microSD card. All PurpleAir data is available online on their website. The devices measure sensor readings in six size bins ranging from 300 nm to 10 μm at approximately a 60-s interval. A proprietary algorithm converts raw sensor measurements to PM<sub>1</sub>, PM<sub>2.5</sub>, and PM<sub>10</sub> mass using assumptions about particle shape and density. We use the CF=ATM data field as provided by PurpleAir, which is actually the higher CF=1 data field on account of mislabeled columns by PurpleAir. The CF=1 data has not been transformed nonlinearly and is a better input into regression models. PurpleAir PM<sub>2.5</sub> is known to strongly correlate ( $R > 0.9$ ) with reference-grade monitors but are subject to biases at high relative humidity in particular (Jayaratne *et al.*, 2018; Malings *et al.*, 2019; Magi *et al.*, 2020; Tryner *et al.*, 2020). Sensitivity to relative humidity has also been identified in other low-cost air pollution monitoring devices (Di Antonio *et al.*, 2018; Jayaratne *et al.*, 2018; Kelleher *et al.*, 2018; Hagan and Kroll, 2020; He *et al.*, 2020). PA-II sensors cost approximately US\$250 per unit which are about 100 times cheaper than reference PM<sub>2.5</sub> monitors, making them attractive for multi-sensor networks. Their use, however, requires careful field calibration in order to achieve high-quality data. Malings *et al.* (2019) developed a multiple linear regression-based calibration method which will be utilized in the following sections.

### 2.2 Sampling Locations and Periods

#### 2.2.1 Kampala

A PurpleAir was collocated at the U.S. Embassy in Kampala, located at Plot 1577 Ggaba Road, about 3 km from the city center, 0.301268 N latitude and 32.591711 E longitude. Sampling began in September 2019 and continues through the present. Also located at the U.S. Embassy is a Met One Beta Attenuation Monitor (BAM-1020), which provides a calibration point for the PurpleAir. Data collection of PM<sub>2.5</sub> with the BAM-1020 has been ongoing at the U.S. Embassy since January 2017 (<https://www.airnow.gov/international/us-embassies-and-consulates/>, last accessed 26 August 2020). We use the September 2019–February 2020 overlapping dataset with the BAM-1020 and PurpleAir for our calibration (see “Field calibration” in “Methods”).

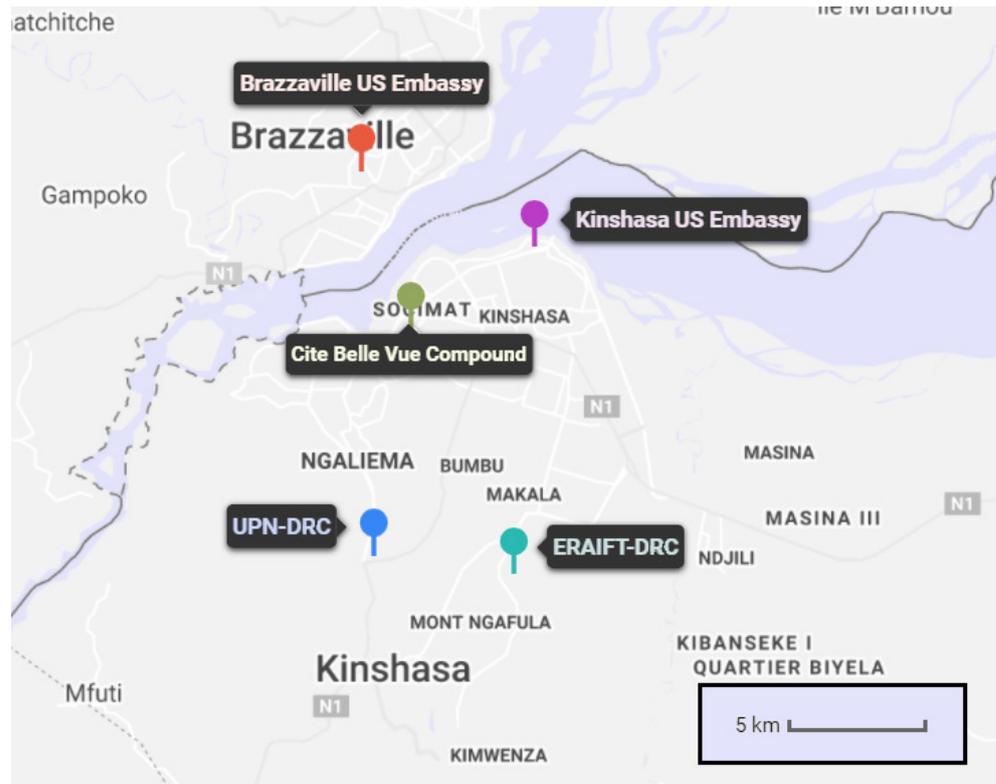
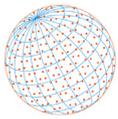
#### 2.2.2 Kinshasa and Brazzaville

Four PurpleAir sensors were deployed throughout Kinshasa with a fifth in Brazzaville. Starting in March 2018 and continuing through present, a device was located at the U.S. Embassy in Kinshasa at 310 Avenue des Aviateurs, latitude 4.3002 S and longitude 15.3138 E. In November of 2019, sensors were added at the Université Pédagogique Nationale (UPN) located on Route de Matadi, latitude 4.4039 S and longitude 15.2572 E, and the Ecole Régionale Postuniversitaire d'Aménagement et de Gestion intégrés des Forêts et Territoires tropicaux (ERAIFT), latitude 4.4103 S and 15.3065 E. A fourth sensor was located in a residential area in the Kintambo area of Kinshasa at the Belle Vue Villas (CBV), latitude 4.3278 S and longitude 15.2722 E, starting in November 2019. Finally, a fifth sensor was located across the Congo River in Brazzaville, Republic of Congo at the U.S. Embassy at latitude 4.2751 S and longitude 15.2561 E, starting in February 2020. A map of all sites is shown in Fig. 1.

### 2.3 Field Calibration

#### 2.3.1 Multiple linear regression

We use both an MLR and a random forest approach for bias-correcting the PurpleAir data towards the reference monitor in Kampala. The collocation of the PurpleAir and the FEM monitor took place between September 2019 and March 2020. A randomly selected 75% of data during that time period is used to build the multiple linear regression model, and the remaining 25% is



**Fig. 1.** Map of sensor locations in Kinshasa and Brazzaville. Background map © Google, 2020.

used for validation. This model was developed using the base R statistics package. The multiple linear regression approach follows a similar methodology as in Malings *et al.* (2019) in which daily averaged raw PurpleAir  $PM_{2.5}$ , relative humidity, and temperature are used as explanatory variables to predict corrected  $PM_{2.5}$  concentration:

$$PM_{2.5} = \beta_0 + \beta_1 \times \text{PurpleAir } PM_{2.5} + \beta_2 \times T (^{\circ}C) + \beta_3 \times RH (\%) \quad (1)$$

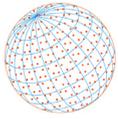
The multiple linear regression model was evaluated based on coefficients of determination ( $r^2$ ) and MAE defined as:

$$MAE = \frac{\sum_{i=1}^{i=N} |PM_i^{ref} - PM_i^{LCS}|}{N} \quad (2)$$

where  $PM$  refers to  $PM_{2.5}$  (in  $\mu\text{g m}^{-3}$ ),  $ref$  is the BAM-1020 reference monitor,  $LCS$  refers to the low-cost sensor data,  $N$  is total number of observations, and  $i$  is the time series variable. Since the MLR and RF methods result in similar correlation and mean bias improvements when the same averaging time periods are used and the MLR approach is more transparent (see “Results and Discussion”), we present further calibrated  $PM_{2.5}$  results based on MLR. Results obtained using the RF approach are not substantially different so they are presented in the supplementary information. The results of the MLR model correction are shown in the “Results and Discussion” subsection “Kampala co-location analysis.”

