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Examining spatiotemporal variability of urban particulate matter and application of high-time resolution data from a network of low-cost air pollution sensors

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Abstract

Traditional air monitoring approaches using regulatory monitors have historically been used to assess regional-scale trends in air pollutants across large geographical areas. Recent advances in air pollution sensor technologies could provide additional information about nearby sources, support the siting of regulatory monitoring stations, and improve our knowledge of finer-scale spatiotemporal variation of ambient air pollutants and their associated health effects. Sensors are now being developed that are much smaller and lower cost than traditional ambient air monitoring systems and are capable of being deployed as a network to provide greater coverage of a given area. The CitySpace project conducted by the US EPA and the Shelby County Health Department included the deployment of a network of 17 sensor pods using Alphasense OPC-N2 particulate matter (PM) sensors integrated with meteorological sensors in Memphis, TN for six months. Sensor pods were collocated with a federal equivalent method (FEM) tapered element oscillating microbalance (TEOM) monitor both before and after the primary study period. Six of the sensor pods were found to meet the data quality objective (DQO) of coefficient of determination (R^2)

Declaration of interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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greater than 0.5 when collocated with the TEOM. Seven pods were decommissioned before the end of the study due to mechanical failure. The six pods meeting the DQO were used to examine the spatiotemporal variability of fine PM ($PM_{2.5}$) across the Memphis area. One site was found to have higher relative $PM_{2.5}$ concentrations when compared to the other sites in the network. The 1-min data from this sensor pod were evaluated to quantify the regional urban background and local-scale contributions to $PM_{2.5}$ at that monitoring location. This method found that approximately 20% of the $PM_{2.5}$ was attributed to local sources at this location, compared to 9% at a local regulatory monitoring site. Additionally, the 1-min data were combined with 1-min wind speed and wind direction data to examine potential sources in the area using the nonparametric trajectory analysis (NTA) technique. This method geographically identified local source areas that contributed to the measured concentrations at the high reading sensor location throughout the course of the study.

Introduction

The use of low-cost air pollution sensors has expanded in recent years. The cost-effectiveness of sensors has increased access to air pollution information, especially for collecting more spatially and temporally resolved data. Sensors have been used to supplement ambient air monitoring (Mead et al., 2013; Snyder et al., 2013; Kaufman et al., 2017), and improve understanding of air quality and health messaging in urban areas (Mead et al., 2013; Kumar et al., 2015; Ramaswami et al., 2016). As sensor technologies progress, it is important to properly understand their limitations and capabilities. While sensors can supplement current air monitoring activities, their data can also lead to erroneous conclusions by groups using them without a proper understanding of data quality and calibration (Rai et al., 2017).

Particulate matter (PM) sensors are currently some of the most popular low-cost air pollution measurement technologies. PM sensors typically estimate particle concentration by light scattering techniques or measure particle size by optical particle counters. The Alphasense OPC-N2 is an optical particle counter measurement device that has been shown to have widely varying correlations with collocated federal equivalent method (FEM) instruments with coefficients of determination (R^2) ranging from 0.11 (Feinberg et al., 2018) to 0.79 [South Coast Air Quality Management District (SCAQMD), 2018]. Varying agreement could result from multiple factors, as the OPC-N2 assumes particles are spherical and of homogenous density, while in practice particle morphology and density are highly variable (Mukherjee et al., 2017). Additionally, OPC-N2 correlations can vary in a laboratory setting when using aerosols of different compositions and also exhibit artifacts related to humidity (Sousan et al., 2016; Feinberg et al., 2018; SCAQMD, 2018). Furthermore, the OPC-N2 has a minimum reported particle measurement size of 0.38 μm, so it has the potential to miss portions of the $PM_{2.5}$ mass depending on the particle size distribution. Due to these factors, it is important to quantify the performance of OPC-N2 sensors under study-specific conditions. Some recent studies have been able to improve the correlation of low-cost air pollution sensors to more reliable measurement methods using correction factors, multivariate models, and machine learning (Crilley et al., 2018; Cross et al., 2017; Zimmerman et al., 2018; Hagan et al., 2018). Even in the absence of improved correlations, the OPC-N2 has been found to replicate some trends, including wind direction (Feinberg et al., 2018).

