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A novel mobile monitoring approach to characterize spatial and temporal variation in traffic-related air pollutants in an urban community

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HIGHLIGHTS

- A novel mobile monitoring approach captured variation in urban TRAP.
- The monitoring approach distinguished spatial variation from temporal variation.
- Spatial distributions are patterned by traffic proximity/surrounding environments.
- Meteorology and temporal changes explain the variability of parallel measurements.
- TRAP concentrations were influenced primarily by traffic/meteorological conditions.

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ABSTRACT

Air concentrations of traffic-related air pollutants (TRAPs) vary in space and time within urban communities, presenting challenges for estimating human exposure and potential health effects. Conventional stationary monitoring stations/networks cannot effectively capture spatial characteristics. Alternatively, mobile monitoring approaches became popular to measure TRAPs along roadways or roadsides. However, these linear mobile monitoring approaches cannot thoroughly distinguish spatial variability from temporal variations in monitored TRAP concentrations. In this study, we used a novel mobile monitoring approach to simultaneously characterize spatial/temporal variations in roadside concentrations of TRAPs in urban settings. We evaluated the effectiveness of this mobile monitoring approach by performing concurrent measurements along two parallel paths perpendicular to a major roadway and/or along heavily trafficked roads at very narrow scale (one block away each other) within short time period (<30 min) in an urban community. Based on traffic and particulate matter (PM) source information, we selected 4 neighborhoods to study. The sampling activities utilized real-time monitors, including battery-operated $PM_{2.5}$ monitor (SidePak), condensation particle counter (CPC 3007), black carbon (BC) monitor (Micro-Aethalometer), carbon monoxide (CO) monitor (Langan T15), and portable temperature/humidity data logger (HOBO U12), and a GPS-based tracker (Trackstick). Sampling was conducted for ~3 h in the morning (7:30–10:30) in 7 separate days in March/April and 6 days in May/June 2012. Two simultaneous samplings were made at 5 spatially-distributed locations on parallel roads, usually distant one block each other, in each neighborhood. The 5-min averaged BC concentrations (AVG ± SD, [range]) were 2.53 ± 2.47 [0.09–16.3] $\mu g/m^3$, particle number concentrations (PNC) were 33,330 ± 23,451 [2512–159,130] particles/cm^3, $PM_{2.5}$ mass concentrations were 8.87 ± 7.65 [0.27–46.5] $\mu g/m^3$, and CO concentrations were 1.22 ± 0.60 [0.22–6.29] ppm in the community. The traffic-related air pollutants, BC and PNC, but not $PM_{2.5}$ or CO, varied spatially depending on proximity to local stationary/mobile sources. Seasonal differences were observed for all four TRAPs, significantly higher in colder months than in warmer months. The coefficients of variation (CVs) in concurrent measurements

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from two parallel routes were calculated around 0.21 ± 0.17, and variations were attributed by meteorological variation (25%), temporal variability (19%), concentration level (6%), and spatial variability (2%), respectively. Overall study findings suggest this mobile monitoring approach could effectively capture and distinguish spatial/temporal characteristics in TRAP concentrations for communities impacted by heavy motor vehicle traffic and mixed urban air pollution sources.

1. Introduction

Growing evidence indicates that living in an area with heavy motor vehicle traffic is associated with increased risks of cardiovascular and pulmonary diseases (Gan et al., 2010; McConnell et al., 2010; Hoek et al., 2013). Numerous epidemiological studies (HEI, 2010 and references therein) suggest that exposure to traffic-related air pollutants (TRAPs) may play a causal role in these increased health risks. Linking TRAP contribution to health outcomes requires an understanding of how concentrations of TRAP vary within communities with multiple sources of TRAP. Because TRAP concentrations can vary significantly in both space and time near roadways (Zhou and Levy, 2007; Karner et al., 2010), information about spatial/temporal variations is crucial in estimating exposure in a community impacted by nearby road traffic.

Early research efforts have focused on TRAP variations between cities (Briggs et al., 2000; Lebret et al., 2000; Hoek et al., 2002) or within cities (Jerrett et al., 2005; Clougherty et al., 2008). However, these studies relied on TRAP measurements on fixed-site monitoring stations or networks, which cannot effectively capture spatial variability at small community scales (Han and Naeher, 2006). To overcome this, mobile monitoring has been recently conducted to assess exposure with high spatial variability in various geographical settings using instrumented vehicles (Hu et al., 2009; Hagler et al., 2010; Tunno et al., 2011; Padró-Martínez et al., 2012; Riley et al., 2014; Lähde et al., 2014), bicycles (Thai et al., 2008; Berghmans et al., 2009; Peters et al., 2013; Pattinson et al., 2014), or pedestrians with monitoring instruments (Kaur et al., 2005; Zwack et al., 2011a, 2011b; Hsu et al., 2014; Rakowska et al., 2014). However, these studies were conducted on single monitoring paths at one time; thus, this linear mobile monitoring approach cannot thoroughly distinguish spatial variation from temporal variation in measured TRAP concentrations. The entangled spatial-temporal variation is somewhat problematic in developing a regression model for measurements from above linear mobile monitoring approach, because temporal autocorrelation issues arise, which may bias the regression estimates (Zwack et al., 2011a, 2011b).

To date, no studies have been conducted to separately evaluate spatial variability and temporal variability in collected mobile monitoring measurements. Therefore, we recognized the need for a new mobile monitoring approach, in which we conducted simultaneous real-time TRAP measurements over short durations (e.g., <1 h) within a small community scale (e.g., <1 km^2). Data obtained from this approach would allow for the assessment of spatial characteristics while controlling for temporal variability in TRAP concentrations.

The goals of our study were to 1) monitor real-time TRAP concentrations on parallel routes in an urban community; 2) characterize spatio-temporal variations in monitored TRAP concentrations; and 3) evaluate the effectiveness of the monitoring approach for discriminating between spatial and temporal variability. This mobile monitoring approach was unique in utilizing mobile devices to concurrently measure real-time TRAP concentrations on the sidewalks of two parallel local residential streets, which were either perpendicular or parallel to heavy-trafficked major roadways, in order to capture spatial variability in neighborhood scale and to minimize the influence of temporal variation.

2. Methods

2.1. Study area

The mobile monitoring was conducted in the Ironbound community, a diverse, Environmental Justice community (~50,000 population) with mixed sources of air pollution, located within the city of Newark, New Jersey. This community covers approximately four square miles (10 km^2), and is bordered by heavily-trafficked major roadways. US Route 1 (123,775 vehicles per day (vpd)) and McCarter Highway (NJ Route 21; 57,984 vpd) border the community (see Fig. 1). In addition, heavy trafficked highways, including NJ Turnpike (Interstate 95; 231,972 vpd), Lincoln Highway (US Route 9; 73,857 vpd), Interstate 78 (153,601 vpd) and Interstate 280 (65,139 vpd), are distant approximately 1 km. Within the community, there are busy local roads such as Ferry Street (15,518 vpd), Raymond Boulevard (17,529 vpd), Lafayette Street (9281 vpd), Magazine Street (7638 vpd), and Van Buren Street (6833 vpd), as well as an active NJ Transit Railroad and a Newark Penn Station. Also this community is close to Newark-Elizabeth Seaport (visited by 7000 diesel trucks per day; Greenberg, 2012) and Newark International Airport, distant approximately 3.5 km from the community. In 2011, a one-day count of trucks that passed through and idled in the community reported 1327 diesel trucks driving on the streets/highways and 41 idling (Greenberg, 2012). In addition to traffic sources, many industrial/commercial facilities are located within the community, ranging from scrap-metal yards to warehouse and distribution centers to the state's largest municipal waste incinerator (920,000 tons/year) and sewage treatment plant (330 million gallons/day).

