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Article

Low-Cost Investigation into Sources of $PM_{2.5}$ in Kinshasa, Democratic Republic of the Congo

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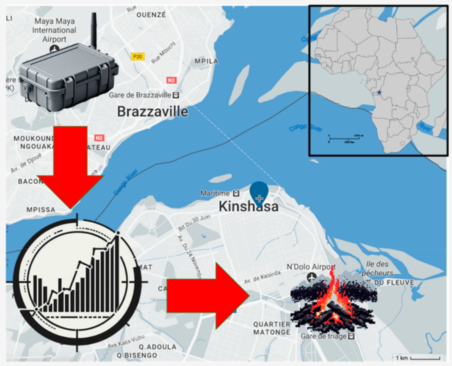

ABSTRACT: Despite having a population of 16.3 million, Kinshasa, Democratic Republic of the Congo (DRC), has had little attention toward air quality monitoring. We deployed a MetOne Beta Attenuation Monitor (BAM-1020) for reference $PM_{2.5}$ and a QuantAQ Modulair, the latter of which includes measurements of gas-phase NO_2, O_3, CO, and CO_2, in addition to PM_1, $PM_{2.5}$, and PM_{10}. Here we present the first results from this aggregated, multisensor, multispecies network in DRC. We first compare the Modulair against the BAM-1020, finding an r^2 of 0.76 and a mean absolute error (MAE) of 6.97 $\mu g\ m^{-3}$ (hourly data). We develop a correction factor using multiple linear regression, improving MAE to 5.54 $\mu g\ m^{-3}$. We leverage gaseous pollutant concentrations, particle size distribution data, and anemometer data to draw conclusions about the sources of $PM_{2.5}$ in Kinshasa. We link factors resolved from a non-negative matrix factorization method using the gaseous and particle bin concentrations to source profiles. We find a 3-factor solution that points to a CO-dominated, supermicron particle source indicative of secondary particles from local combustion, along with a submicron particle-dominated source indicative of primary particles from combustion and a regional biomass burning source. Our results highlight the need for the implementation of clean air solutions in the DRC.

KEYWORDS: *particulate matter, sensors, ozone, nitrogen oxides, sources*

1. INTRODUCTION

Ambient fine particulate matter, or $PM_{2.5}$ (particles with diameters less than 2.5 micrometers), is a major public health issue, contributing to between 3 and 4 million premature deaths around the world.[1,2] In addition to being a human health crisis, this is also a major equity issue, with air pollution disproportionately impacting the poorest and most vulnerable segments of the population.[3] $PM_{2.5}$ is a complex mixture with both anthropogenic sources (including vehicles, power generation, agricultural burning, cooking, and wildfire smoke) and natural sources (desert dust, sea spray). Gaseous pollutants such as ozone (O_3), carbon monoxide (CO), nitrogen oxides ($NO_x = NO + NO_2$), and sulfur dioxide (SO_2) are produced in varying amounts by many of the same anthropogenic sources and also contribute to the air pollution health burden. $PM_{2.5}$ is a subset of the ambient aerosol, which exerts net cooling radiative effects on the climate and modulates cloud properties.[4,5]

In Africa, air pollution exposure has been linked to 1 million premature deaths annually, and without intervention, these numbers are likely to climb.[6] In many African countries, environmental policy makers are limited in their ability to craft mitigation policies due to a dearth of reliable measurements.[7] This lack of $PM_{2.5}$ exposure data, coupled with a lack of health data, results in a high degree of uncertainty in the burden of disease estimates in Africa. One of the most undermonitored locations on the African continent also happens to be one of the most populous and fastest growing. Kinshasa, Democratic Republic of Congo, has a rapidly increasing estimated population of 16.3 million people, but little to no ambient air quality monitoring. To our knowledge, there are no national ambient air quality standards in place, and government action on air quality is minimal. As a first step in addressing this gap, McFarlane et al. (2021)[8] deployed and analyzed a small network of 5 low cost sensors from 2018 onward, finding daily mean $PM_{2.5}$ levels of around 43.5 $\mu g\ m^{-3}$, more than 8 times the current WHO guideline. While this

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study provided the first much-needed estimates of $PM_{2.5}$, there is still much to be done in characterizing the city's air quality and, crucially, identifying sources of the pollution.