## 2.4 Satellite Data

We use remote sensing data from the NASA Aqua and Terra satellites, which contain the Moderate Resolution Imaging Spectroradiometer (MODIS). MODIS views the Earth surface over the Congo region once per day with a daily overpass time around 12:30. We specifically use the aerosol optical depth (AOD) at 550 nm wavelength using the Multi-Angle Implementation of



Atmospheric Correction (MAIAC) Level 2 gridded data over land surfaces at 1 km pixel resolution (MCD19A2) (Lyapustin *et al.*, 2018). We convert the pixel data in the H19V9 tile to latitude and longitude points using the MODLAND Tile Calculator (<https://landweb.modaps.eosdis.nasa.gov/cgi-bin/developer/tilemap.cgi>, last accessed 25 Aug 2020). Cloudy pixel data are removed as part of this data product, and only “best-quality” flagged data are used in our analysis. Data are available on the NASA Earth data repository (<https://earthdata.nasa.gov/>, last accessed 25 Aug 2020). We use daily MAIAC data from January 2018 through July 2020 in our analysis.

## 2.5 Meteorological Data

We use the NOAA National Centers for Environmental Information land-based station data for meteorology. In Kinshasa and Brazzaville, the most complete temperature records are at the N’Djili International Airport (Kinshasa) and Maya-Maya International Airport (Brazzaville). Temperature, relative humidity, and wind speed are mostly a complete record at these locations. Greater than 58% of precipitation data between September 2017 and August 2020 are missing at each of these stations, rendering any precipitation analysis impossible. We therefore use temperature, relative humidity, and wind speed data from N’Djili Airport to analyze the impact of weather on PM<sub>2.5</sub> observations.

## 3 RESULTS AND DISCUSSION

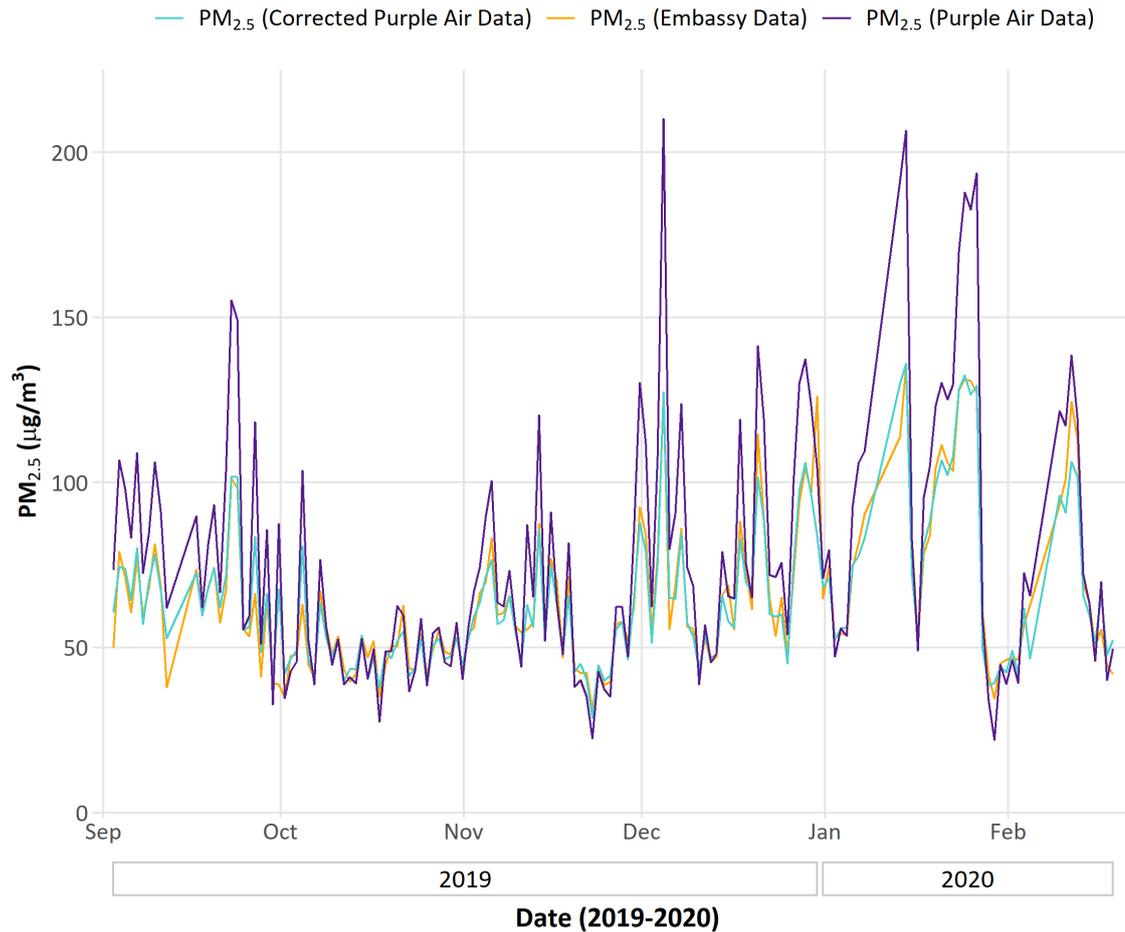
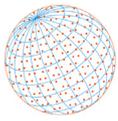
### 3.1 Kampala Co-location Analysis

In Table 1 we present the regression parameters for the Kampala co-location. Correlation between raw PurpleAir data and Embassy BAM-1020 is high ( $r^2 = 0.88$ ). The overall MAE in the raw data compared to the embassy BAM is  $14.8 \mu\text{g m}^{-3}$  which is partially driven by a large overprediction during times of very poor air quality (values greater than  $100 \mu\text{g m}^{-3}$ ). Values less than  $100 \mu\text{g m}^{-3}$  show less bias compared to the BAM-1020. Using the MLR model to correct the raw PM<sub>2.5</sub> data towards FEM standard using the BAM-1020 results in a reduction of MAE to  $3.4 \mu\text{g m}^{-3}$ , quantified using only the remaining 25% of the collocated data reserved for testing and validation. The corrected PurpleAir PM<sub>2.5</sub> data (turquoise line in Fig. 2) shows a substantial improvement in comparison against BAM PM<sub>2.5</sub>. Correlation is also improved by the MLR model ( $r^2 = 0.96$ ). Though hourly averaged PM<sub>2.5</sub> data from the PurpleAir and the BAM-1020 are noisy and therefore not as well suited for MLR, we also build an MLR model for the hourly averaged PM<sub>2.5</sub> data, which we only apply to any analysis that uses hourly mean data instead of daily mean data. Table 2 also contains the hourly based MLR statistics.