2.2. Monitoring area and location

The mobile monitoring approach employed portable devices to concurrently measure real-time TRAP concentrations on the sidewalk of two parallel roads. The two adjacent roadways were either perpendicular or parallel to heavy-trafficked major roadway in the study area. This approach could allow us to capture spatial variability in neighborhood scale and to minimize the influence of temporal variation.

Four sampling areas (A–D in Fig. 1) and two parallel sampling routes (I and II at each sampling area in Table 1) were specifically selected in response to residents' concerns about heavy traffic, especially diesel trucks passing through the community. The sampling areas (A and B) were selected to monitor school-walking children's exposure to TRAPs from the nearby highway (US Route 1) and busy local roads (Ferry St. for the area A and Wilson Ave. for the area B). Situated in the commercial district of downtown

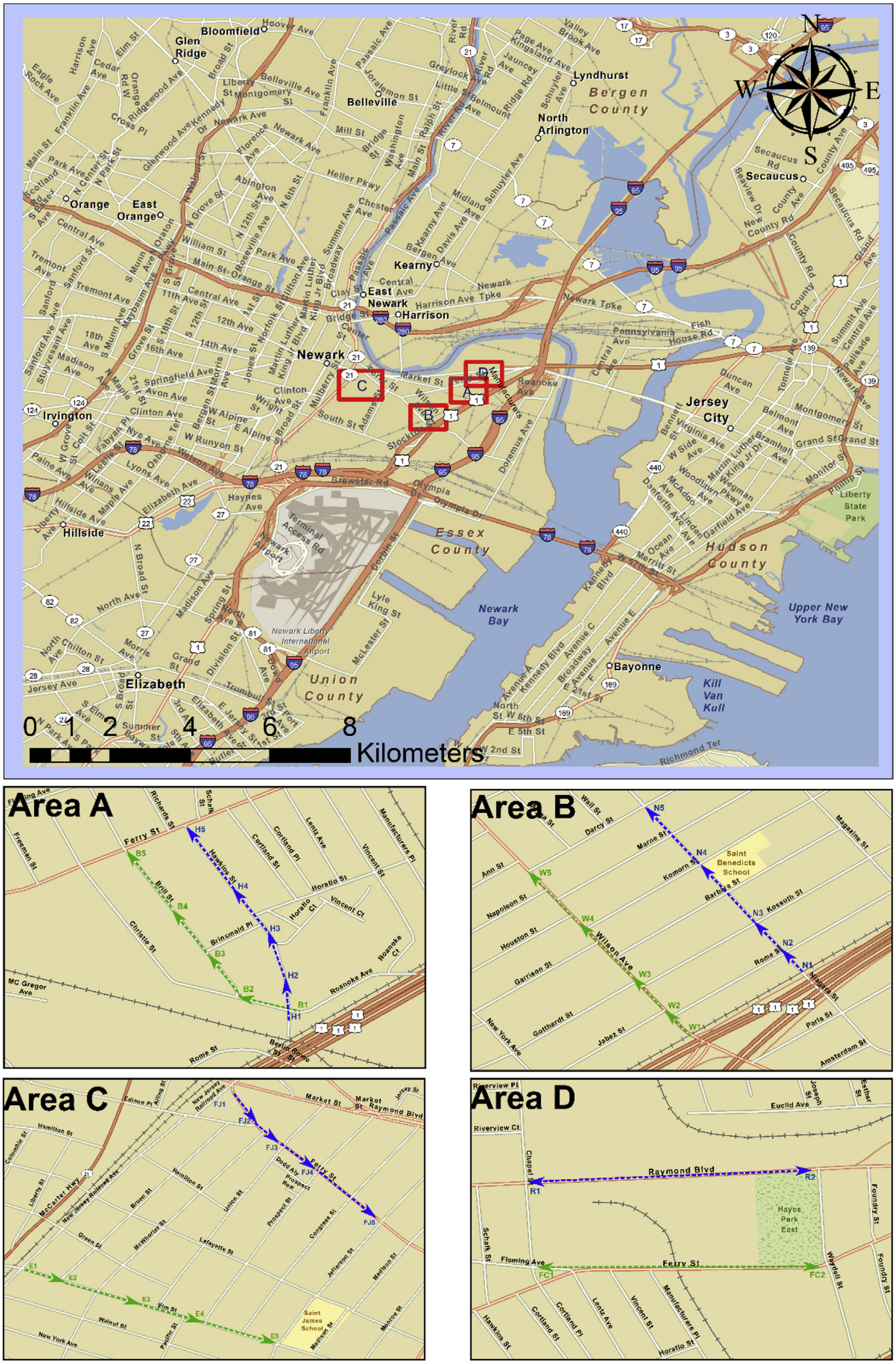

Fig. 1. The location of the study monitoring areas (A–D) and locations in Ironbound community, Newark, NJ.

Table 1
The description of the four monitoring areas (A–D) and two monitoring routes (I and II) in Ironbound community, Newark, NJ.

Area	Route	Primary road (traffic counts)	Local roads (traffic counts)	Comments
A	I. Brill St. II. Hawkins St.	US Rt. 1 (123,775 vpd)	Ferry St. (15,518 vpd)	• Residential area • An elementary school
B	I. Wilson Ave. II. Niagara St.	US Rt. 1 (123,775 vpd)	Wilson Ave. (no data) Magazine St. (7638 vpd)	• Residential area • A church/nursery
C	I. Elm St. II. Ferry-Jefferson St.	McCarter Hwy. (57,984 vpd)	Lafayette St. (9281 vpd) Ferry St. (15,518 vpd)	• Commercial district • Downtown of Newark city • NJ transit railroad/station • An elementary school
D	I. Ferry-Chapel St. II. Raymond Blvd.	N/A	Ferry St. (15,518 vpd) Raymond Blvd. (17,529 vpd)	• Industrial area • Diesel truck traffic to industrial facilities and Newark-Elizabeth Seaport

Newark, the sampling area of C was chosen to monitor shoppers'/commuters' exposure to TRAPs on local roads (Ferry St. and Market St.) as well as from the major roadway (McCarter Highway) and an active railway/station (NJ Transit Railroad and Newark Penn Station) with electric and diesel-electric train traffic. To monitor walkers' exposure to TRAPs on adjacent diesel truck-passing roads, the sampling area (D) and two parallel routes (Raymond Blvd. and Ferry St.-Chapel Ave.) were particularly selected. The two local roads are the primary truck routes connecting industrial/seaport facilities to downtown Newark.

Two different scripted walking pathways were defined and conducted. In sampling areas A–C, a one-way monitoring was conducted via walking and then stopping for 5 min at each of five pre-determined locations (i.e., sampling locations of 1 through 5, with increasing distance up to 500 m from the major roadway) on each route, where monitoring was conducted on sidewalks along the roadways (Fig. 1). A monitoring period of five minutes at each stationary location was selected to get constant reading values. In the sampling area for D, a round-trip monitoring was conducted on two fixed locations (i.e., sampling locations of 1 and 2, parallel to nearby diesel truck-trafficked roadway). This scripted pathway was specifically chosen to estimate community members' exposure to TRAPs while walking on these local roads with diesel truck-traffic (Fig. 1). The stationary 5-min monitoring was conducted at two fixed locations 1 and 2. However, in this attempt, additional monitoring was conducted on the way between two fixed locations (i.e., walking along the pathways from 1 to 2 and 2 to 1, respectively). Walks from one location to the next took 3–4 min (walking speed ~0.3 m/sec). A repeated 5-min monitoring was followed at the fixed location 1 to finish the scripted pathway/mobile monitoring for the study area of D.

2.3. Monitoring season and round

To characterize seasonal variations in TRAP concentrations, the monitoring was conducted in two seasons, cooler months between March and early April (averaged temperature ranged from 43 °F to 66 °F) and warmer months between late May and June (57–90 °F). The selection of monitoring day was based on the criteria of 1) non-consecutive weekday and 2) non-rainy day, to incorporate various meteorological conditions and traffic variations in the community. The monitoring time was focused on morning session only in this pilot study (i.e., from 7:30 a.m. to 10:30 a.m.) to obtain high TRAP exposure conditions in each sampling day.