The use of low-cost sensors for $PM_{2.5}$ and gaseous pollutants has rapidly proliferated across the African continent and around the world.[8−14] A key issue remains the reliability of this data, and the strengths and weaknesses of these devices are becoming better characterized.[15−19] While common in North America and Europe, co-location studies of reference monitors and low-cost sensors are rare in Africa. McFarlane et al. (2021)[12] carried out a one-year colocation of a PurpleAir $PM_{2.5}$ monitor against a Federal Equivalence Method (FEM) Met One $PM_{2.5}$ Beta Attenuation Monitor (BAM-1020) located at the U.S. Embassy in Accra, Ghana. The authors found moderate bias in the manufacturer-reported $PM_{2.5}$ data (6.2 μg m^{-3}) and developed correction factors using a variety of methods to reduce the mean absolute error (MAE) to 2.2 μg m^{-3}. Raheja et al. (2023)[20] carried out the first multivendor, multisensor long-term colocation and correction factor study in Africa, using FEM monitors and three sensor brands, PurpleAir, Clarity Movement, and QuantAQ, finding the lowest bias and highest correlation with the QuantAQ devices. Recently, a FEM monitor (Met One BAM-1020) became available in Kinshasa, allowing for a similar colocation analysis and correction factor development to take place.

Here we present results from a recent field campaign for PM and gases in the severely under-monitored megacity of Kinshasa. We go beyond previous studies in Kinshasa and wider Africa by (1) leveraging newly available reference data to build a more locally-specific $PM_{2.5}$ correction factor for a widely-used low-cost monitoring device; (2) collect data on gaseous pollutants such as NO, NO_2, O_3, CO, and CO_2; and (3) apply a novel non-negative matrix factorization approach, supplemented by wind speed and direction data, to identify sources of $PM_{2.5}$ pollution in the center of Kinshasa. Following the approaches used in previous studies,[21,22] we demonstrate the utility of low-cost monitoring devices for $PM_{2.5}$ and select gases in inferring aerosol sources. While these previous efforts have relied on an aerosol chemical speciation monitor (ACSM) to complete the source identification, for the first time, we conduct this method without such equipment in a fully low-cost manner. This pollution source information is actionable for air quality managers and policymakers in crafting potential mitigation strategies.

2. METHODS

2.1. Site Sampling Details. The sampling site selected for this work is at the Embassy of the United States of America in Kinshasa, located at 310 Avenue des Aviateurs, latitude 4.3002 S and longitude 15.3138 E. The site is located in the Gombe municipality, which is an urban area that hosts Kinshasa's main central business district and several important governmental offices. Traffic is often severe in this municipality, and other polluting activities, such as waste burning, have been frequently observed. The site is also close to a major train station and the Congo River, both of which are the sites of regular shipping and port activities. A map of the location with a photo of the site is shown in Supporting Information, Figures S1 and S2.

2.2. Instrumentation. Beginning in March 2022, a Met One Beta Attenuation Monitor 1020 (BAM-1020) was installed at the U.S. Embassy in Kinshasa. The BAM-1020 is certified as a U.S. EPA Federal Equivalent Method monitor for ambient $PM_{2.5}$.[23] BAM-1020 gives real-time (hourly or higher) measurements of $PM_{2.5}$ using the principle of beta ray attenuation by a filter tape medium that is laden with size-selected particles sampled from the ambient air.[24] The instrument is operated by the U.S. State Department, and data are publicly available from their website (see Data Availability Statement). The cost of a BAM-1020 is at least $25,000, not inclusive of shelter and other considerations.

Also, in March of 2022, at the same location, a QuantAQ Modulair device was installed on top of the shelter housing the BAM-1020, at a height of about 3 meters off the ground (Figures S1 and S2). The Modulair is a multipollutant air quality measurement solution that leverages several types of low-cost sensors to provide real-time PM_1, $PM_{2.5}$, PM_{10}, CO, NO_2, NO, O_3, and CO_2 concentrations at a time resolution of 1 min. The cost of a Modulair instrument is approximately $5,000. Data are uploaded in real time via cellular connection and are also saved locally on an SD card. The Modulair was outfitted with a Davis Sonic Anemometer to measure the wind speed and wind direction at the site. The Modulair includes five gas sensors each from Alphasense (CO-B4, NO-B4, NO_2-B43F, O_X-B431, and CO_2 IRC-A1) and two optical particle sensors (Plantower PMS5003 and Alphasense OPC-N3). These gas sensors work by allowing air to diffuse into an electrochemical cell with a series of electrodes at which an oxidation−reduction reaction occurs to generate a current that is proportional to the gas concentration. An exception to this is the CO_2 sensor, which is an infrared detector rather than an electrochemical cell sensor. Limitations of the gas sensors include cross sensitivity with other gases that are not intended to be sampled,[25] cross sensitivity with temperature,[26] and lifetime of the sensors.[27] Further details on the gas sensors and their performance against reference monitors can be found in the literature.[28−30]

For particulate matter, the combination in the Modulair of both the Alphasense optical particle counter, which is skillful at estimating coarse PM ($PM_{10-2.5}$) and the aerosol size distribution above 350 nm, and the Plantower optical particle sensor, which is skillful at estimating submicron aerosol, results in a higher accuracy estimate of PM than either sensor alone.[31] This setup also allows for an accurate estimate of PM_{10} and coarse PM, which cannot be done with a Plantower-based device alone.[15] Optical particle sensors and counters have been rigorously tested in both laboratory and select field environments.[12,32−37] Consensus is emerging that correction factor models developed locally or in conditions representative of environmental variables (temperature, humidity) and aerosol properties (size, composition) are necessary for scientifically defensible use of these simple devices,[9] which we describe in the following section.