We apply the correction factors developed from the long-term MLR collocation in Kampala to each of the five PurpleAir PM<sub>2.5</sub> monitors deployed in Kinshasa and Brazzaville. Kampala is just under 2000 km away from Kinshasa; however, this is the closest reference PM<sub>2.5</sub> monitor to Kinshasa. The climates of Kinshasa and Kampala are quite similar as both lie within the center of the tropics. Both cities have two wet seasons that peak around October–November and March–April. Unlike Kampala, Kinshasa has a true dry season in which there is no or very little precipitation. Kampala’s “drier” season coincides with Kinshasa’s dry season (June–August). Annual mean temperature and relative humidity are  $30.4^\circ\text{C}$  and 80% in Kinshasa and  $27.8^\circ\text{C}$  and 75% in Kampala. Differences in emissions characteristics in the two cities are also a possible influence on applicability of our calibration. Thus, we also analyzed emissions data from the Diffuse and Inefficient Combustion Emissions Inventory in Africa (DICE-Africa), comparing source profiles for SO<sub>2</sub>, black carbon (BC), and organic carbon (OC) emissions in a  $25 \text{ km} \times 25 \text{ km}$  grid boundary in each city. Results (Fig. S1) indicate that the source profiles have many similarities in the two cities,

**Table 1.** Regression coefficients of the MLR model.

	Daily model	Hourly model
$\beta_0$	64.7	86.9
$\beta_1$	0.52	0.55
$\beta_2$	-0.23	-1.28
$\beta_3$	-0.59	-0.55

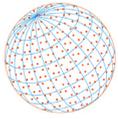


**Fig. 2.** Performance evaluation and calibration of PurpleAir PM<sub>2.5</sub> versus Federal Equivalent Method (FEM) PM<sub>2.5</sub> between September 2019 and February 2020 at the U.S. Embassy in Kampala, Uganda. Raw daily data is shown in purple, FEM data in orange, and corrected low-cost sensor data (using the MLR method) in turquoise.

**Table 2.** Statistics of the MLR and RF models.

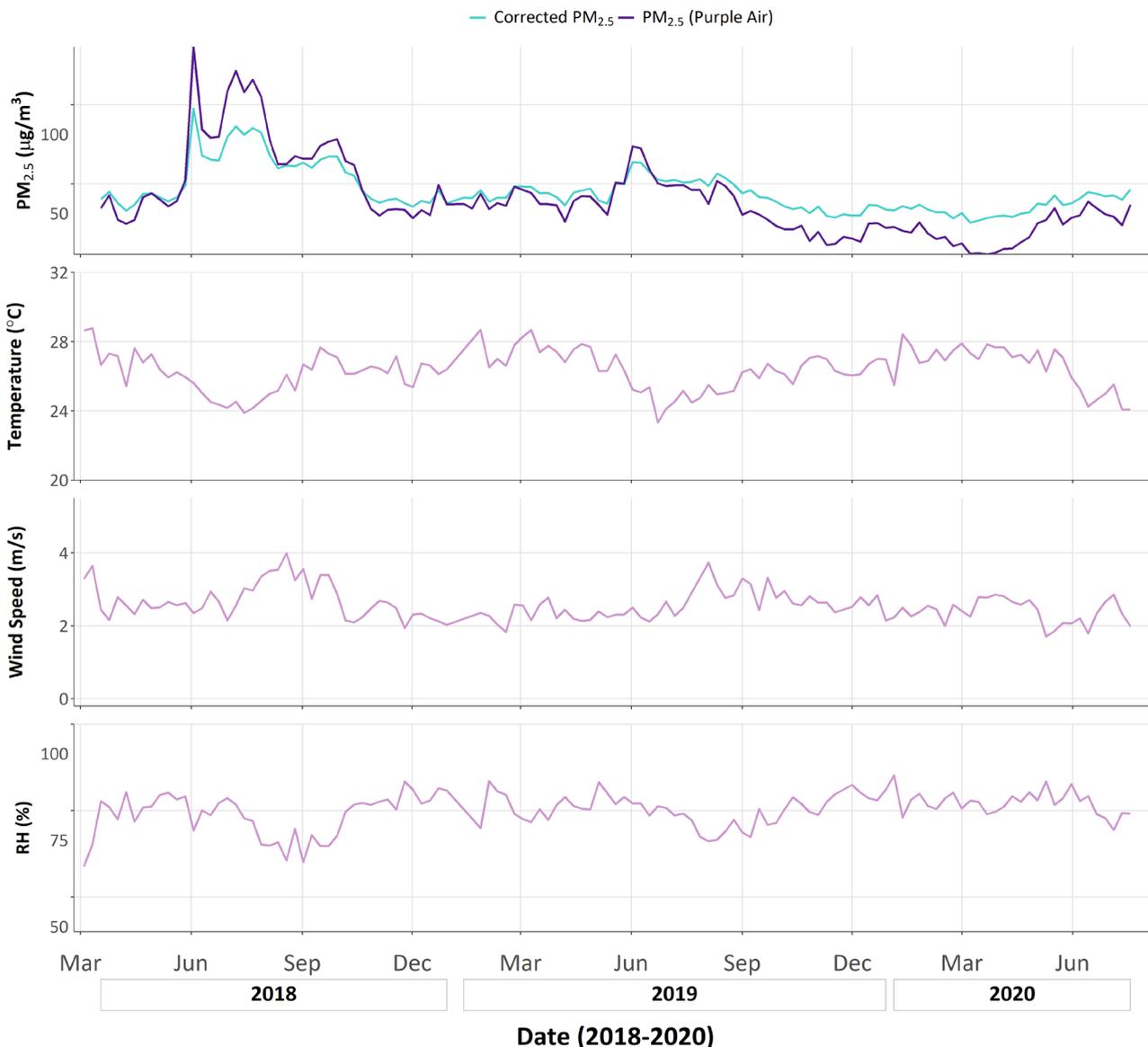
Model	Averaging time period	R <sup>2</sup>	Mean absolute error (µg m <sup>-3</sup> )
Raw PurpleAir data	Daily	0.88	14.8
	Hourly	0.88	20.3
Multiple linear regression	Daily	0.96	3.4
	Hourly	0.90	7.3
Random forest	Daily	0.86	5.8
	Hourly	0.91	7.2

in particular household fuel usage, which comprises about 50–75% of the total emissions of SO<sub>2</sub>, BC, and OC in each city. Though the total emissions are slightly higher in Kinshasa compared to Kampala, the similar source mix further justifies applicability of sensor calibrations between the two cities. Qualitative information about particle size in the two cities can be obtained through satellite retrievals of the Angstrom exponent, which we present in Fig. S2. The 2019 annual mean Angstrom exponent as retrieved by MODIS Terra Deep Blue retrieval algorithm is about 1.5 in Kampala and 1.6 in Kinshasa, indicating qualitative similarity in particle size distributions in each city. Though the geographic distance between Kinshasa and Kampala is a limitation of the work, given the similarities between the two environments, estimates of emissions sources, qualitative similarity in particle size, and the paucity of reference monitoring and resources for such monitoring in sub-Saharan Africa, we consider our sub-continental calibration to be sufficient for further analysis.