2.4. Instrumentation and field setup

The four traffic-related air pollutants (i.e., black carbon (BC), particle number concentration (PNC), particulate matter less than 2.5 μm in diameter ($PM_{2.5}$), and carbon monoxide (CO)) were particularly selected to achieve study objectives. We utilized a variety of real-time monitors (Table 2) to detect and record air concentrations in a resolution of one second. The micro-aethalometer (AE51, Aethlabs, San Francisco, CA) and the personal aerosol monitor (AM510 SidePak Personal Aerosol monitor, TSI Inc., Shoreview, MN) were connected with discrete sampling lines and positioned securely inside the staff-worn sampling backpack. The CO Measurer (T15n, Langan Products Inc., San Francisco, CA), the Temp/RH logger (HOBO U12, Onset Corp., Bourne, MA), and the global positioning system (GPS) device (Trackstick mini, Telespial Systems Inc., Burbank, CA) were placed in the front pouch of the sampling backpack, exposed directly to ambient air. The handheld particle counter (CPC 3007, TSI Inc., Shoreview, MN) was carried by the study staff all monitoring sessions. The two parallel monitoring routes in each sampling area were walked by the two study staff simultaneously, and the recorded time deviations between stops on the parallel paths were mostly below 2 min.

2.5. Quality assurance and quality control

To ensure data quality assurance and quality control, all real-time monitors were calibrated using the methods described in manufacturer's manuals and underwent background and flow checks prior to conducting each monitoring session. Prior to the start of the monitoring campaign in March 2012, the real-time monitors were checked for the side-by-side comparison. The two CPCs had 8% relative difference in their 2-h averaged measurements, which was within the instrument specifications. Similar 9% relative differences were obtained from the measurements of two co-located SidePaks and micro-aethalometers, respectively. The Teflon-coated glass fiber filters used for collecting particles in the micro-aethalometers were replaced at each monitoring run to avoid filter overloading. The operation of real-time monitors followed the manufacturer-recommended protocols. Additional GPS data was retrieved and plotted in a map to track the walking pathway during the mobile monitoring. Also, the logged time in GPS data was cross-checked with time documented in the sampling sheet to ensure a time and location for each mobile monitoring.

Table 2
The monitoring equipment used for the study.

Equipment (Manufacturer)	Measuring	Sensitivity/Resolution (Accuracy)	Operation range	Resolution
MicroAeth Aethalometer AE51 (MicroAeth)	Black carbon	0.001 $\mu g/m^3$ ($\pm$0.1 $\mu g/m^3$)	0–1 mg/m^3	1 s
Condensation Particle Counter 3007 (TSI)	Ultrafine particle counts	1 particle/cm^3 ($\pm$20%)	0–100,000 particles/cm^3 with a size of 0.01 –1.0 μm	1 s
SidePak Personal Aerosol Monitor AM510 (TSI)	$PM_{2.5}$	0.001 mg/m^3	0.001–20 mg/m^3 with a size of 0.1–10 μm	1 s
T15n CO Measurer (Langan)	Carbon monoxide	0.05 ppm	0–1000 ppm	1 s
HOBO U12 Temp/RH Data Logger (Onset)	Temperature/relative humidity	0.05 °F ($\pm$0.63 °F) 0.03% ($\pm$2.5%)	0–158 °F 5–95%	1 s
Trackstick Mini (Telespial)	Geological coordinate position	<160 dBm	N/A	<10 s

2.6. Data acquisition, data collection, and data processing

2.6.1. Monitored traffic-related air pollution data

Real-time TRAP concentrations were downloaded from each monitor and converted to excel spreadsheet format. However, the raw BC data was very unstable, due to a use of very short averaging time (i.e., 1-s) and a vibration/motion artifact of the instrument during the mobile monitoring (Cai et al., 2013). Therefore, we post-processed the raw BC data using a post-cleaning technique described by Hagler et al. (2011). Other monitoring data did not require post-processing. Outlying or influencing data was checked with field/instrument logs to ensure the data integrity. On a date of 3/20/2012, an open fire was observed by a study staff while walking on Raymond Blvd. in the sampling area of D. This resulted in very high BC and $PM_{2.5}$ concentrations, recorded as 34 and 84 $\mu g/m^3$ during the walking from the location 1 to 2 and 23 and 116 $\mu g/m^3$ (from 2 to 1 on the round trip), respectively. These concentrations were 2–3 times higher than calculated outlying BC (10 $\mu g/m^3$) and $PM_{2.5}$ (38 $\mu g/m^3$) concentrations, estimated as a mean plus 3 times standard deviation of monitoring data in the area on that date. Therefore, those very high four measurement data, affected by the open fire on 3/20/20212, were excluded in the dataset. Otherwise, PNC and CO data were not elevated significantly during the same period; thus, PNC and CO data were not excluded.

2.6.2. Meteorological variables

Temperature (°F), relative humidity (%), wind speed (m/sec) and wind direction (0–360°) data were obtained from a nearby National Ambient Weather Station located in the Newark International Airport, distant ~3.5 km south of the Ironbound community. The hourly quality controlled local climatological data was available in the National Climatic Data Center (http://cdo.ncdc.noaa.gov/qclcd/QCLCD, accessed on 1/8/2016); therefore, hourly measurements between 6:51 a.m.–10:51 a.m. were selected and used for data analyses. The radial wind direction data were converted to three categories; upwind, downwind and parallel from the primary road in each sampling area. Specifically, for sampling areas A and B, upwind was defined as <30° or >240°, downwind was defined as between 60 and 210°, and parallel was defined as either between 30 and 60° or between 210 and 240°. For sampling area C, radial degrees for defining downwind and upwind directions were opposite to conditions, because the primary road (McCarter Highway) in sampling area C is oppositely located to the primary road (US Route 1) in sampling areas A and B. Categorical wind direction in sampling area D was not determined, because that information would not be used in later data analyses.

2.6.3. Traffic counts and proximity to roadways

The annual average daily traffic (AADT) data and geographic data (e.g., Geo database and road layers) were obtained through the New Jersey Department of Transportation and the New Jersey Geographical Information System (GIS) portal (http://www.state.nj.us/dep/gis/index.html, accessed on 1/8/2016). Proximity to road (i.e., a straight distance from the edge of a nearby roadway to a sampling location) was obtained for the later regression analysis (section of 2.7.5) by conducting spatial joins of measurement locations with a road polygon in ArcGIS (ver. 10.2).

2.7. Data analysis

2.7.1. Descriptive statistics for TRAP concentrations

Descriptive statistics for monitored TRAP concentrations were calculated, including mean, standard deviation (SD), median (Med), and interquartile range (IQR, a range between 25 and 75 percentiles). The monitored concentrations were tailed to the right; therefore, log-transformation (base of e) was performed for all TRAP concentrations prior to conducting any statistical analyses.

2.7.2. Mean comparisons for spatio-temporal variability in TRAPs

To determine differences were significant in sampling areas (A–D), an analysis of variance (ANOVA) test was conducted. If there was a significant difference ($p < 0.05$), multiple comparisons (using a Duncan grouping in SAS's GLM procedure) were followed to further examine the differences in the comparison group. Student's T-test was conducted for the mean comparison for two sampling routes at each area (i.e., monitoring route I vs. route II) and for two sampling seasons (cold months vs. warm months).

2.7.3. Correlation analysis for TRAP concentrations

Spearman correlations (r_s) were calculated between 5-min averaged TRAP concentrations, stratified by each sampling area and sampling season. Higher correlation coefficients (e.g., $r_s > 0.75$ and $p < 0.05$) indicate the two variables are highly corresponding each other.