Low-cost PM sensors have the potential to create or expand measurement networks, enabling the collection of ambient environmental data for smart city initiatives or other purposes. Numerous studies have shown that sensor networks can allow researchers, community groups, and planning organizations to better understand air pollution sources, air quality trends, and limitations of sensors. Gao et al. (2015) deployed a network of fine PM ($PM_{2.5}$) sensors in Xi'an, China. The network of sensors was able to locate a $PM_{2.5}$ hotspot while already in a high concentration urban environment. Jiao et al. (2016) deployed a four-site network $PM_{2.5}$ sensors in Atlanta, GA. The sensor network was able to demonstrate spatiotemporal homogeneity for PM. The U.S. EPA and SCAQMD deployed a network of multi-pollutant sensors in the South Coast Basin (California) to evaluate the ability of sensors to supplement air quality monitoring and examine spatial and temporal variability of pollution (Williams et al., 2018). This study found that sensors can aid in air quality monitoring during controlled conditions but found that the OPC-N2 PM sensors had significant data losses due to sensor failure at several of the measurement sites.

The CitySpace project described in this manuscript included a long-term deployment of Alphasense OPC-N2 PM sensors in Memphis, TN and the surrounding area (U.S. EPA, 2018a). The main goal of the CitySpace project was to better understand the utility of emerging air sensor technology when deployed in a sensor network. Additionally, this project evaluated whether sensor technology could provide useful supplemental information to existing regulatory ambient air monitoring. This manuscript reports on a network of 17 p.m. sensors deployed from October 2016 to March 2017. The spatiotemporal variability of PM in the Memphis area was estimated, and potential nearby sources of PM were evaluated using nonparametric trajectory analysis (NTA).

Methods

2.1 Sensor Pod Design and Deployment

EPA developed a solar-powered sensor package for measuring urban PM and meteorological parameters (U.S. EPA, 2018a). PM was measured by an Alphasense OPC-N2 sensor while wind speed and wind direction were measured by an Airmar 110WX meteorology sensor. Temperature and relative humidity (RH) were measured by a Vaisala temperature and RH sensor. The OPC-N2 sensor reported mass concentration estimates of different PM size fractions ($PM_{2.5}$, PM_{10}, etc.). This project focused on reported $PM_{2.5}$ values. Values reported by the sensor were logged without any conversion. A total of 17 p.m. sensor pods were deployed in Memphis, TN (Fig. 1a) from October 2016 to March 2017. Additional collocation periods were conducted at the Shelby Farms monitoring site, the easternmost site labeled in Fig. 1b, both 1-week before and for up to 6 weeks after the main study period, where sensor pods were placed alongside a tapered element oscillating microbalance (TEOM). The collocated TEOM collected hourly $PM_{2.5}$ mass concentration measurements. Sensor pods transmitted data to EPA's VoIP Enterprise Routing (VIPER; U.S. EPA, 2018b) wireless network-based communications system while also storing data locally on Secure Digital (SD) cards. Measurements were recorded every minute.

2.2 Quality Assurance

Data were transmitted directly from the field via the VIPER system and manually retrieved on a weekly timeframe from the SD card. The manual data retrieval allowed a visual inspection of the pods and their general operational status. During some of these inspections, there was indication that the pods moved likely due to high wind conditions. These data were flagged, and the wind data was removed. VIPER records were used to provide daily notification of pod operational status, but ultimately the pulled SD card information was used to establish the analysis database.