2.3. Colocation Analysis and Correction Factor Development. The Modulair device was colocated with the BAM-1020 for the entirety of the campaign. However, frequent BAM-1020 instrument outages and malfunctions restricted the time that both instruments were fully functioning to December 2022. Thus, we use hourly-averaged data from both instruments from December 1 of 2022 through December 21, 2022 as both an evaluation period and a correction factor development period. Longer evaluations of QuantAQ Modulair devices have previously been published in similar environments in West Africa.[20] Both datasets were first cleaned for large negative numbers, NaNs, and physically unrealistic values (such as relative humidity greater than 100%). This removed less than 1% of the dataset. After the samples were cleaned, descriptive statistics such as Mean Absolute Error (MAE), a measure of bias, and coefficient of determination (r^2) were calculated to evaluate the performance of the manufacturer-reported $PM_{2.5}$ data against the FEM instrument. Following the methods of McFarlane et al. (2021)[8] and others, we employ a 10-fold cross validation method with an 80%/20% training/testing data split, randomly selected in the 3 weeks of hourly data. We use the 80% folds to fit a multiple linear regression of the form:

$$\mathrm{PM}_{2.5} = \beta_0 + \beta_1 \times \mathrm{ModulairPM}_{2.5} + \beta_2 \times \mathrm{RH}(\%) \quad (1)$$

where β_0, β_1, and β_2, are the regression coefficients, RH is the relatively humidity in percent, $\mathrm{ModulairPM}_{2.5}$ is the manufacturer-reported $PM_{2.5}$ concentration, and $PM_{2.5}$ is the corrected final concentration. A multiple linear regression with relative humidity and manufacturer-reported $PM_{2.5}$ concentration as the explanatory variables is selected, as it is the most interpretable method and has been shown several times to work well for sensor calibration methods, including explanatory variables such as RH, which are known to impact aerosol optical properties and thus measurement by optical devices.[9,11,12,17,18,38−40] As there are no reference gas analyzers in Kinshasa and very few on the entire African continent, a similar evaluation and correction factor analysis were not possible for the gas sensors. However, the gas sensors were calibrated in the lab and placed in an environmental chamber for an extended period of time with consistently varied temperature and RH changes in order to mimic the environment in which the instrument is deployed. The calibration mathematical model follows the methods of Cross et al. (2017).[41] Environmental conditions and cross-sensitivity with other gases has been shown to hinder the performance of similar types of gas sensors.[42]

2.4. Non-Negative Matrix Factorization. In order to better understand the sources of $PM_{2.5}$ pollution in Kinshasa, we employ non-negative matrix factorization (NMF). NMF is an unsupervised machine learning algorithm[43] which factors the time series dataset of PM and gases into a linear combination of two matrices. The algorithm groups data together by covariance to obtain physically interpretable factors, which can then be attributed to emissions sources. We follow the methodology of Hagan et al. (2019) and Yang et al. (2022),[21,22] where further details can be found. The method is similar to Bousiotis et al. (2022)[44] and Bousiotis et al. (2023)[45] who use positive matrix factorization (PMF) to infer aerosol sources. Our time series input matrix includes the entire campaign at 5 min resolution of CO, O_3, NO, and NO_2 signals, expressed in change in voltage between the working and auxiliary electrodes (ΔmV), and the particle counts per volume (cm^{-3}) in 6 size bins from the Alphasense OPC-N3. The six lowest diameter size bins represent particle sizes detectable by the OPC-N3 and also less than 2.5 μm; specifically 0.35−0.46 μm (Bin 0), 0.46−0.66 μm (Bin 1), 0.66−1.0 μm (Bin 2), 1.0−1.3 μm (Bin 3), 1.3−1.7 μm (Bin 4), and 1.7−2.3 μm (Bin 5). For the gas sensors, using the "raw" voltage differences across electrodes, which is proportional to target gas concentration, affords a first-order correction for temperature and humidity effects.[22] While this cannot eliminate all biases in electrochemical sensors, it is especially important in a setting like Kinshasa where reference gas analyzer data are not available. Yombo Phaka et al. (2023)[46] deployed a Multi-Axis Differential Optical Absorption Spectroscopy instrument (MAX-DOAS) to estimate NO_2 columns in Kinshasa between 2019 and 2021, but the time period and the type of data (vertical column densities) are incompatible with our surface mixing ratio NO_2 data.