2.7.4. Variance analysis for concurrent TRAP measurements

To characterize differences in two concurrent TRAP measurements (i.e., from parallel routes I and II) within a sampling area, we explored the variability in the paired measurements. The difference was represented by calculating a coefficient of variation (CV), obtained from the standard deviation of two measurements and divided by the mean of the two. These self-normalized CVs indicate relative deviation in the monitored TRAP concentrations on two parallel routes at the same time. We note that, in this analysis, the dataset was limited to sampling areas of A–C. Because, in the sampling area of D, two monitoring routes (see Fig. 1) were not perpendicular to the primary roadway (i.e., US Route 1), and dominant traffic impacts were significantly from adjacent roadways (e.g., Ferry St. and Raymond Blvd for monitoring routes I and II, respectively). Therefore, for this variance analysis, we did not include data from the sampling area of D. Since the calculated CVs were tailed to the right; thus, a log-transformation (base of e) was conducted prior to conducting statistical analyses.

A one sample *t*-test was initially conducted whether the calculated CVs are different from the hypothetical normal distribution (mean of zero and a variance of one squared standard deviation) (McDonald, 2013). If the difference was significant ($p < 0.05$), the measured differences were not negligible due to significant spatial variations from the two measurements. These differences may be attributable to 1) sampling-related factors such as differences in sampling area (A–C), sampling location (1–5), sampling season (cold and warm), and sampling round (1–13); 2) meteorological factors, such as variations in RH, wind speed, and wind direction (downwind, upwind, and parallel); 3) TRAP concentration levels; and/or 4) random or instrumental errors that are not associated with above factors. The continuous variables (RH, wind speed, concentration level) were assigned as three categories: high (>66%), middle (33–66%), or low (<33%). To elucidate which factor significantly contributes to the overall variability and compare with uncorrelated errors (e.g., non-tested factors such as instrumental errors or random experimental variations), a variance component analysis was conducted using a convergence method (restricted maximum likelihood in SAS's VARCOMP procedure). The identified significant factors indicate which components (e.g., proximity to traffic sources, meteorological variations, and community characteristics) contribute to the differences between the two parallel measurements of TRAP concentrations.

2.7.5. Linear regression analysis for concurrent TRAP measurements

To determine whether our mobile monitoring approach can adequately represent the spatial variability within a neighborhood scale and further examine explanatory variables' impacts on predicted TRAP concentrations, we conducted a multiple linear regression analysis for the TRAP concentrations on routes I and II, respectively. In this multiple linear regression analysis, we restricted TRAP concentration data by the following selection criteria: 1) the sampling locations should be perpendicular to primary and secondary (local) roadways and 2) traffic count data should be available on both primary and secondary (local) roads. These restrictions were given to obtain source strength at each monitoring location, calculated by traffic count (vpd) and proximity data (m). Thus, only the sampling area of A satisfied above criteria.

To develop a multiple linear regression model, eight independent explanatory variables were collected. The variables include: 1) source intensity from the primary road (defined as traffic counts per hour divided by the proximity to the edge of the primary road), 2) source intensity from the secondary (local) road, 3) three meteorological data such as temperature, relative humidity, and wind speed, and 4) three categorical variables of wind direction. The categorical wind direction variables were replaced with numeric dummy variables and used in SAS's REG procedure. Among the eight independent explanatory variables, the final variables were selected by the forward selection method (default entry: $p < 0.5$) in SAS's REG procedure. The maxr and backward selection methods were additionally conducted to confirm no biases in variable selection method used. The multiple linear regression model was constructed using an equation (1):

$$Ln(Y_i) = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_8 X_{i8} + \varepsilon_i \tag{1}$$

Where, $Ln(Y_i)$ is a log-transformed TRAP concentration on each monitoring routes I and II,

β_0 is an intercept estimate,
$\beta_1 - \beta_8$ are model parameter estimates,
$X_{i1} - X_{i8}$ are model predicting variables, including primary road intensity, local road intensity, temperature, relative humidity, wind speed, and categorical wind directions of up, down and parallel, and
ε_i is an error term for the model.

To further evaluate whether the final regression models were consistent with TRAP measurements either collected on route I or route II, we conducted a multivariate regression analysis (using mtest statement) for each TRAP (Littell et al., 2002; SAS Institute Inc., 2011). We hypothesized that all significant predicting parameters were the same across the two models (equation (2)). If this was rejected ($p > 0.05$), an alternative hypothesis (equation (3)) would be accepted (UCLA, 2016). This implied two regression models were significantly different; therefore, the predicted TRAP concentrations would not be similar. All statistical analyses were conducted on SAS ver. 9.4 (SAS Inc., Cary, NC).

$$H_0: \ REG\ Mode\ on\ Route\ I = REG\ Model\ on\ Route\ II \tag{2}$$

$$H_a: \ REG\ Model\ on\ Route\ I \neq REG\ Model\ on\ Route\ II \tag{3}$$

3. Results and discussion

3.1. Spatial variability

The TRAP (BC, PNC, $PM_{2.5}$, and CO) concentrations monitored in the study are presented, mean ± SD and median (IQR), in Table 3. The results showed significant differences between two parallel routes in the sampling areas of A (for PNC) and B (for BC and $PM_{2.5}$). Except for these three cases, there were no significant differences between the two parallel monitoring routes. In the comparison of TRAP concentrations between the four sampling areas, we found there were significant differences for PNC and $PM_{2.5}$ measurements. The PNC data showed significantly higher concentrations on the order of A = B > D > C. On the other hand, $PM_{2.5}$ data were significantly higher in sampling areas of A–C than in the area of D. These differences between sites may be related to differences in local traffic sources and atmospheric behaviors of TRAPs in ambient air, which vary over time at these routes but not sampled simultaneously.

Spatial differences by a distance from the major roadway (sampling areas of A–C only) were examined by plotting TRAP concentrations with five distance bins (0–50 m, 50–100 m, 100–200 m, 200–350 m, and 350–500 m from the edge of primary roadways) in Fig. 2. Gradient decay pattern was observed for BC and PNC measurements, and multiple comparison tests (a Duncan grouping) showed the differences were significant for the distance bin of 0–50 m against other four distance bins (i.e., 50–100 m, 100–200 m, 200–350 m, and 350–500 m). This decaying pattern from the major roadway was previously reported in field studies (Roorda-Knape et al., 1998; Zhu et al., 2002; Padró-Martínez et al., 2012; Lähde et al., 2014) which monitored TRAP concentrations from the heavy trafficked highway and observed decreasing trend of TRAP concentrations with distances. However, in our data, the spatial distribution was not decreasing (CO) or not significantly downward trend ($PM_{2.5}$). Previous meta-analysis studies categorized $PM_{2.5}$ as "less rapid or gradual decay" (Karner et al., 2010), or "inert pollutant and high background" (Zhou and Levy, 2007). Thus, $PM_{2.5}$ may not clearly show a decay pattern with increasing distance from the major roadways, if there are many regional PM

Table 3
TRAP measurements (mean ± SD & Med (IQR)) at each monitoring area in Ironbound community, Newark, NJ.