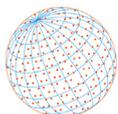


### 3.2 PM<sub>2.5</sub> Time Series at Each Sampling Location

Fig. 3 shows both the corrected (turquoise) and raw (purple) monthly averaged PurpleAir PM<sub>2.5</sub> data collected at the U.S. Embassy in Kinshasa (see “Methods” and Fig. 1) from March 2018 through July 2020. Often the calibrated data and raw data are within 10  $\mu\text{g m}^{-3}$  of each other, except when the PM<sub>2.5</sub> is above 100  $\mu\text{g m}^{-3}$  or below 25  $\mu\text{g m}^{-3}$ . The 95% confidence interval for daily averaged raw data ranges between  $\pm 0.1$  to  $\pm 0.5 \mu\text{g m}^{-3}$ , depending on the exact month in the data. PM<sub>2.5</sub> data are nearly always above WHO air quality guidelines (10  $\mu\text{g m}^{-3}$  on an annual mean basis, 25  $\mu\text{g m}^{-3}$  on a 24-h mean basis). The 2018 average PM<sub>2.5</sub> was 54.4  $\mu\text{g m}^{-3}$ , which was followed by a decrease in 2019 (43.5  $\mu\text{g m}^{-3}$ ). Through July 2020 (time of last data collection), the average is 35.7  $\mu\text{g m}^{-3}$ , though PM<sub>2.5</sub> is typically high in August and later in the year. The 2018 average also does not include the months of January and February, which are typically lower in PM<sub>2.5</sub>. In addition to this, the decrease in PM<sub>2.5</sub> between 2018 and 2019 is not expected to be related to emissions reductions. Emissions trends in recent years for DRC are not well known. However, to our knowledge there has been no emissions control mitigation or measures in the last 3 years. Meteorological data are also limited in Kinshasa and Brazzaville. In Fig. 3 we also plot the Kinshasa station’s available meteorological variables from January 2018 to August 2020. To

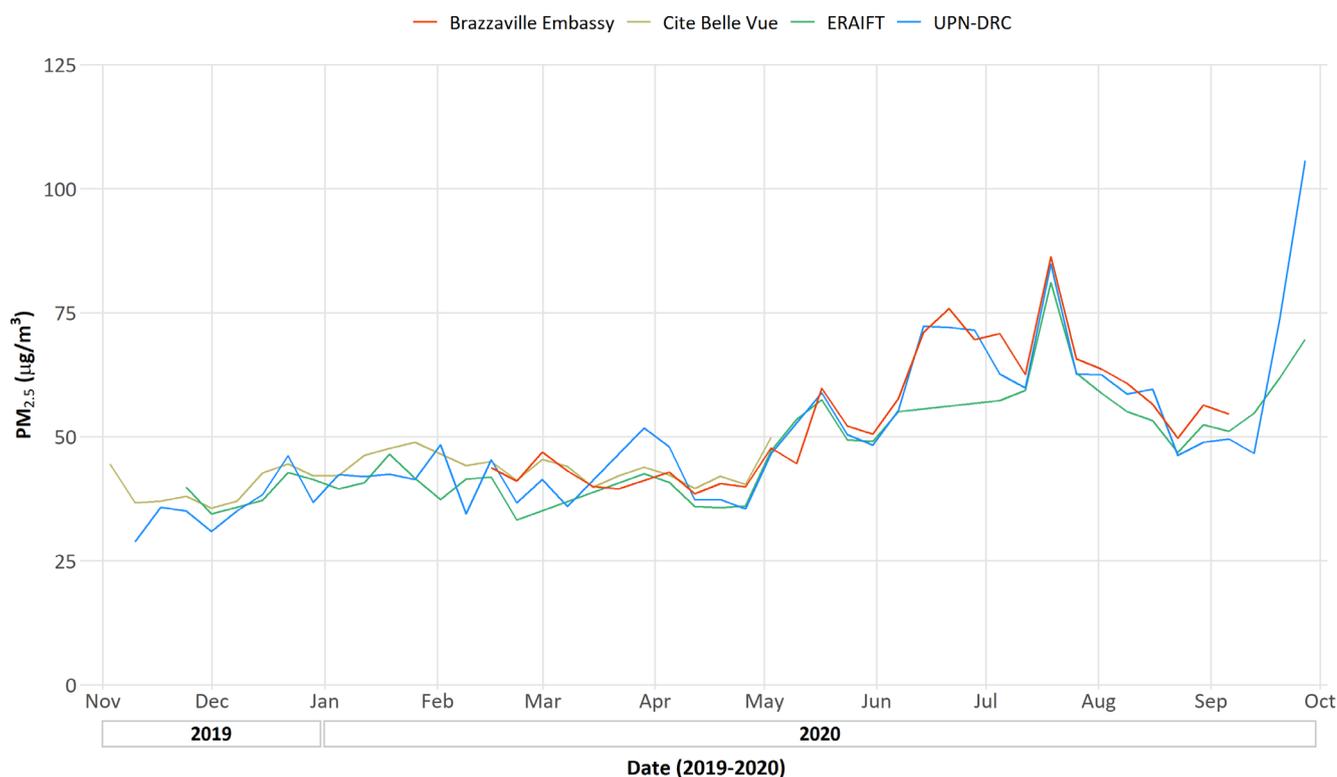


**Fig. 3.** Weekly mean raw (purple) and corrected (turquoise) PM<sub>2.5</sub> data, as well as weekly mean temperature ( $^{\circ}\text{C}$ ), wind speed ( $\text{m s}^{-1}$ ), and relative humidity (%) (NOAA data) at the Kinshasa U.S. Embassy site between March 2018 and July 2020.

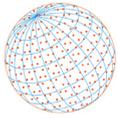


first order, several previous studies have reported that on a large scale,  $PM_{2.5}$  can be positively correlated with temperature, negatively correlated with wind speed, and positively correlated with relative humidity (Jacob and Winner, 2009; Fiore *et al.*, 2015; Westervelt *et al.*, 2016). As seen in Fig. 3, dry season July 2019 temperatures are approximately the same between 2018, 2019, and 2020, suggesting that the temperature effects on  $PM_{2.5}$  cannot explain the observed decrease in  $PM_{2.5}$  in 2020. Relative humidity in 2020 is slightly higher or roughly the same compared to either 2019 or 2018, inconsistent with the strong 2020  $PM_{2.5}$  decreases. Wind speed is slightly lower in 2020 compared to 2018 or 2019, which would also have the effect of likely increasing  $PM_{2.5}$ , and therefore cannot explain the observed decreases in  $PM_{2.5}$ . We conclude that the decrease in  $PM_{2.5}$  between 2018, 2019, and 2020 cannot be directly attributed to at least these three meteorological factors. Another plausible explanation is a potential decrease in wildfire activity in the Congolese rainforest. Burned area was shown to decline by  $\sim 1.3\% \text{ y}^{-1}$  between 2003 and 2017 in the Central African Republic and South Sudan (Jiang *et al.*, 2020), thousands of kilometers from Kinshasa. Closer to Kinshasa, burned area was found to largely remain unchanged over the same time period. Given these contrasting results, it is not likely that fire activity is the main driver of observed  $PM_{2.5}$  decreases either, although it may contribute partially. We will later attribute the 2020 decrease at least partially to decreases in activity associated with COVID-19 lockdown.