The input matrix includes 10 species (particle bins and gases) at 1 min resolution beginning on May 5, 2022 and ending on November 13, 2022, for a total of 165864 data points. NMF is performed on the whole matrix using the scikit-learn python implementation. The input matrix (Y) is decomposed into a timeseries of factors matrix (U) and a factor composition matrix (V^T), the latter of which can be used to find the contribution of each species (bins and gases) to a given factor, as shown in eq 2:

$$Y \approx UV^T \quad (2)$$

The factor composition matrix gives a breakdown of the percent contribution of an individual species to a specific factor, which can then be interpreted physically for attribution to sources. At this step, previous studies have correlated their factors with aerosol chemical speciation monitoring (ACSM) to carry out the source apportionment. In a resource-limited environment, such as Kinshasa, this is not feasible. We therefore aim to demonstrate the first truly low-cost source attribution using this method, relying on only the NMF output and wind speed and direction data.

A three-factor NMF solution is chosen as the most optimal solution. An iterative cross-validation "hold-out" approach described in detail in ref22 is used to calculate the mean squared error of each rank solution. As can be seen in Figure S3, a three-factor solution minimizes the mean squared error. There is little difference between errors between a 2-, 3-, or 4-factor solution, meaning that any of these solutions would be acceptable. We therefore conducted NMF with both a 2- and 4-factor solution and found negligible differences in results with the main difference being a combination of two combustion factors into one, or the expansion of the two combustion factors into three. Since the 3-factor solution provides the most interpretable results, we move forward with a 3-factor solution for the main results.

3. RESULTS

Our colocation of the Modulair with the BAM-1020 is shown in Figure S4. The relationship between the hourly-mean manufacturer-reported Modulair $PM_{2.5}$ data and the hourly BAM-1020 $PM_{2.5}$ is linear, with data falling very close to the 1:1 line (Figure S4a). Additionally, during the three-week colocation time period in December 2022, the Modulair $PM_{2.5}$ very closely tracks the BAM-1022 timeseries (Figure S4b). The r^2 of the $PM_{2.5}$ comparison is 0.758, the Mean Absolute Error (MAE), 6.97 $\mu g\ m^{-3}$, and the Mean Normalized Bias (NMB), 3.2%, which shows a rather high degree of accuracy of these devices, even without correction and calibration. Raheja et al. (2023)[20] also found good performance of the Modulair-PM (same as the Modulair, but lacks gas sensors) in Accra, Ghana. Notwithstanding this accuracy, we perform a correction factor analysis using multiple linear regression as described in section 2.3, resulting in the following equation:

$$\mathrm{PM}_{2.5} = 4.32 + 0.65 \times \mathrm{ModulairPM}_{2.5} + 0.082 \times RH \quad (3)$$

with the units and abbreviations as described previously. Applying this correction factor to the remaining 20% of the data held out for validation results in a modest improvement in MAE (5.53 $\mu g\ m^{-3}$) and MNB (nearly zero) and a statistically