Area	Routes[a]	BC[b] ($\mu g/m^3$)		PNC[b] ($\# \times 10^3/cm^3$)		$PM_{2.5}$[b] ($\mu g/m^3$)		CO[b] (ppm)	
A	I. Brill St.	2.72 ± 2.75 1.73 (3.29)	0.73	33 ± 24 24 (28)	**0.02**	8.64 ± 8.71 5.96 (6.68)	0.94	1.13 ± 0.46 1.10 (0.54)	0.09
	II. Hawkins St.	2.73 ± 2.67 1.77 (2.50)	I = II	47 ± 36 37 (40)	**I < II**	7.62 ± 6.00 5.23 (6.39)	I = II	1.34 ± 0.76 1.10 (0.54)	I = II
B	I. Wilson Ave.	3.25 ± 3.26 2.12 (1.79)	**0.02**	34 ± 19 29 (16)	0.77	9.95 ± 8.58 7.09 (8.13)	**0.01**	1.22 ± 0.40 1.15 (0.62)	0.27
	II. Niagara St.	2.28 ± 2.10 1.89 (1.78)	**I > II**	41 ± 28 36 (40)	I=II	6.52 ± 3.82 4.75 (6.99)	**I > II**	1.38 ± 0.68 1.17 (0.57)	I = II
C	I. Elm St.	2.28 ± 2.26 1.56 (1.45)	0.53	24 ± 16 21 (14)	0.38	9.65 ± 8.20 7.03 (6.25)	0.08	1.11 ± 0.42 1.08 (0.61)	0.08
	II. Ferry-Jefferson St.	2.04 ± 1.92 1.48 (1.16)	I = II	28 ± 18 23 (25)	I = II	7.66 ± 6.09 5.67 (6.52)	I = II	1.32 ± 0.87 1.12 (0.31)	I = II
D	I. Ferry-Chapel St.	2.37 ± 2.37 1.82 (1.75)	0.21	28 ± 13 27 (17)	0.74	11.1 ± 8.69 7.87 (8.20)	0.08	1.08 ± 0.43 1.08 (0.54)	0.12
	II. Raymond Blvd.	2.55 ± 1.99 2.07 (2.21)	I = II	33 ± 20 29 (32)	I = II	9.83 ± 8.96 7.90 (9.09)	I = II	1.21 ± 0.59 1.09 (0.37)	I = II
Mean comparisons in sampling areas (p-value and Duncan grouping, if feasible)		p = 0.14		**p < 0.01** **A = B > D > C**		**p < 0.01** **A = B = C ≤ D**		p = 0.14	

Bold significance indicates $p < 0.05$.
Notes:
[a] The mean comparison between two monitoring routes (route I vs. route II) was conducted for each area and TRAP; results were provided as a p-value and Duncan grouping.
[b] BC (1-s as processed); PNC, $PM_{2.5}$, and CO (1-s as measured).

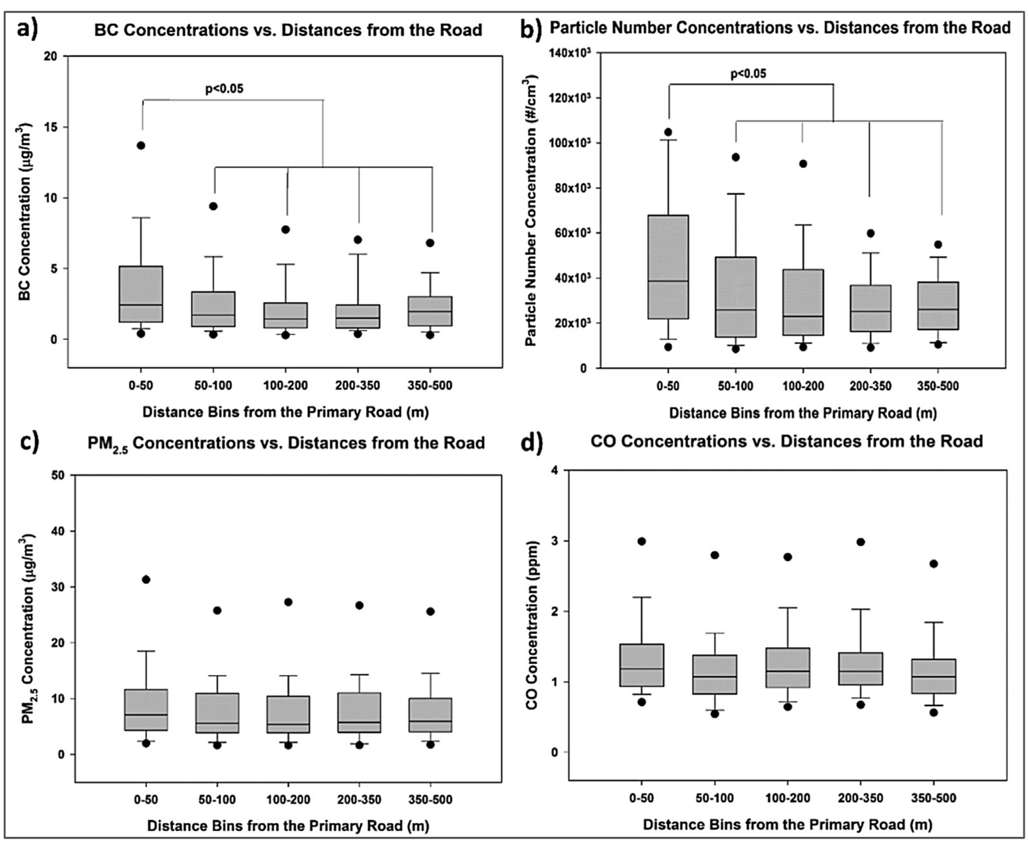

Fig. 2. Box plots for a) BC, b) PNC, c) $PM_{2.5}$, d) CO measurements vs. five distance bins (0–50 m, 50–100 m, 100–200 m, 200–350 m, and 350–500 m) from the primary road in sampling areas (A–C only) in Ironbound community, Newark, NJ. Notes: a) Multiple comparison results were displayed in the figure, if the significance was significant ($p < 0.05$) by a Duncan grouping method. b) BC (1-s as processed); PNC, $PM_{2.5}$, and CO (1-s as measured).

sources (industrial facilities, traffic emissions from local roadways, or emissions from commercial sector) in the monitoring area. The ironbound community, part of the city of Newark, is an urbanized area with many other local and regional PM sources, which contribute to the PM level and variation and thus the less significant $PM_{2.5}$ decaying pattern was expected.

Unexpectedly, for CO, there was no clear spatial trend with distance from the US Route 1 highway. The absence of previously reported near-highway CO gradients may be due to lower emissions of more modern vehicles, or lower precision and spatial resolution of our measurements. Alternatively, higher relative concentrations of CO emissions from local traffic sources may have diminished the gradient, although concentrations at all distances from the highway were relatively low with median concentrations slightly above 1 ppm. Local street traffic, although lighter in volume, may have relatively greater CO emission rates due to more acceleration and the stop-and-go driving compared with highway traffic (Kittelson et al., 2004).

Another scripted mobile monitoring for the sampling area of D is displayed in Fig. 3. The measurements were made along the curbside of heavy truck trafficked roadways, so the traffic impact was expected to be similar with all monitoring locations along the routes. As expected, the spatial patterns were not significantly different for all sampling locations and TRAPs. The busy truck trafficked roadways were located parallel and very close (<5 m from the edge of the road). Therefore, the traffic impact was constant all over the monitoring sessions in the area of D. Taking into account spatial patterns for monitored TRAPs in the community, the spatial impact of TRAPs depends on the proximity to source, and the pattern can be weakening under the presence of local sources or through atmospheric dilution processes such as with strong winds and under high mixing conditions.

3.2. Temporal variability

Significant seasonal differences were observed for all TRAP concentrations, higher in cold months (March–April 2012) than in warm months (May–June 2012) (Fig. 4). These results are consistent with previous findings in the literature. Significantly higher TRAP concentrations were monitored in cold vs. in warm seasons (Hu et al., 2009; Wang et al., 2011; Padró-Martínez et al., 2012). This seasonal difference can be attributable to higher vehicle exhaust emissions and greater atmospheric stability (less vertical mixing) during cold months (Zhu et al., 2006; Olofson et al., 2009). Within each season, concentrations were different ($p < 0.05$) by the sampling day (round). On the date of 3/20/2012, elevated BC, $PM_{2.5}$ and CO concentrations were monitored, and the PNC measurements were elevated on a different date of 3/28/2012. These seasonal and daily variations may be caused by changes in meteorological factors (e.g., wind direction, temperature, mixing height, etc.) that vary by day and also significantly affect the formation, dispersion and removal mechanisms of air pollution (Krudysz et al., 2009). In addition, temporal heterogeneity of TRAP concentrations can be influenced by the location and lay-out of roads and the dynamics of the traffic (volume, speed, fleet composition) (Peters et al., 2013). Overall, the observed spatio-temporal variability in TRAP concentrations could be driven by the spatio-temporal variability of traffic sources and altered by atmospheric processes with meteorological changes.