A project-specific quality assurance project plan was developed prior to the start of the study and was used to review raw data and finalize the data set. Quality assurance considerations included timestamps, electronic signatures, reviewed raw data, appropriate dates, filenames and pod associations. One-minute $PM_{2.5}$ data from the OPC-N2 sensors were screened to remove potential artifacts and to detect obviously erroneous RH and temperature data. Measurements were removed when $PM_{2.5}$ measured extreme values (less than zero and greater than 200 μg/m^3), RH reported values were below zero or greater than 95%, or recorded temperatures were less than −10 °C or greater than 60 °C. Previous experimentation and operation of the sensor in multiple environmental settings with the OPC-N2 identified that $PM_{2.5}$ mass concentration estimates greater than 200 μg/m^3 had a low probability of being statistically relevant and were often associated with high RH events (Reece et al., 2017; Feinberg et al., 2018). In this project, the occurrence of reported $PM_{2.5}$ estimates greater than 200 μg/m^3 was rare (e.g., only 70 min above this threshold were reported by Unit 16 throughout the entire study, all of which occurred when the RH was 99.9%). $PM_{2.5}$ values less than zero normally indicated that a sensor pod malfunctioned. Sensor failure was evident during high RH events by either a complete loss of signal (flat baseline response), a response that reported values between 0 and 2 μg/m^3 and remaining there for an extended period (hours or even days), or atypical $PM_{2.5}$ estimations over 200 μg/m^3. Reece et al. (2017) found similar problems with sensor failure or low-quality data during periods of high and sustained RH. In this study, there were some instances where sensors were able to re-establish a nominal response once lower RH conditions occurred without operator attention. Often the sensor would have to be manually cycled (on/off) to re-establish normal functionality. Several sensors permanently failed following one of the high RH events. To address the anticipated RH impacts, we developed automated QA routines that searched for signs of sensor failure and flagged these time periods for exclusion in data analysis. After screening procedures, the remaining 1-min $PM_{2.5}$ mass concentrations were averaged to hourly concentrations. At least 45 min of valid data were required to calculate an hourly average (i.e., 75% data completeness).

2.3 Sensor Data Analysis

To understand the performance of the OPC-N2 sensor, hourly $PM_{2.5}$ mass concentrations were estimated and compared to hourly $PM_{2.5}$ data from the TEOM FEM monitor. Crilley et al. (2018) suggested that correlation between the OPC-N2 sensor and reference monitors can be improved when adjusting for humidity effects. However, an attempt to develop an improved linear regression including RH via a training set approach using the caret package in R statistical software (Version 3.4.3) found RH was not a significant predictor at a 0.05

confidence level. Sensor pods that exhibited a coefficient of determination (R^2) greater than 0.5 during the collocation periods (Fig. 1b) were used to examine the spatiotemporal variation of $PM_{2.5}$ in the Memphis area.

The data from each sensor pod that met the correlation criterion were calibrated to better reflect the TEOM concentrations based on the linear regressions of the hourly average $PM_{2.5}$ concentrations from the final collocation period (i.e., the sensor data were normalized using the slopes and intercepts from the regression analysis). This calibration helped remove varying biases when comparing the sensor pods to each other (for example one sensor could exhibit a slope of 2 when compared to the TEOM, while another could exhibit a slope of 0.5). The calibrated sensor data were then compared to each other using the Pearson correlation to examine how temporal trends agree between sites and coefficient of divergence (CoD) to examine the difference in concentrations between sites (Kim et al., 2005; Wongphatarakul et al., 1998).

The high-time resolution measurement data allowed for improved understanding of contributions to the measured PM. For a given site, the low-varying component was identified as taking the rolling 60-min 5th percentile concentration (Bukowiecki et al., 2002). For example, for a given 1-min measurement within a complete 60-min window, the low-varying component of its signal would be identified as the third lowest measurement from the 30 min both before and after that measurement. The remaining concentration from each site was then assigned as the high-varying component of the concentration (i.e., the difference between the 1-min measurement value and the low-varying component for the surrounding 60-min window). In this analysis, the low-varying component of the concentration was indicative of regional contributions and the high-varying component was indicative of the local contribution to $PM_{2.5}$ concentrations. This allowed for overall estimates of local and background impacts at a site without necessarily requiring an entire network of measurements.