In Fig. 4 we plot the monthly averaged corrected  $PM_{2.5}$  for each of the four other sites (Fig. 1). Data collection began at three of these four sites in November 2019 (UPN, ERAIFT, and Cité Belle Vue), and in February 2020 at the Brazzaville U.S. Embassy, continuing through September 2020. Each of the sites show a similar seasonality, with lower concentrations in November 2019 through April 2020, coinciding with the rainy season.  $PM_{2.5}$  concentrations in June and July are higher at  $60\text{--}70 \mu\text{g m}^{-3}$  from  $40 \mu\text{g m}^{-3}$  in the rainy season. This is qualitatively consistent with the typical seasonal behavior at the longer-term U.S. Embassy Kinshasa location, though the dry season rebound in  $PM_{2.5}$  in 2020 at the Kinshasa embassy is smaller than at the other four sites. As with the Kinshasa embassy site, corrected  $PM_{2.5}$  levels are nearly always above WHO guidelines, even in the rainy season.



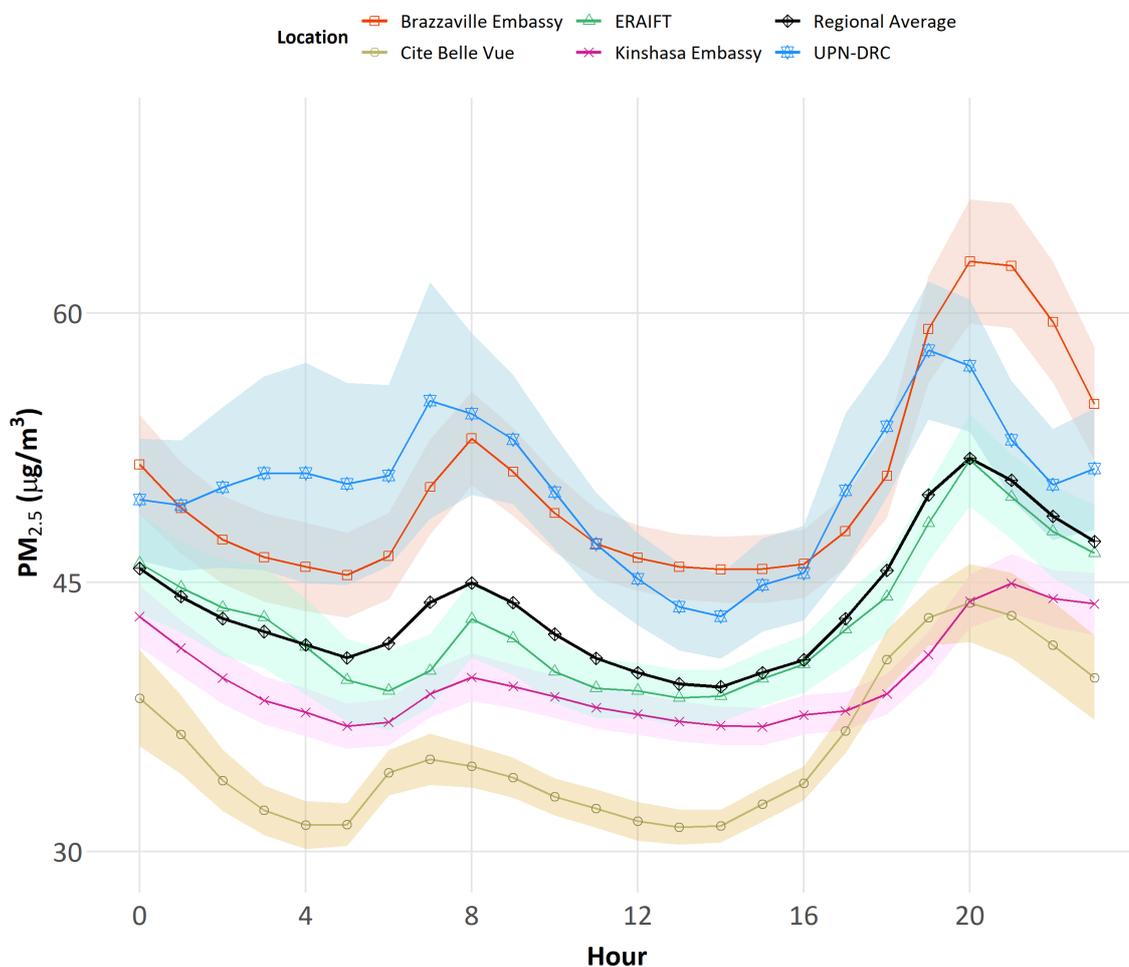
**Fig. 4.** Monthly mean corrected data at 4 sites (excluding the Kinshasa embassy) between November 2019 and July 2020. Shaded areas indicate the 95% confidence interval of the monthly average values.



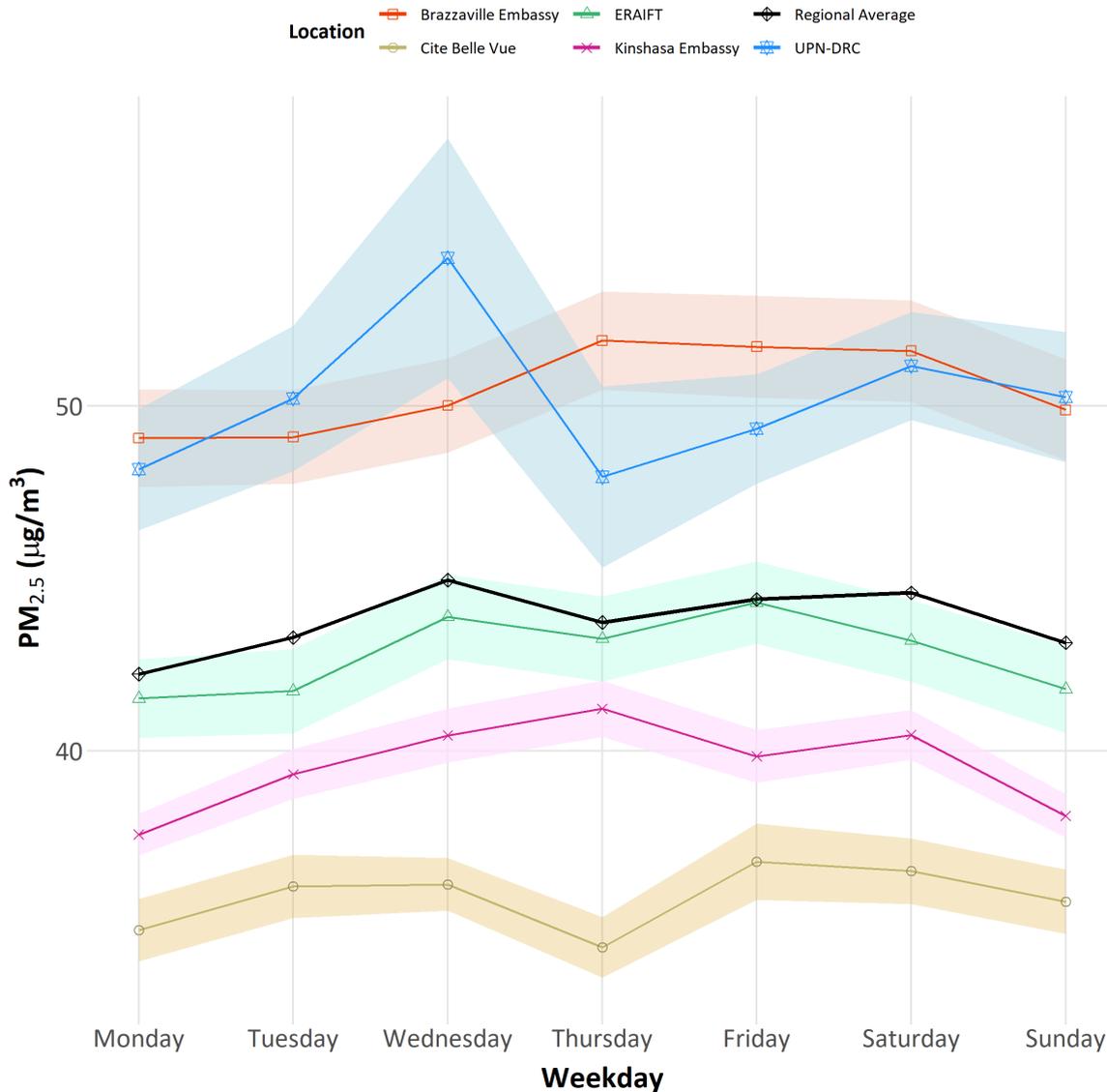
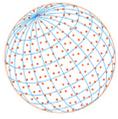
### 3.3 Diurnal and Weekly Profiles at Each Sampling Site