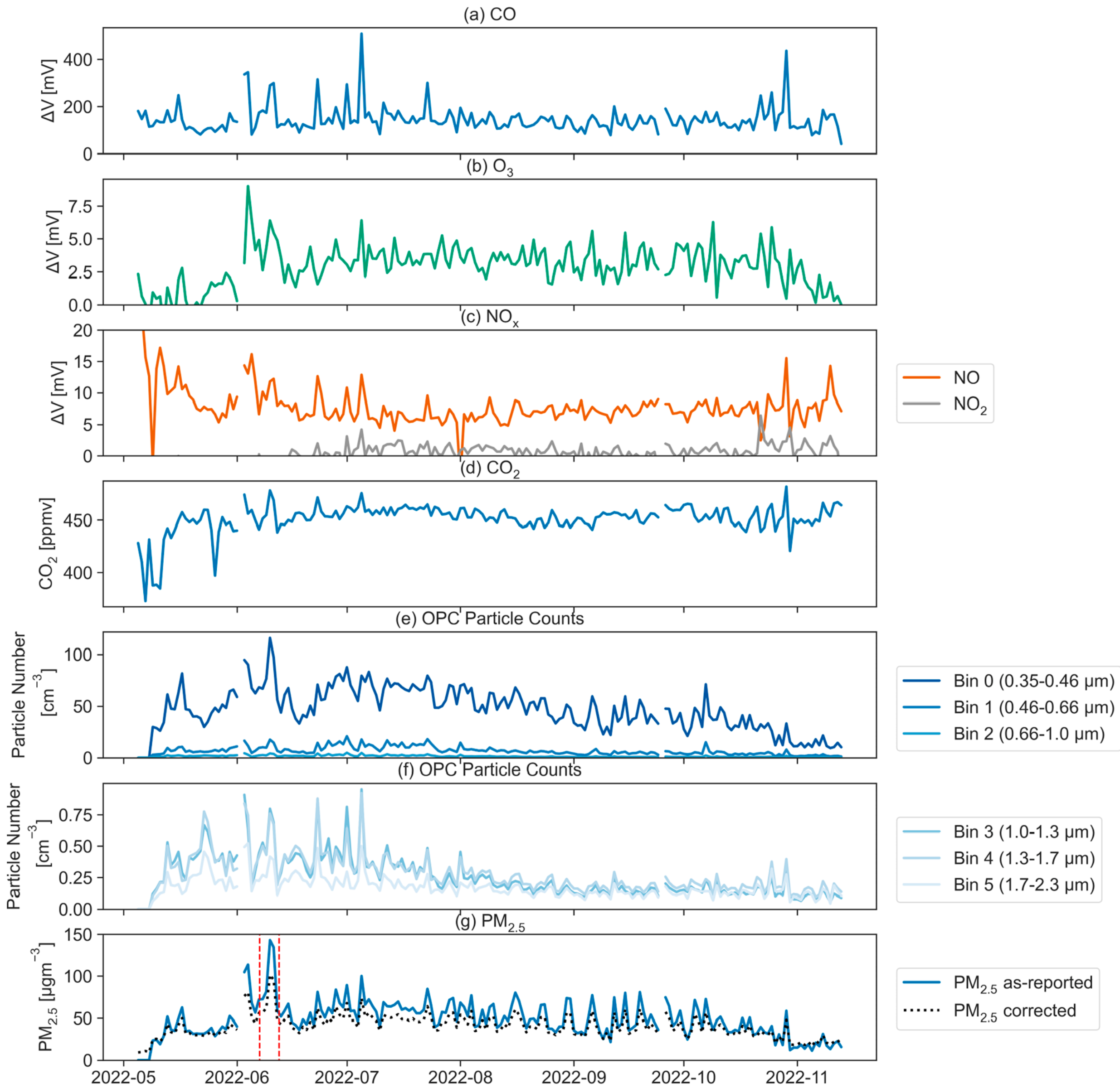

Figure 1. Daily mean gas-phase signal in mV for CO (a), O_3 (b), NO_x (c), CO_2 (d); bin-resolved particle number concentration (cm^{-3}) (e, f) and $PM_{2.5}$ ($\mu g\ m^{-3}$) (g) during the entire campaign. Red dashed lines in panel (g) indicate the extreme pollution episode.

insignificant improvement in r^2 (0.761). Since a lower MAE is preferable, we move forward with applying this correction factor to our $PM_{2.5}$ data. Manufacturer-reported Modulair $PM_{2.5}$ data includes a κ-Köhler-based built-in correction factor, which may result in a less critical role for RH in our multiple linear regression equation.[31]

Figure 1 shows the daily-averaged full campaign timeseries of all gases (Figure 1a–d), particle number (Figure 1e,f), and $PM_{2.5}$ mass (Fig. 1g). Due to a lack of reference standards for each of the gas-phase species, we elect to present the voltage differences which are proportional to mixing ratio in ppb,[47,48] except for CO_2, which is presented in ppm (Fig. 1d). CO levels are mostly flat for the campaign period, especially during July through October, with some daily peaks occurring before and after this time window. As evidenced by the diurnal profile between June 7 and June 11 (Figure S5), CO follows a similar repeated diurnal profile during most of the campaign with mid-afternoon peaks. O_3 (Figures 1b and S5) varies more throughout the campaign period especially in May in which the O_3 signal is close to zero. This May time period of low O_3 also corresponds to a high period in NO_x, which suggests that the titration of O_3 takes place by high NO_x concentrations. O_3 is consistent at noon local time maximum in the diurnal profile, a few hours before CO, when photochemical production of ozone is highest. Daily mean NO_x signal is generally flat as well throughout the campaign, though diurnally the signal tends to be mostly out of phase with the O_3 signal, as NO and NO_2 are cycled back and forth to produce O_3. NO also exhibits 6am/6pm peaks corresponding to traffic patterns. CO_2 mixing ratios are between 400 and 450 ppm during the campaign, close to ambient levels, though this should be treated with caution since the data has not been compared against a reference CO_2 monitor.