The sensor data was also analyzed using nonparametric trajectory analysis (NTA) to understand PM source contributions. The NTA method uses wind and pollutant concentration data to inform potential source types and regions (Henry et al., 2011). NTA uses wind data to calculate urban-scale back trajectories and assigns the associated measured concentration to each point on the trajectory. In this analysis, 50-min trajectories were used. Finally, NTA calculates an expected concentration for each point within the analysis area by calculating the weighted average of those associated concentrations for all nearby trajectory points. The shape and location of high expected concentration areas can inform whether sources contributing to high concentrations are distributed or points sources and can potentially identify regions containing high-impact point sources. The technique can also be combined with the high/low frequency analysis, enabling analysis of only the local concentration, in attempt to clarify results. This technique was applied to measurements from the Douglass site, which is in a known environmental justice area. Due to the previously mentioned movement of the sensor nodes, wind data were obtained from the Memphis International Airport (NOAA National Centers for Environmental Information, 2018), approximately 15 km south of the Douglass site, and were used for the NTA analysis.

Results and Discussion

3.1 Sensor Pod Performance

A summary of data completeness, range of QA screened hourly average measurements, and correlations from different colocation periods are presented in Table 1. Measurement ranges represent concentrations reported by the OPC-N2 sensors before normalization. Three sensor pods never consistently collected data during the study (Units 10, 12, and 19). Four additional pods stopped the collecting data in the middle of the study (Units 2, 8, 13, and 20), and one pod failed towards the end of study (Unit 7).

The high failure rate was in part due to the periods of high and sustained humidity. The period of collocation used for regression is also included as the sensor pods that failed during data collection were not included in the final collocation. Of the 17 sensor pods, six had R^2 values greater than 0.5, which was previously chosen as a data quality metric for use in examining the spatiotemporal variability of urban PM in the area. While these six sensor pods had correlations that met the data quality metric, they also had wide ranges of slopes and intercepts when compared to the reference monitor. To better compare concentrations between sites, $PM_{2.5}$ estimations from the OPC-N2 sensors were normalized based on their regressions with the collocated TEOM during the post-deployment collocation period. The results from these collocated regressions are presented in Table 2. Fortunately, the sensors that met the data quality objective were well distributed within the study area, and their locations are shown in Fig. 1b.

3.2 Spatiotemporal Analysis of Sensor Data

After adjusting the hourly sensor pod data based on linear regression to the TEOM, they could be used to examine the spatiotemporal variability of $PM_{2.5}$ in the study area. Pearson correlation (R) was calculated as a measure of difference in temporal trends between sites while CoD was used to estimate spatial variability. To calculate R and CoD, sensor pod data collected from the Shelby Farms site were compared with the data from each of the other five sites. This was done to show how each site would compare with the regulatory monitoring site (Shelby Farms). Table 3 shows the R, CoD, and mean hourly $PM_{2.5}$ mass concentrations for each site when compared to Shelby Farms. The Pearson correlations from each comparison were relatively high, implying that there is low temporal variability of $PM_{2.5}$ in the Memphis area. This is unsurprising, as PM tends to be regionally dominated, and all sites tend to rise and fall over time. A CoD greater than 0.2 is typically representative of spatial heterogeneity, while a CoD less than 0.2 indicates spatial homogeneity (Wongphatarakul et al., 1998). Most sites had CoD values less than 0.2 when compared to the Shelby Farms site, except for the Douglass site. The Douglass site had the highest $PM_{2.5}$ concentrations of the six sites examined in this study. This site is in a known environmental justice area containing a large railyard and multiple $PM_{2.5}$ point sources therefore, higher $PM_{2.5}$ concentrations were expected.

3.3 High-time Resolution Data Analysis

The elevated $PM_{2.5}$ concentrations at the Douglass site prompted further examination of that site using techniques suited for high-time resolution data. The first of which was using the high- and low-varying components of the $PM_{2.5}$ measurements. This is a useful technique, as it allows for estimation of the regional background PM contribution with data from a single site. Using this analysis, the high-varying component of the hourly data averaged 2.7 μg/m^3, or about 20% of the total $PM_{2.5}$ mass. In contrast, at the Shelby Farms site, the high-varying component of the hourly signal averaged 0.8 μg/m^3, or about 9% of the total $PM_{2.5}$ mass for the same time period. A Wilcoxon Signed-Rank test of pairwise local contributions found the local contribution at the Douglass site to be higher at a 0.05 confidence level.