3.3. Inter-pollutant correlations

Inter-pollutant correlations varied by the sampling area and sampling season (Fig. 5). Among the TRAP pollutants, the particulate phase of BC, PNC and $PM_{2.5}$ had stronger correlations than the gaseous CO. Among the three possible pairs (i.e., BC-PNC, BC-$PM_{2.5}$, and PNC-$PM_{2.5}$), the pair of BC and $PM_{2.5}$ was the strongest. The correlation coefficients were strongest in the area of A, and

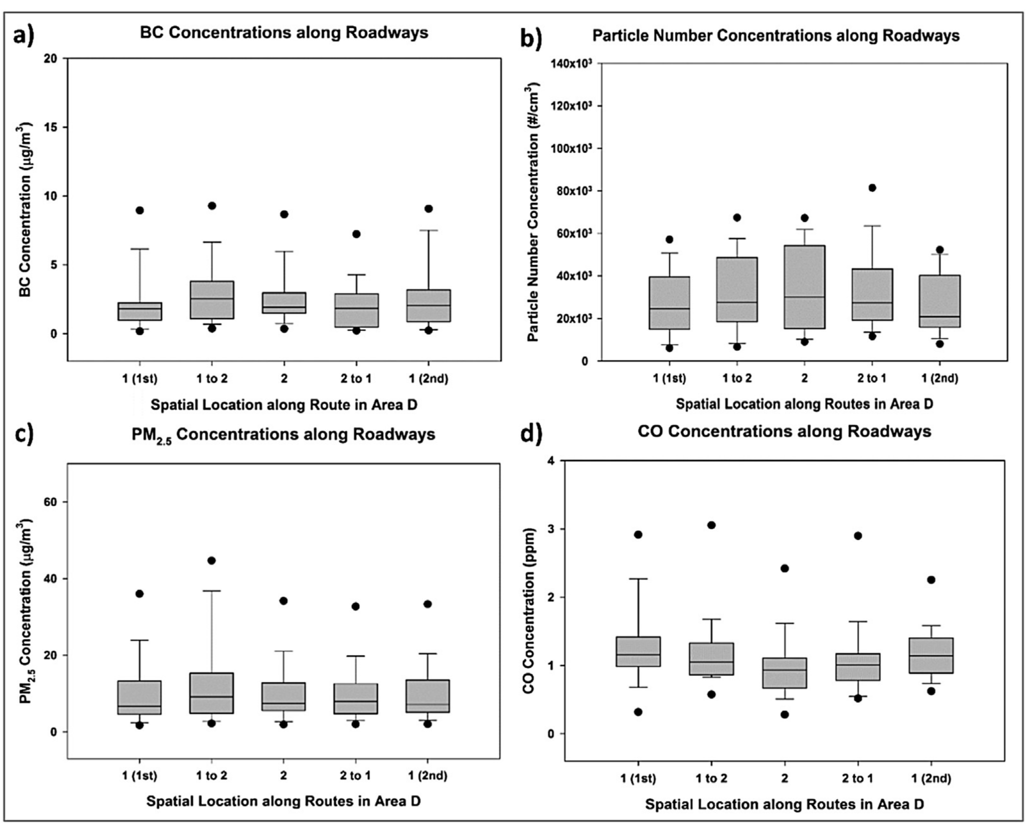

Fig. 3. Box plots for a) BC, b) PNC, c) $PM_{2.5}$, d) CO measurements on diesel truck trafficked routes in the sampling area of D in Ironbound community, Newark, NJ. Notes: a) The label of 1(1st) and 1(2nd) indicates an initial and repeat 5-min monitoring at the location 1, respectively; and the label of 1–2 and 2to1 indicates mobile monitoring during the course of staff walking from the location 1 to 2 and the location 2 to 1, respectively. b) BC (1-s as processed); PNC, $PM_{2.5}$, and CO (1-s as measured).

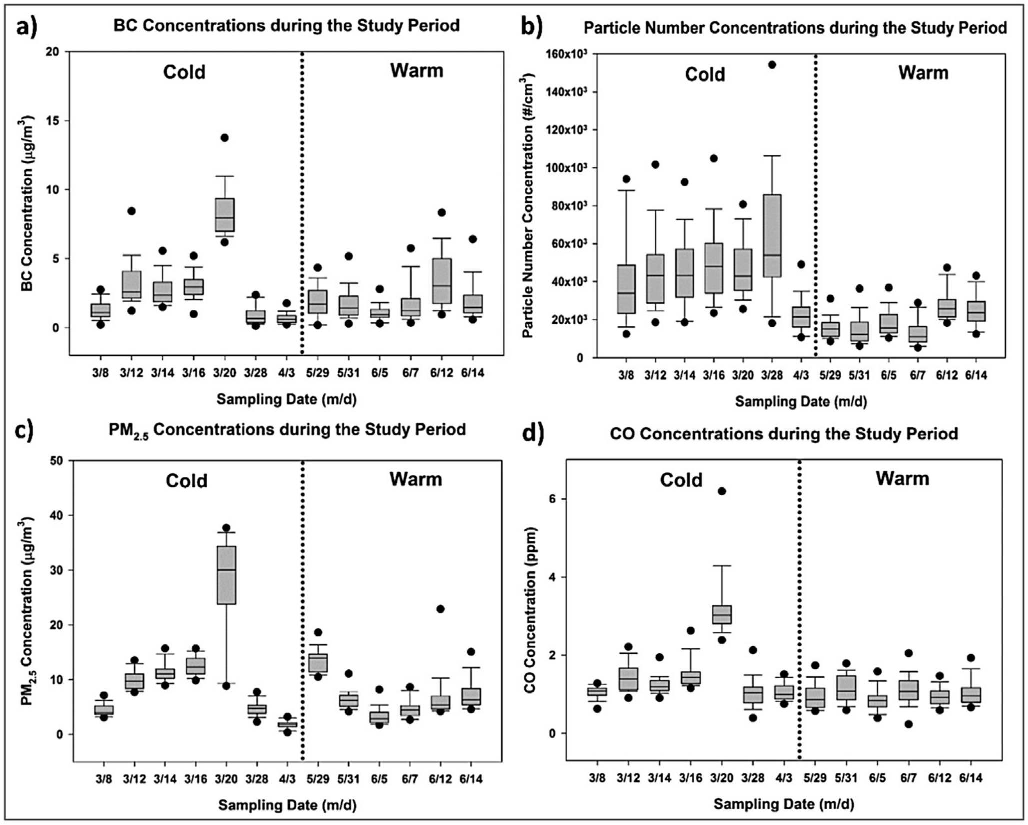

Fig. 4. Box plots for daily a) BC, b) PNC, c) $PM_{2.5}$, d) CO measurements combined from four sampling areas in Ironbound community, Newark, NJ. Note: BC (1-s as processed); PNC, $PM_{2.5}$, and CO (1-s as measured).

a) Area A

	BC	PNC	$PM_{2.5}$	CO
BC	-	0.54	0.77	0.38
PNC		-	0.39	0.55
$PM_{2.5}$			-	0.42
CO				-

b) Area B

	BC	PNC	$PM_{2.5}$	CO
BC	-	0.46	0.71	0.45
PNC		-	0.34	0.41
$PM_{2.5}$			-	0.35
CO				-

c) Area C

	BC	PNC	$PM_{2.5}$	CO
BC	-	0.29	0.68	0.36
PNC		-	0.28	0.37
$PM_{2.5}$			-	0.32
CO				-

d) Area D

	BC	PNC	$PM_{2.5}$	CO
BC	-	0.31	0.74	0.30
PNC		-	0.35	0.24
$PM_{2.5}$			-	0.34
CO				-

e) Cold Months (March-April)