We present in Fig. 5 the  $PM_{2.5}$  over the diurnal cycle in each of the Kinshasa-Brazzaville locations using the entire datasets available for each site. Each site tends to have similar diurnal variability, though the magnitude of the  $PM_{2.5}$  concentrations is different at each location. There is typically a very early morning minimum in the diurnal trend at all sites, around 05:00 West Africa Time (WAT), followed by a morning peak at around 08:00. Local traffic emissions and household cooking are expected to be a major contributor to these peaks. Except at UPN-DRC, there is a steady increase throughout the course of the day, as local activity such as cooking and preparing of food, open burning, and other sources begin to contribute to  $PM_{2.5}$ . The highest  $PM_{2.5}$  values of the day then peak at about 18:00–20:00, coinciding with evening vehicle traffic and cooking. After 20:00,  $PM_{2.5}$  values start to drop quickly overnight. The highest  $PM_{2.5}$  values occur at the Brazzaville embassy and UPN-DRC, peaking at around  $60 \mu\text{g m}^{-3}$  in the evening. The lowest  $PM_{2.5}$  values occur at Cité Belle Vue, which is a higher-end residential area where some foreign diplomats tend to live. These areas are less likely to use high-emitting cooking and open burning practices, potentially explaining the lower  $PM_{2.5}$ . However, the  $PM_{2.5}$  data at Cité Belle Vue is also only available for the mostly wet season, which can also potentially explain the lower  $PM_{2.5}$  values. The 5-site average is shown in black in Fig. 5 and ranges from about  $40 \mu\text{g m}^{-3}$  at minimum to above  $50 \mu\text{g m}^{-3}$  at the peak.

Average  $PM_{2.5}$  concentration by day of the week is plotted for each site and the area average in Fig. 6. Generally, there are substantial differences in the weekly  $PM_{2.5}$  variation between each location. As in the diurnal variation (Fig. 5), Brazzaville and UPN-DRC have the highest  $PM_{2.5}$  of all the sites, around  $50\text{--}55 \mu\text{g m}^{-3}$ . CBV on average is about  $10 \mu\text{g m}^{-3}$  lower, though this is likely



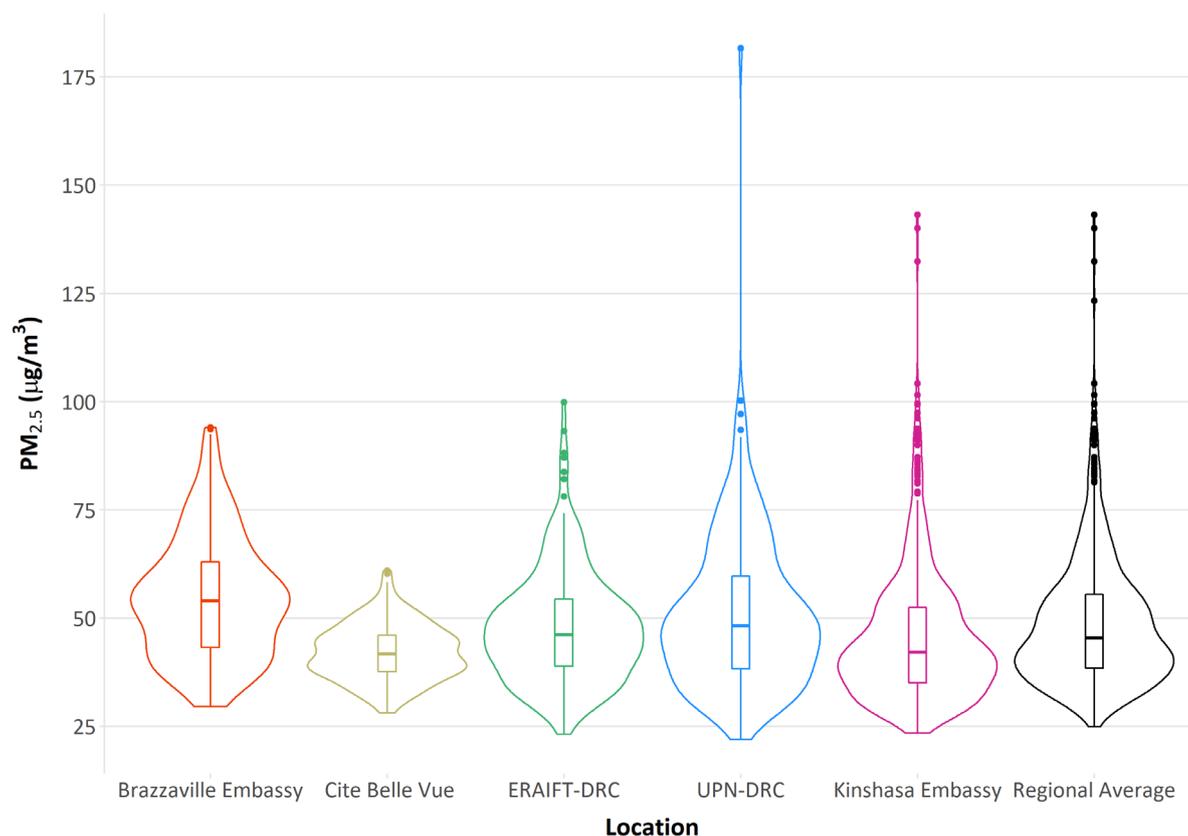
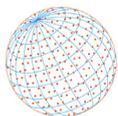
**Fig. 5.** Diurnal average  $PM_{2.5}$  for the entire data record at each of the 5 sites and the site-wide average (black). Shaded areas indicate the 95% confidence interval of the hourly averages. Hour indicates the local time (West Africa Time).