NTA was performed using data from the Douglass site (N = 90138 min) to better understand influences of higher $PM_{2.5}$ concentrations at that site. Fig. 2 shows the NTA results at the Douglass site using the normalized sensor pod $PM_{2.5}$ signal (a) and the high-varying component of the $PM_{2.5}$ signal as defined in the previous analysis (b). On both plots, the green point in the center is the measurement site and the blue circles represent $PM_{2.5}$ point sources as identified by the 2014 National Emission Inventory (NEI; U.S. EPA, 2016). The area shown in each map is a 10 km by 10 km square. For the total $PM_{2.5}$ signal (Fig. 3a), the locations with the highest expected measured concentrations are centered around the measurement site, with lobes that extend in multiple directions. This implies that the highest concentrations occur during calm winds where there is potential for accumulation of local emissions. In this case, concentrations are likely influenced by the accumulation of local traffic emissions in the area in addition to point sources and regional contributions. While the OPC-N2 sensor is likely unable to detect fresh PM emissions from traffic, it would be able to detect aged aerosol associated with traffic activity. The lobes that point outward from the center likely represent elevated $PM_{2.5}$ concentrations that are associated with winds that have significant sources in those directions. Both the total and the high-varying signal have lobes that point out toward the east. This region contains a rail line nearby with significant traffic and a significant point source. Within the southern lobe is another point source, an additional rail track, a bus terminal, and significant motor vehicle traffic areas. Other lobes that also have lesser but still elevated expected $PM_{2.5}$ concentrations tend to align with locations such as large traffic interchanges. The NTA results using the total $PM_{2.5}$ signal and the high-varying $PM_{2.5}$ signal are very similar. This may be expected, as impacts from local sources should lead to the highest expected concentrations. However, it is good confirmation to show that the local signal is driving the highest expected concentrations in the total signal.

Conclusions

A network of sensor pods measuring $PM_{2.5}$ and local meteorological conditions was deployed around Memphis, TN for approximately six months. Several sensor pods failed during the long-term deployment, and when collocated with an FEM TEOM, only 6 of the 17 deployed sensor pods met the data quality objective of R^2 greater than 0.5. However, those 6 pods well distributed geographically and were used to examine spatiotemporal variability of urban $PM_{2.5}$ in Memphis. The spatiotemporal analysis found that the hourly $PM_{2.5}$ averages shared similar trends between sites, and the Douglass site had elevated $PM_{2.5}$ concentrations compared to the rest of the study area. The Douglass site is in an environmental justice area and elevated $PM_{2.5}$ concentrations were anticipated. A variance method and NTA were used to better understand potential source contributions to $PM_{2.5}$.

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The high- and low-variance method estimated the local contribution to $PM_{2.5}$ at the Douglass site to be 2.7 μg/m^3, or about 20% of the total signal. NTA was used to identify local regions which were associated with high concentrations and found that numerous local sources contributed to the highest concentrations, including a railyard, multiple point sources, roadways, and a bus terminal.