	BC	PNC	$PM_{2.5}$	CO
BC	-	0.42	0.85	0.68
PNC		-	0.35	0.31
$PM_{2.5}$			-	0.59
CO				-

f) Warm Months (May-June)

	BC	PNC	$PM_{2.5}$	CO
BC	-	0.40	0.43	0.05
PNC		-	0.18	0.06
$PM_{2.5}$			-	0.06
CO				-

0.00 0.50 1.00

Fig. 5. Spearman correlation matrix for the subset of data: a) area A, b) area B, c) area C, d) area D, e) cold months and f) warm months. Notes: a) The shaded color indicates the strength of correlation coefficient for each correlation pair; and the underlined correlation coefficient is significant at the significance level of $p < 0.05$. b) BC (1-s as processed); PNC, $PM_{2.5}$, and CO (1-s as measured).

followed in areas of B and C. For the sampling area of D, the correlation coefficients (r_s) were not as strong as the other areas (A–C), and the pair of CO and PNC was not significant ($p > 0.05$). Comparing Spearman coefficients between two seasons (cold vs. warm seasons), correlations were much stronger in cold months than warm months. These inter-pollutant correlations were characterized by the strength of TRAP concentrations, which are significantly higher at locations closer to traffic sources and in monitoring times during cold months. The similar temporal characteristics were reported in field studies. Patton et al. (2014) reported varied correlation coefficients by monitoring neighborhoods, higher in the neighborhoods close to highways and lower in urban background neighborhoods. Also, authors reported seasonal and diurnal variations, that were higher in cold months (November to March) than in warm months (April to October) as well as higher during morning rush hour (04:30–10:00) than midday (10:00–14:00) or afternoon rush hour (14:00–22:00). Kassomenos et al. (2014) reported substantially higher correlation coefficients for TRAPs during cold season and at traffic sites than during warm season and at background sites.

3.4. Characterization of differences in CVs

The calculated CVs were located around 0.2 for all TRAPs (BC = 0.25 ± 0.22; PNC = 0.21 ± 0.15; $PM_{2.5}$ = 0.19 ± 0.15; CO = 0.16 ± 0.13), and significantly different ($p < 0.05$) from the hypothetical population with mean (=0) ± SD (=1). The variance component analysis results were summarized in Table 4. Among the four components that we tested, the meteorological variation was the most significant component, explaining ~25% (5–54%) of overall variance. About 19% of the total variance was attributable to temporal variation (i.e., season and round). The remaining two components were variation in spatial differences and concentration levels, comprising 2.2% and 5.8%, respectively. On the other hand, random or instrumental errors constituted the remaining ~49%.

The variance component analysis showed the short-term temporal variability (i.e., varying meteorological conditions) and long-term temporal variability (i.e., seasonal and daily changes) partitioned approximately 25% and 19%, respectively, of total variability. This suggests our parallel mobile monitoring approach could be applied for further discerning shorter and longer temporal variations as well as spatial variations in monitored TRAP concentrations, which varies with time and in space. However, more research is required to confirm this finding with more than two concurrent measurements in similar urban settings. Future efforts towards increasing sampling days and periods in a day (e.g., morning/afternoon rush hours and night time) on multiple parallel routes are suggested to reduce the temporal variability in real-time TRAP concentrations. Peters et al. (2013) conducted a mobile monitoring using a platform of bike riding, and demonstrated approximately 20 repeated mobile measurements achieved constant TRAP concentrations during a monitoring period of three weeks (one season) at two urban locations in Belgium.

3.5. Evaluation of mobile monitoring approach

The final regression models were developed and provided in Table 5, on the left side for route I (Brill St.) and right side for route II (Hawkins St.) in the area of A only. All final models were significant ($p < 0.01$) and explained the variability in the range of 0.37 (R^2; CO on Hawkins St.) to 0.76 (R^2; $PM_{2.5}$ on Brill St.). No significant heteroscedasticity (White test), autocorrelation (Durbin-Watson test), and multicolinearity (VIF) issues were found. The strength of predicting variables varied by TRAP (standardized coefficients and partial R^2). In general, meteorological variables (wind speed, wind directions) were dominant variables in the models. Temperature was significant and negatively associated with BC, PNC, and CO concentrations, which are consistent with our observation of higher TRAP concentrations in cold months than warm months (Section 3.2). For $PM_{2.5}$, temperature was not finally selected for both routes, due to the fact that RH dominantly contributed ~60% of total variability and inversely related with temperature. The source strength of primary (i.e., US Route 1) and secondary (local) (i.e., Ferry St.) roadways were significant variables for BC and PNC for both routes I (Brill St.) and II (Hawkins St.). However, weaker associations were found for CO and no association for $PM_{2.5}$. These are consistent with our spatial variability (see Section 3.1.) and literature data. BC and PNC are two TRAP pollutants, gradually decaying with increasing distance from the traffic source. Otherwise, $PM_{2.5}$ in urban areas has various regional sources, for example, directly emitting from traffic, industrial facilities, commercial shops and other miscellaneous sources, as well as secondarily generated via atmospheric processes. Therefore, traffic source strength may not be significant in the final regression model for $PM_{2.5}$. The final regression model for CO is consistent with observations in Section 3.1. No noticeable gradient decay patterns for CO, were observed, presumably due to limited precision of the measurements or higher background levels of CO in this urban environment.

The multivariate regression analysis showed CO ($p = 0.02$) and $PM_{2.5}$ ($p < 0.01$) models were significantly different ($p < 0.05$), if regression models were re-established with selected parameters only (bolded in Table 5) for routes I and II, respectively. Otherwise, BC and PNC regression models were not significantly different ($p = 0.35$ and $p = 0.22$, respectively) under the same conditions. These discrepancy results imply that the linear relationship between monitored TRAP concentrations and explanatory variables is significantly affected by the variable of source strength. As observed in previous spatial variability (Section 3.1) and Fig. 2, BC and PNC measurements showed significant differences between the closest location (i.e., a distance bin of 0–50 m from the primary

Table 4
The variance component analysis for the calculated CVs by contributing factors: 1) spatial variation (sampling area and sampling location), 2) temporal variation (sampling season and sampling round), 3) meteorological variation (relative humidity, wind speed, and wind direction), 4) concentration level, and uncorrelated error.

TRAPs	Area	Location	Season	Round	RH	Wind speed	Wind direction	Concentration level	Uncorrelated error
BC	2.5%	0.2%	37.6%	0.0%	0.0%	16.1%	7.3%	2.5%	33.8%
PNC	0.0%	0.0%	0.0%	15.6%	0.0%	16.0%	0.9%	1.5%	66.0%
$PM_{2.5}$	3.0%	2.1%	0.0%	4.3%	24.7%	0.0%	29.1%	7.2%	29.6%
CO	1.0%	0.0%	15.9%	1.1%	0.0%	4.9%	0.0%	11.8%	65.4%
Mean	1.6%	0.6%	13.4%	5.2%	6.2%	9.3%	9.3%	5.8%	48.7%
Sub-total	Spatial variation		Temporal variation		Meteorological variation			Concentration variation	Uncorrelated error
	2.2%		18.6%		24.7%			5.8%	48.7%

Note: BC (1-s as processed); PNC, $PM_{2.5}$, and CO (1-s as measured).

Table 5
The final multiple linear regression models for each TRAP and monitoring route with variables of traffic strength and meteorological data.