**Fig. 6.** Day-of-the-week averages for  $PM_{2.5}$  for the entire dataset at each of the 5 sites, and the site-wide average. Shaded areas indicate the 95% confidence interval of the daily averages.

due to a limited data range that mainly includes the wet season. Sunday is generally one of the lowest days for  $PM_{2.5}$  in all sites (except CBV), coinciding with a low point in economic activity during the week. Each site has typically two days of the week in which  $PM_{2.5}$  peaks, though which day varies by site. At UPN-DRC, there is an early week peak Wednesday and then a lower Saturday peak, with a minimum on Thursday. Conversely, the Kinshasa embassy and Brazzaville embassy are highest on Thursday, and ERAIFT-DRC is highest on Friday. This variation among weekday  $PM_{2.5}$  is likely explained by variation in type of location. Residential, educational, and diplomatic locations are represented among the five sites, each of which have different source signatures, emissions patterns, and micrometeorology.

Fig. 7 summarizes all daily mean data at all five sites and the 5-site average in a violin plot. Distributions of  $PM_{2.5}$  are mostly unimodal and right-skewed, with the majority of data points located around  $50 \mu\text{g m}^{-3}$ . As previously discussed, UPN-DRC and the Brazzaville embassy have the highest median and quartile ranges for  $PM_{2.5}$ . The highest daily mean extreme value (nearly  $180 \mu\text{g m}^{-3}$ ) is observed at the Kinshasa embassy. However, the Kinshasa embassy has the most extreme values with several daily means greater than  $100 \mu\text{g m}^{-3}$ , though it also represents the longest data record length. The  $PM_{2.5}$  distributions at every site except for Cité Belle Vue each have “long tails” with nonzero density as concentrations approach  $100 \mu\text{g m}^{-3}$ , indicating a higher



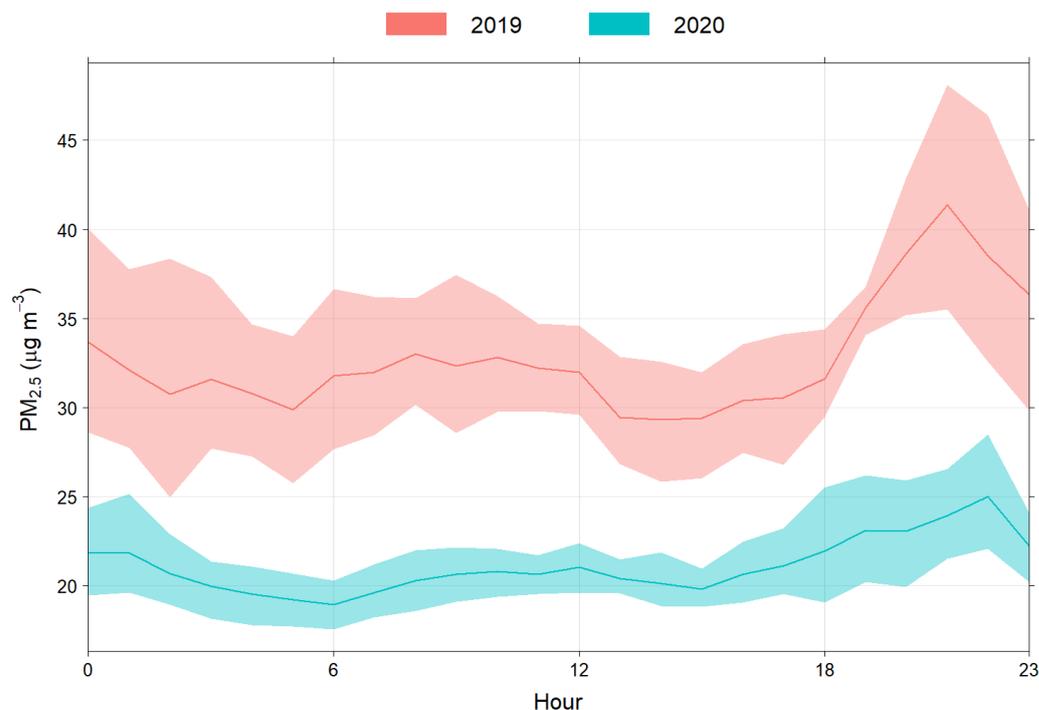
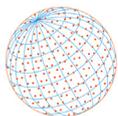
**Fig. 7.** Violin plot of daily averaged  $PM_{2.5}$  values for the entire dataset at each location and for the site-wide average. Boxes represent median and interquartile range.

frequency of poor air quality at these locations compared to other sites. The 5-site average median daily  $PM_{2.5}$  value is  $42.1 \mu\text{g m}^{-3}$ , a factor of 4 higher than the WHO annual mean guideline of  $10 \mu\text{g m}^{-3}$ .

### 3.4 Impact of COVID-19 lockdown on $PM_{2.5}$ in Kinshasa

We use our 29-month dataset (beginning March 2018) at the Kinshasa embassy to assess the potential changes in  $PM_{2.5}$  concentrations attributable to COVID-19-related stay-at-home orders in Kinshasa. The governor of Kinshasa announced a total lockdown for the city starting on 28 March, which was later postponed. Starting 6 April, Gombe, the administrative and commercial center of Kinshasa where the U.S. Embassy is located, was closed for two weeks. We plot and compare the April for 2019 and 2020 in Fig. 8. On average, April 2020 daily mean  $PM_{2.5}$  is about  $14.7 \mu\text{g m}^{-3}$  lower than the same time period in 2019, about a 40% decrease, larger than the amount of  $PM_{2.5}$  reduction in China during COVID-19 quarantine orders (Shi and Brasseur, 2020). In particular, the evening peak around 20:00 seen clearly in 2019 is mostly absent in 2020. Other than a flattening of the evening peak, the 2020 trend follows 2019 very closely, though offset by at least  $10 \mu\text{g m}^{-3}$ . Natural variability including fire activity may play a role in these decreases, though our preliminary meteorological analysis (see Fig. 3 and associated discussion) suggests that meteorology cannot explain the observed  $PM_{2.5}$  decreases. Daily mean  $PM_{2.5}$  in April 2018 was  $3.8 \mu\text{g m}^{-3}$  lower compared to April 2019, indicating that there was not an April  $PM_{2.5}$  decreasing trend prior to the COVID-19 pandemic.

We also analyze satellite observations of AOD at 550 nm wavelength using the MAIAC Level 2 gridded data over land surfaces at 1 km pixel resolution. Fig. 9 shows MAIAC AOD for January–June 2018, 2019, and 2020, and a 2020-versus-2019 difference over the Congo region. AOD levels are elevated over the larger region and especially over Kinshasa and Brazzaville (located around 15.3 E latitude and 4.3 S latitude). Contrary to the surface-level  $PM_{2.5}$  data, AOD was higher in January through July 2019 than 2018. Columnar AOD data is a very different measure than