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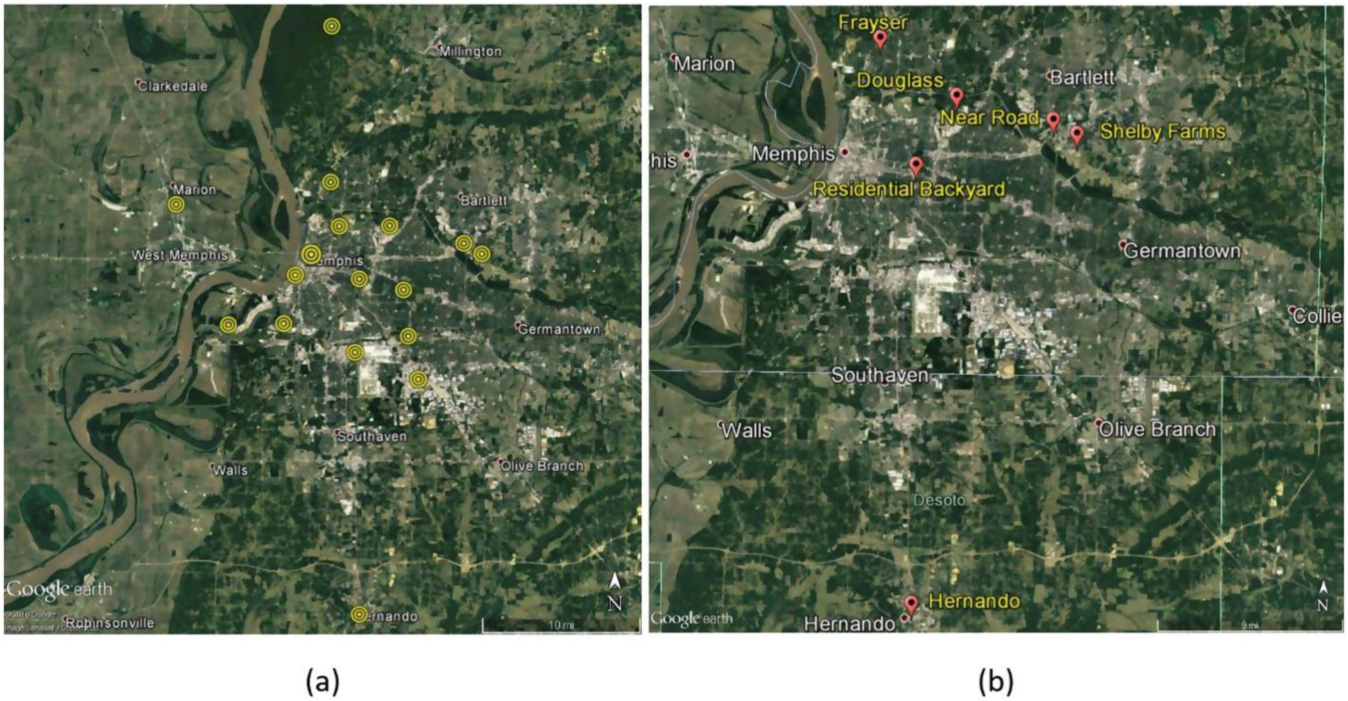

Figure 1.

Map of sensor pod locations (a) and map of sensor pod locations that met the data quality objective and used for further analysis (b).