Figure 1e,f shows the daily mean particle number concentrations (cm^{-3}) in 6 size sections between 0.35 and 2.3 μm. As expected, the smaller particles contribute much more to particle number, with the most abundant number of particles existing in Bin 0 (0.35–0.46 μm). Figure 1g shows

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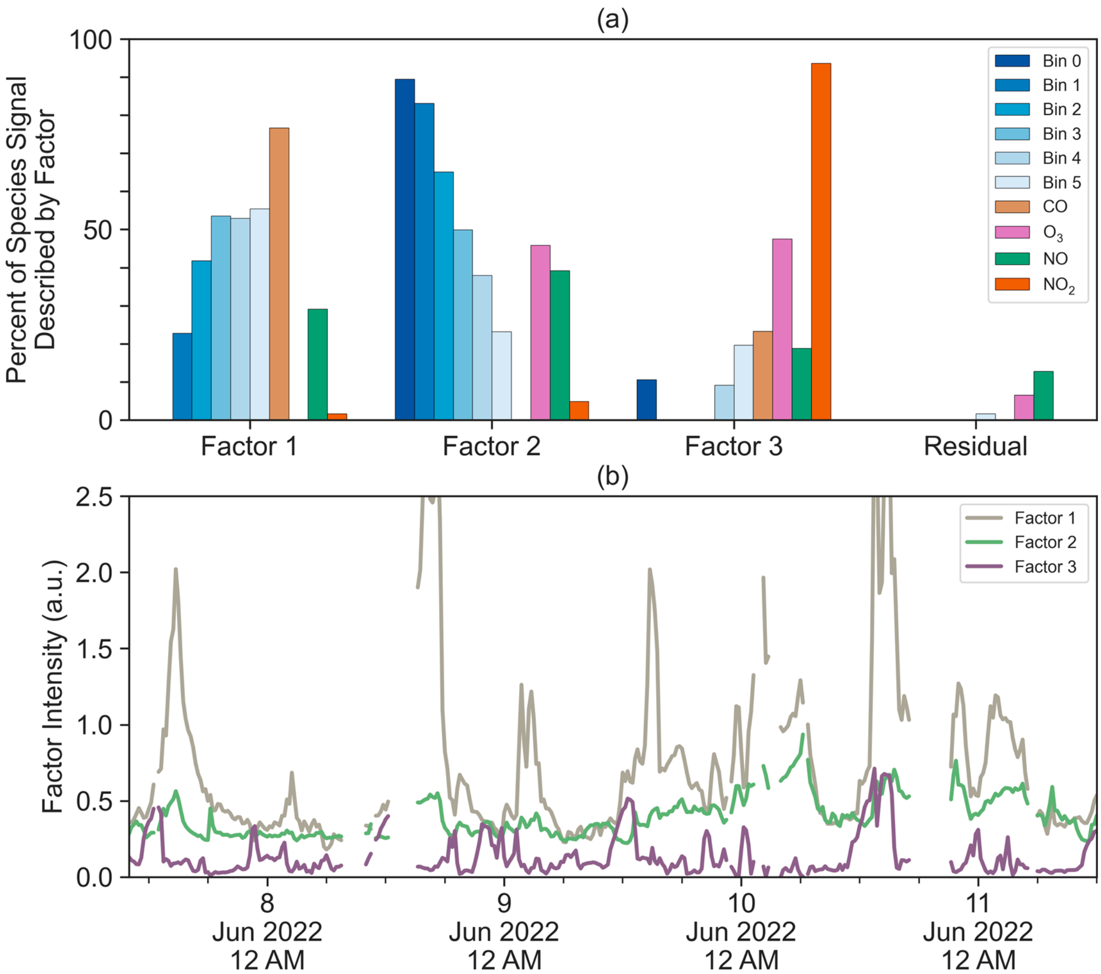

Figure 2. NMF results for a 3-factor solution. (a) Fraction of each species associated with a given factor for the entire campaign period. (b) Diurnal profile of each factor intensity in arbitrary units (a.u.) during the extreme pollution episode. Residual refers to difference between the NMF reconstruction and the original input matrix

daily mean $PM_{2.5}$ both corrected (dashed black line) and uncorrected (solid blue line). The campaign average corrected $PM_{2.5}$ is 40.3 $\mu g\ m^{-3}$, which is about 8 times the WHO daily mean guideline of 5 $\mu g\ m^{-3}$. McFarlane et al. (2021a)[8] found a daily mean between 2019 and 2021 of about 43.5 $\mu g\ m^{-3}$ across 4 sites in Kinshasa (including the same U.S. Embassy site) across all seasons, consistent with our results and showing that little has changed with $PM_{2.5}$ pollution in Kinshasa since 2021. Figure 1e shows that $PM_{2.5}$ concentrations are generally higher in the dry season months of June, July, and August and tend to decline as the rains come in by late September and October. $PM_{2.5}$ daily mean concentrations reached upwards of 100 $\mu g\ m^{-3}$ during a 4 day period from June 7−11 (mean of 71.5 $\mu g\ m^{-3}$), highlighted by the red dashed lines in Figure 1e. The diurnal profiles during this 4 day extreme pollution episode include expected anthropogenically influenced peaks during times of intense human activity (evening rush hour), but concentrations remain high in the evenings as well, especially on June 10, pointing to potential boundary-layer-mediated impacts or regional sources such as biomass burning.