TRAPs	Route I (Brill St.)				Route II (Hawkins St.)			
	β	Std. β[a]	Pr > |t|	Model/Partial R^2	β	Std. β[a]	Pr > |t|	Model/Partial R^2
Ln(BC[b]) (μg/m^3)			<0.01	0.61			<0.01	0.46
Intercept	2.00	0.00	0.03	–	2.30	0.00	<0.01	–
Downwind[c]	1.56	0.54	<0.01	0.37	1.05	0.39	<0.01	0.25
Temperature[c]	−0.03	−0.38	<0.01	0.15	−0.02	−0.25	0.02	0.08
Wind speed[c]	−0.09	−0.18	0.14	0.06	−0.15	−0.32	<0.01	0.10
Primary road[c]	0.01	0.19	0.04	0.02	0.01	0.13	0.22	0.01
Local road[c]	0.01	0.14	0.13	0.02	0.01	0.12	0.26	0.01
RH	0.01	0.12	0.33	0.01	–	–	–	–
Upwind	–	–	–	–	−0.22	−0.11	0.33	0.01
Ln(PNC[b]) (#/cm^3)			<0.01	0.72			<0.01	0.66
Intercept	12.03	0.00	<0.01	–	10.39	0.00	<0.01	–
Upwind[c]	−0.78	−0.56	<0.01	0.47	−0.49	−0.32	0.01	0.20
Temperature[c]	−0.03	−0.48	<0.01	0.21	−0.03	−0.45	<0.01	0.37
Primary road[c]	0.01	0.21	0.01	0.03	0.01	0.10	0.25	0.01
Local road[c]	0.01	0.10	0.24	0.01	0.01	0.11	0.21	<0.01
Wind speed	–	–	–	–	0.16	0.47	<0.01	0.04
RH	–	–	–	–	0.02	0.44	0.01	0.04
Downwind	0.13	0.07	0.37	<0.01	–	–	–	–
Ln($PM_{2.5}$[b]) (μg/m^3)			<0.01	0.76			<0.01	0.69
Intercept	0.32	0.00	0.66	–	1.52	0.00	0.01	–
RH[c]	0.01	0.23	0.08	0.61	0.01	0.49	0.02	0.59
Wind speed[c]	−0.18	−0.39	<0.01	0.05	−0.10	0.41	0.02	0.04
Upwind[c]	−0.93	−0.45	<0.01	0.03	−0.60	−0.45	<0.01	0.06
Temperature	0.03	0.33	<0.01	0.07	–	–	–	–
Ln(CO[b]) (ppm)			<0.01	0.60			<0.01	0.37
Intercept	0.67	0.00	0.01	–	0.88	0.00	<0.01	–
Parallel	0.40	0.52	<0.01	0.45	–	–	–	–
Temperature[c]	−0.01	−0.40	<0.01	0.13	−0.01	−0.39	<0.01	0.14
Local road[c]	0.01	0.10	0.30	0.01	−0.01	−0.36	<0.01	0.08
Upwind	–	–	–	–	−0.17	−0.26	0.05	0.10
Downwind	–	–	–	–	0.19	−0.17	0.20	0.02
Primary road	–	–	–	–	−0.01	−0.21	0.13	0.04
Wind speed	−0.02	−0.10	0.31	0.01	–	–	–	–

Notes:
[a] Std. β: standardized coefficient.
[b] BC (1-s as processed); PNC, $PM_{2.5}$, and CO (1-s as measured).
[c] Bolded parameters were particularly selected for later multivariate regression analysis for testing whether the parameters were different across two regression models (developed on routes I and II, respectively).

roadway) and the rest of 4 locations (i.e., distances from 50 to 500 m). Thus, the developed regression models and subsequently predicted BC and PNC concentrations may not be significantly different, because two multiple linear regression models share similar extent of spatial characteristics from both routes. Otherwise, CO and $PM_{2.5}$ were opposite. Because CO and $PM_{2.5}$ concentrations were not spatially different; thus, final regression models could not pick up source strength-related variables in their final models (see Table 5). Overall, the multivariate regression analysis suggests some of TRAP measurements could be different on parallel routes, even in a narrow neighborhood scale (e.g., one or two blocks distant each other). The difference can be influential for less rapidly decreasing (e.g., $PM_{2.5}$) or steeply decreasing (e.g., CO) from major highways with high background or different emission sources within urban communities.

3.6. Study limitations and recommendations for future research

There were limitations of this study. First, monitoring was only conducted in the weekday morning in order to capture the relatively high emissions from traffic at these times. More monitoring on weekends and other time periods during weekdays (e.g., afternoon rush hour, or nigh-time) should be conducted to capture temporal patterns at different times on different days of a week. Second, the study result from variance component analysis may be limited to urban communities with similar environmental and weather conditions, considering approximately half of the variance was still not explained by the examined factors and relatively small number of samplings per season at one period of time (i.e., during morning rush hour). Third, the regression analysis was conducted for one urban neighborhood (i.e., specifically for the sampling area of A in this manuscript), due to limitation of geographical location and availability of traffic counts. Thus, more studies should be conducted in areas with different road configurations/layouts. Fourth, a monitoring period was conducted for two seasons and with a total 13 individual rounds, due to budget limitation. Extension of mobile monitoring up to four seasons with more sampling rounds and sampling time (e.g., afternoon rush hour and night-time) would be desirable to capture effects of variation in meteorological conditions, traffic mix and volume, and eventually dispersion patterns that significantly affect spatio-temporal variability in TRAP concentrations. Fifth, meteorological data of wind speed/direction was obtained from an airport about 3.5 km south of the Ironbound community. The microenvironmental meteorological conditions in the neighborhood of buildings and busy streets may have differed somewhat from conditions at the airport. Real-time, on-site meteorological data measurement is recommended for future mobile monitoring study for more accurate measurement of meteorological factors. Finally, although the overall monitoring design attempted to capture spatial characteristics regardless of temporal effects, the monitored data still incorporate a certain level of temporal factors (e.g., a time difference was approximately 30 min between the beginning and end of a single route's monitoring period). Therefore, our monitoring approach could not completely separate spatial characteristics from entangled temporal variations; subsequent analysis results and conclusions drawn in this study may have some uncertainties that are associated with effects from varying time in a single monitoring route. The enhancement of mobile monitoring by employing simultaneous measurements with multiple monitors on a single route is suggested to improve this monitoring approach by helping to control for short-term temporal variability.

4. Conclusions

This study employed a new mobile monitoring approach to capture spatial/temporal characteristics in TRAP concentrations within a community with heavy diesel traffic and local urban air pollution sources. The novel aspect of this mobile monitoring approach was the simultaneous measurement along parallel pathways to assess spatial gradients in TRAP concentrations, while controlling temporal variations. This approach may have advantages over simple linear mobile measurements, in which sequential measurements change in both space and time. Parallel measurements may help to disentangle spatial and temporal variability in urban neighborhood settings near roadways where TRAP concentrations change rapidly in space and time.

In this study, spatio-temporal variability depended on the strength and density of pollutant sources (i.e., traffic proximity) and meteorological factors that govern the formation, dispersion and removal mechanisms in ambient air. The observed spatial/temporal characteristics were consistent with findings in previously published literature and general knowledge in atmospheric chemistry. Results from simultaneous monitoring on two parallel routes, which were perpendicular to and distant up to 500 m from a primary roadway, showed this mobile monitoring approach could reliably capture spatial patterns for each TRAP.

This monitoring methodology could be applied for research efforts towards an accurate estimation of community exposure to TRAPs in urban areas with heavy traffic emissions and general urban air pollution sources. By taking simultaneous, real-time measurements on roadside, this mobile monitoring approach may be especially useful for community-engaged research to characterize local, community-specific exposures to TRAP. Future improvements can be directed towards minimizing temporal variations with multiple measurements on a single route as well as maximizing spatial characterization with finer resolution.

Disclaimer

The findings and conclusions in this article are those of the authors and do not necessarily represent the views of the National Institute of Environmental Health Sciences (NIEHS). Mention of any company or product does not constitute endorsement by NIEHS.

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