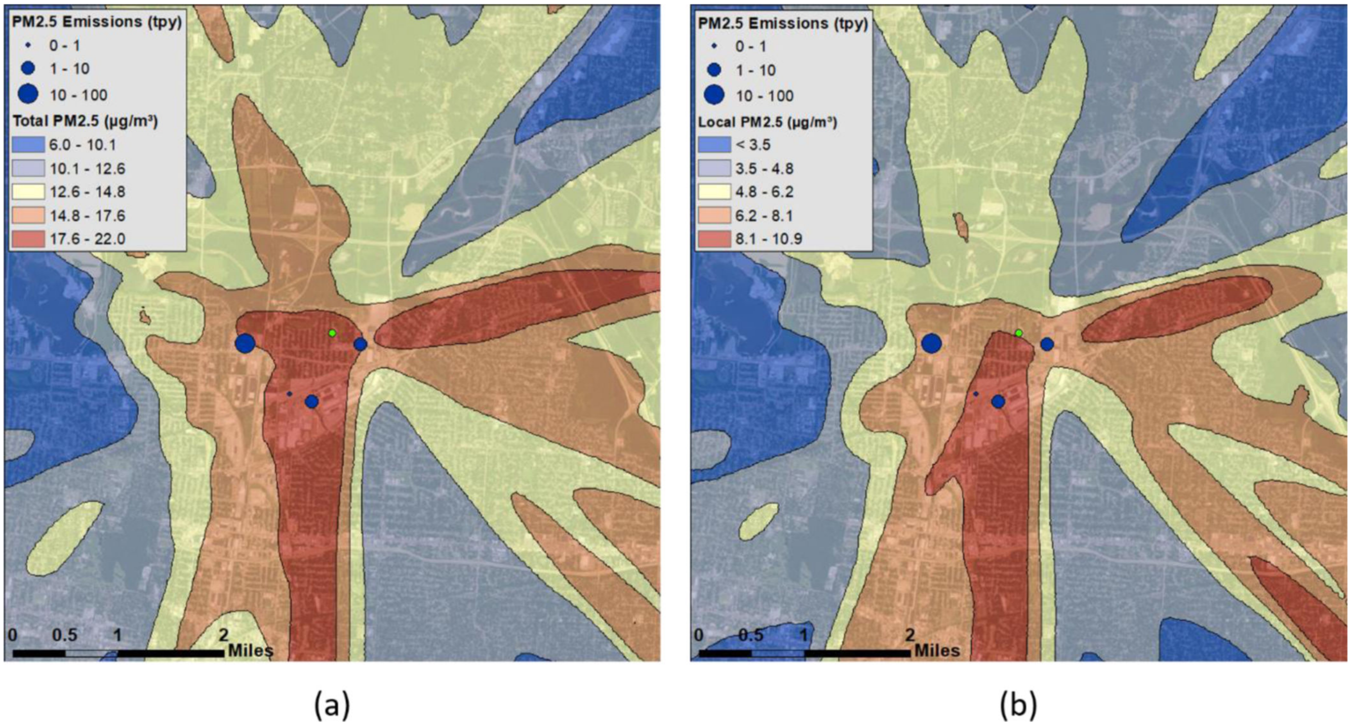

Fig. 2.

NTA results of the expected 1-min $PM_{2.5}$ mass concentrations for total $PM_{2.5}$ (a) and high-varying $PM_{2.5}$ (b) at the Douglass monitoring location calculated over the six-month study period

Table 1

Hourly Summary and Correlation Statistics of deployed Sensor Pods

Sensor Pod	Number of Valid Hours	Measurement Range (μg/m^3)	R^2	Regression Period	Comments
Unit 1	2056	0 – 86	0.58	Post	
Unit 2	648	0 – 93	0.14	Pre	Failed to operate nominally after 12/16/16
Unit 3	1663	0 – 75	0.20	Post	
Unit 4	1475	0 – 42	0.57	Post	
Unit 5	1470	0 – 24	0.81	Post	
Unit 6	1659	0 – 71	0.43	Pre	
Unit 7	1313	0 – 54	0.21	Pre	Failed to operate nominally after 2/12/17
Unit 8	1410	0 – 57	0.18	Pre	Failed to operate nominally after 1/10/17
Unit10	219	0 – 16	NA	NA	Never operated nominally, including during colocation
Unit 11	2116	0 – 146	0.52	Post	
Unit 12	126	0 – 42	0.10	Pre	Never operated nominally
Unit 13	86	0 – 82	0.27	Pre	Failed to operate nominally after 12/3/16
Unit 14	1638	0 – 45	0.53	Post	
Unit 16	1752	0 – 52	0.52	Post	
Unit 18	1253	0 – 64	0.24	Post	
Unit 19	NA	NA	0.47	Pre	Failed after initial collocation
Unit 20	798	1 – 94	0.17	Pre	Failed to operate nominally after 11/28/16

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Table 2

Collocated regression statistics for sensor pods meeting data quality objective

Sensor Pod	Location	Slope	Intercept	R^2
Unit 1	Residential Backyard	1.84	3.04	0.58
Unit 4	Near Road	2.23	2.48	0.57
Unit 5	Douglass	5.49	0.64	0.81
Unit 11	Hernando	1.36	3.52	0.52
Unit 14	Frayser	1.73	3.40	0.53
Unit 16	Shelby Farms	1.50	4.15	0.52

Table 3

Spatiotemporal analysis results

Sensor Pod	Location	Pearson Correlation*	CoD*	Mean Hourly Concentration
Unit 1	Residential Backyard	0.87	0.12	10.2
Unit 4	Near Road	0.94	0.11	8.5
Unit 5	Douglass	0.82	0.26	12.7
Unit 11	Hernando	0.84	0.12	7.7
Unit 14	Frayser	0.78	0.11	8.4
Unit 16	Shelby Farms	NA	NA	8.4

*When compared with Shelby Farms site