Results of the NMF analysis over the entire campaign time period are shown in Figure 2a. In particular, the contribution of each species (gases and particle bins) to a given factor is shown in panel (a). The most optimal solution consisted of three interpretable factors. Factor 1 is CO-dominated with 80% of the CO signal, with secondary contribution from particles sized between 1.0 and 2.3 μm in diameter (Bins 3, 4, and 5). The diurnal cycle of factor intensity during the extreme pollution episode is shown in Figure 2b. Factor 1 mostly consists of 6 a.m. and 6 p.m. peaks corresponding to traffic patterns. The diurnal profile for the entire campaign period (May through November) is shown in Figure 3 and is mostly consistent with the shorter-term diurnal profile. Given the dominance of the CO signal and the supermicrometer

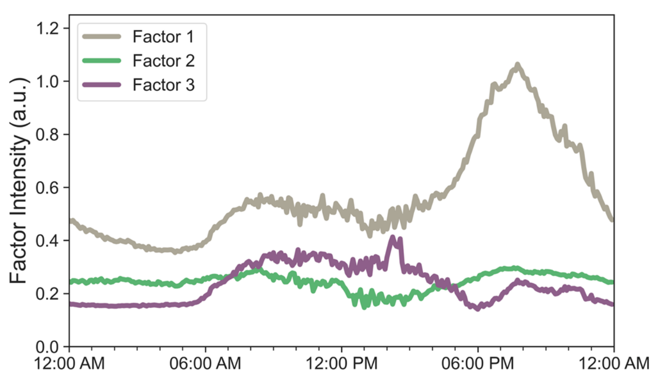

Figure 3. Diurnal profile of each factor intensity (a.u.) for the entire measurement campaign between May and November.

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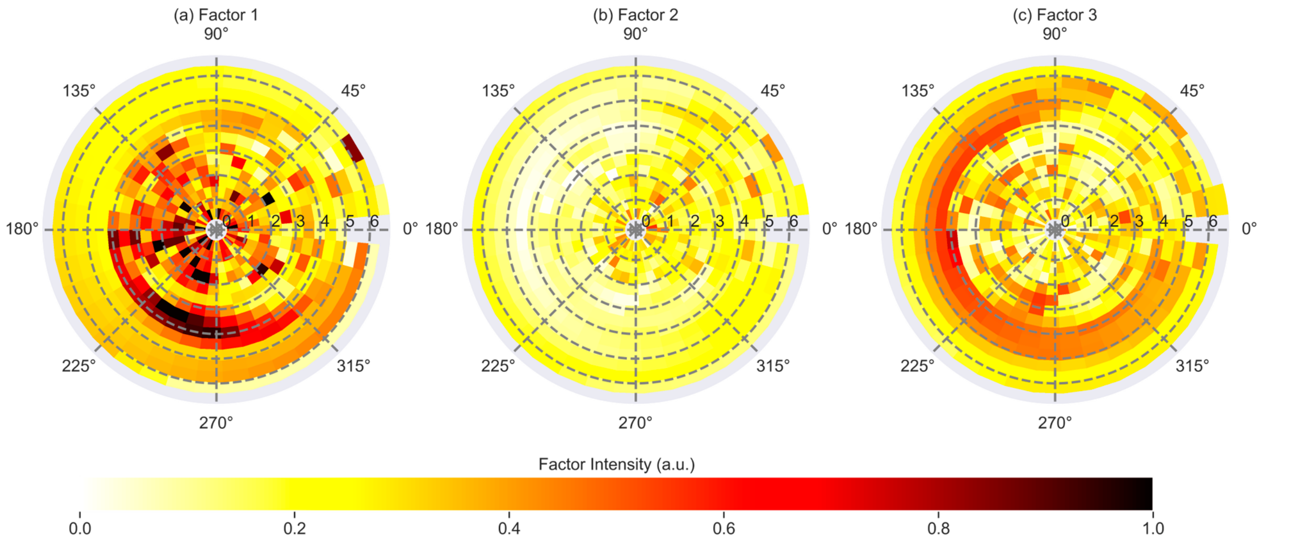

Figure 4. Factor intensity (a.u.) as a function of wind direction (degrees) and wind speed (m s^{-1}) for Factors (a) 1, (b) 2, and (c) 3.

particles, which suggests some particle growth and aging, we expect that this factor is indicative of local vehicular emissions and probably secondary particles.