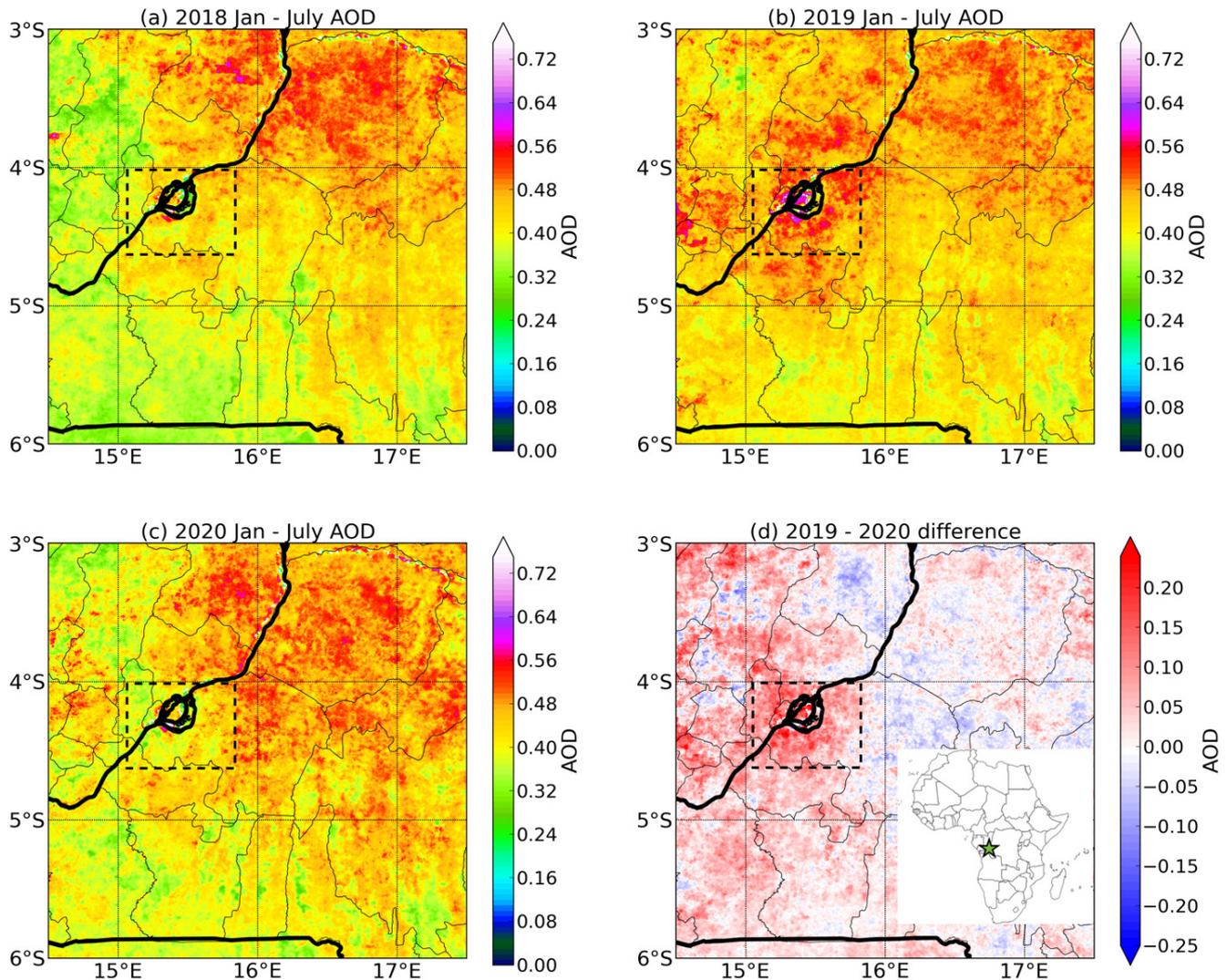
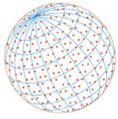
**Fig. 8.** Analysis of PM<sub>2.5</sub> changes during COVID-19 at the Kinshasa U.S. Embassy. Averaging time period is 6–20 April. Top: diurnal PM<sub>2.5</sub> in 2019 and 2020 by day of the week. Bottom left: diurnal mean PM<sub>2.5</sub>. Bottom middle: monthly mean PM<sub>2.5</sub>. Bottom right: day-of-the-week average. Shaded region represents the 95% confidence interval in the mean.

surface-level PM<sub>2.5</sub> and do not necessarily vary together (Li *et al.*, 2015; Van Donkelaar *et al.*, 2016). Compared to 2019, AOD in 2020 is about 0.1–0.2 lower than 2019, but only 0.05 lower than 2018. These decreases are qualitatively consistent with our hypothesis of COVID-19 lockdown impacts on air pollution in the Congo region, though could also be consistent with changes in fire activity. Malings, Westervelt, *et al.* (2020) further explored connections between MAIAC AOD and surface PM<sub>2.5</sub> in both Africa and North America, including applications for converting column AOD to surface PM<sub>2.5</sub>.

## 4 CONCLUSIONS

Every year, air pollution causes millions of premature deaths and a host of illnesses in cities worldwide. Sub-Saharan Africa, where the dearth of air pollution monitoring gives rise to high uncertainty in estimates of exposure and health impacts, is particularly affected. Although the Kinshasa-Brazzaville megalopolis is home to approximately 14 million inhabitants, systematic, long-term air quality data was not publicly available for this region prior to this study. Hence, we deployed five low-cost sensors throughout Kinshasa-Brazzaville in March 2018 and used an MLR model developed for Kampala, a city with comparable environmental conditions, to calculate suitable correction factors. The PM<sub>2.5</sub> concentration averaged 46.1 µg m<sup>-3</sup> across the monitoring network over the study period, indicating very poor air quality in both Kinshasa and Brazzaville. The levels peaked during the dry season (June–August) and dropped by 5–10 µg m<sup>-3</sup> (on average) during the wet season, owing to the dominant role of wet scavenging, but even the latter values were approximately 4 times higher than the WHO guideline.

Furthermore, the decrease in PM<sub>2.5</sub> between 2018 and 2020 cannot be ascribed to meteorology, although the paucity of available data limited our analysis. Despite some variation between the study sites, the average concentrations fell within 10 µg m<sup>-3</sup> of each other, suggesting a coherent set of sampling locations that represents normal city-wide conditions. Generally, the maximum hourly PM<sub>2.5</sub> values occurred around 20:00 WAT, corresponding to the daily early-evening peak



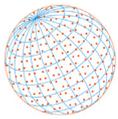
**Fig. 9.** MAIAC Level 2 550 nm AOD at 1 km resolution over the Congo region for a January–July average in (a) 2018, (b) 2019, and (c) 2020, and (d) the difference between 2019 and 2020. Boundaries represent Level 2 administrative boundaries (districts and communes) provided by the United Nations Office for the Coordination of Humanitarian Affairs. The black dashed box indicates the Kinshasa-Brazzaville region and the inset in (d) shows the broader location within the African continent.

in activity. Similarly, the minimum daily values occurred on Sundays, corresponding to the weekly trough in activity. In addition, compared to the same month from the previous year, the daily mean dropped by  $14.7 \mu\text{g m}^{-3}$  during April 2020—the period of the COVID-19 lockdown—which cannot be explained by meteorological changes alone. Satellite observations of the aerosol optical depth qualitatively confirm our surface-based results.

Our work represents the first step in evaluating the air quality of a fast-growing megacity in sub-Saharan Africa. Future research should address the limitations of this study, including the lack of a local reference-grade monitor in Kinshasa, the absence of robust weather data, and the brevity of the sampling period, as well as explore the potential for better adapting air quality models and satellite observations to Kinshasa and the Congo.

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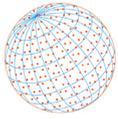
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## SUPPLEMENTARY MATERIAL

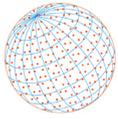
Supplementary data associated with this article can be found in the online version at <https://doi.org/10.4209/aaqr.200619>

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