Factor 2 is a particle-dominated factor, especially by the smaller sizes as measured by the Modulair. Ninety percent of the signal of particle sizes between 0.35 and 0.46 μm (Bin 0) belongs to factor 2, and each submicrometer particle bin contributes well over 50%. The diurnal cycle of this particle-dominated factor includes morning and evening peaks, largely similar in pattern to factor 1 (Figures 2b and 3). We therefore expect this factor to correspond with fresh emissions from combustion activities, possibly from small local fires or cooking activity. Previous work has shown that fresh BC can be emitted in the accumulation mode size range from solid fuels such as firewood and charcoal,[49,50] which are the most common burned fuels for cooking in Kinshasa. Factor 3 is dominated almost entirely by NO_2, with greater than 90% contribution of the total NO_2 signal to factor 3, followed by the contribution of O_3 close to 50%, which may be indicative of photochemical production of secondary aerosols. Additionally, the diurnal profile for factor 3 is different than either factor 1 or factor 2, with consistent high intensity during the daylight hours, but low intensity overnight. The NO_2 signal likely indicates combustion, though whether this is vehicle combustion, wildfire, or other is not straightforward to isolate. We therefore rely on measurements of wind speed and direction to assist in the source identification of factor 3.

Figure 4 shows the factor intensity for each factor as a function of the wind speed and wind direction. The CO-dominated factor (factor 1) is associated with calmer winds (3−4 m/s) from the S and SW of the site, which is also the direction of the busiest vehicular activity of Kinshasa, providing corroborating evidence of that factor being associated with vehicular combustion. The highest intensity associated with factor 2 occurs mostly with wind speeds less than 3 m/s, furthering evidence that this could be fresh emissions. Local surveillance also uncovered substantial industrial crushing and quarry activities potentially producing primary particles N and NW of the site along the banks of the Congo River, which is internally consistent with the factor 2 wind rose intensity (Figure 4). Finally, factor 3 is strongly associated with higher wind speeds (4−5 m/s) from a wider direction, indicative of regional transport. Additionally, the daytime elevated diurnal profile (Figures 2b and 3) of a factor of 3 hints at a regional source that is facilitated by high daytime boundary layer heights needed for long-range transport, with limited long-range transport at night when the boundary layer shrinks. We expect factor 3 to represent a regional combustion source, likely biomass burning from fires in the Congo rainforest during the dry season.

4. DISCUSSION

Kinshasa, DRC, has long been neglected by the air quality community. In 2019, a 5-node PurpleAir network was deployed in the city.[8] Calibrated annual average $PM_{2.5}$ for 2019 in Kinshasa was estimated at 43.5 μg m^{-3}, more than 8 times higher than the WHO air quality guideline of 5 μg m^{-3}. We conducted expanded measurements, including, for the first time, surface gaseous pollutant mixing ratios, with the goal of investigating and identifying predominant sources of the observed $PM_{2.5}$ concentrations in the city. Using a newly deployed FEM monitor at the U.S. Embassy, we confirm the previous $PM_{2.5}$ results and find that $PM_{2.5}$ concentrations have remained at 8 times the WHO guidelines since the 2019 network was established. We demonstrate that the QuantAQ Modulair, which costs at least an order of magnitude lower than the FEM BAM-1020, can provide accurate information in Kinshasa to within about 10% error, which unlocks potential for high-density monitoring in Kinshasa in the near future despite resource limitations. Further, despite the satisfactory performance, we develop a multiple linear regression-based correction factor for these devices which improves the accuracy of the data even further. We also identify three sources of $PM_{2.5}$ using gas-phase and particle size distribution data: local traffic combustion, local solid fuel burning, and regional biomass burning. Each of these activities has been observed to happen with high occurrence nearly year-round and at certain times of day based on local expertise. Information on sources of pollution is actionable for policymakers and other stakeholders and is needed in order to propose solutions and mitigation strategies. While our study gets us closer to this goal, we acknowledge some caveats. Future work should include instrumentation, such as ACSM or elemental analysis of quartz or Teflon filters, for more traditional source

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apportionment studies that will allow the analysis to go deeper. This will require significant investment into air quality instrumentation and research in Kinshasa, a city that is projected to exceed 35 million people by 2050.[51]

■ ASSOCIATED CONTENT

Data Availability Statement

U.S. Embassy data used in this study are available here: https://www.airnow.gov/international/us-embassies-and-consulates/#Congo$Kinshasa

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acsestair.3c00024.

Additional materials including site map, site photo, minimization of error for choosing number of solutions in NMF, and auxiliary results (PDF)

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