On-bicycle exposure to particulate air pollution: Particle number, black carbon, PM$_{2.5}$, and particle size

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HIGHLIGHTS

- Monitored particulate air pollution for 85 h (1426 km) in a city while cycling.
- ~50% of Black Carbon (BC) and Particle Number (PN) concentrations were from near-traffic emissions.
- BC and PN were correlated with street type and declined short distances from major roads.
- Presence of nearby trucks was associated with highly elevated concentrations of particulates.

ARTICLE INFO

ABSTRACT

Inhalation of air pollution during transport is an important exposure pathway, especially for certain modes of travel and types of particles. We measured concentrations of particulate air pollution (particle number [PN], black carbon [BC], fine particles [PM$_{2.5}$], particle size) using a mobile, bicycle-based monitoring platform during morning and afternoon rush-hour to explore patterns of exposure while cycling (34 days between August 14 and October 16, 2012 in Minneapolis, MN). Measurements were geo-located at 1 s intervals along 3 prescribed monitoring routes totaling 85 h (1426 km) of monitoring. Mean morning [afternoon] on-road concentrations were 32,500 [16,600] pt cm^{-3}, 2.5 [0.7] µg m^{-3} BC, 8.7 [8.3] µg m^{-3} PM$_{2.5}$, and 42 [39] nm particle diameter. Concentrations were correlated with street functional class and declined within small distances from a major road (e.g., for PN and BC, mean concentration decreased ~20% by moving 1 block away from major roads to adjacent local roads). We estimate the share of on-bicycle exposure attributable to near-traffic emissions (vs. regional pollution) is ~50% for PN and BC; ~25% for PM$_{2.5}$. Regression models of instantaneous traffic volumes, derived from on-bicycle video recordings of nearby traffic, quantify the increase in particle-concentrations associated with each passing vehicle; for example, trucks were associated with acute, high concentration exposure events (average concentration-increase per truck: 31,000 pt cm^{-3}, 1.0 µg m^{-3} PM$_{2.5}$, 1.6 µg m^{-3} BC). Our findings could be used to inform design of low-exposure bicycle networks in urban areas.

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1. Introduction

During the past decade, US federal agencies have launched programs aimed at promoting healthy, sustainable communities (CDC, 2012; HUD, 2012); one commonly cited strategy is to encourage bicycle travel. Cycling can benefit individuals (e.g., increased physical activity (Andersen et al., 2000; Hamer and Chida, 2008)) and society (e.g., reduced emissions (Grabow et al., 2011); shifting demand from the vehicle network (Ewing and Cervero, 2001)). However, decision-makers have little evidence-based guidance on how best to design bicycle networks that minimize exposure to environmental hazards such as particulate air pollution.

Exposure to particulate air pollution is an important risk factor for cardiovascular disease in urban areas (WHO, 2009). Multiple studies report adverse health effects associated with within-city concentration gradients of fine particulate matter (PM$_{2.5}$ (Jerrett et al., 2005; Miller et al., 2007)) and that urban air quality is correlated with the built environment (Bechle et al., 2011; Clark et al., 2011; Hankey et al., 2012). The within-city health studies of PM$_{2.5}$ and mortality (Jerrett et al., 2005; Miller et al., 2007) report

similar differences in risk as the larger, between-city cohort studies that have guided policy on ambient air pollution (Pope et al., 2009; Hoek et al., 2013). In addition, researchers have shown that concentrations of traffic-related pollutants on high traffic roads (i.e., freeways) decrease rapidly as distance from the roadway increases (Karner et al., 2010; Zhang et al., 2002; Zhu et al., 2002). A key question for urban planners is how to best design bicycle networks to minimize exposure to air pollution.

Exposure to particulate air pollution during transport is an important exposure pathway (Dons et al., 2011). For example, detailed measurements on 62 people in Flanders, Belgium found that the ~6% of people's time spent in transport accounts for an average of 30% of total inhaled Black Carbon (BC; Dons et al., 2012). An earlier study in California estimated that in-vehicle exposure to diesel particulate matter accounted for 28–55% of total exposure (Fruin et al., 2004). Multiple studies have investigated exposure for various modes of transport and concluded that cycling is generally among the most exposed if accounting for breathing rates (Dons et al., 2012; Bigazzi and Figliozzi, 2014; Int Panis et al., 2010). Traffic-related pollutants, including pollutants not currently regulated by the EPA (e.g., BC, particle number [PN]), could play a significant role in the within-city health disparities related to air pollution (Gauderman et al., 2007; Peters et al., 2004; Wilhelm and Ritz, 2002). Exposure to PN and BC while cycling impacts lung function, exacerbates asthma, and changes heart rate variability (Strak et al., 2010; Weichenthal et al., 2011). Risk assessment studies have shown that cycling is overall health promoting (de Hartog et al., 2010; Rojas-Rueda et al., 2011); however, health benefits from physical activity may be reduced in the presence of air pollution for certain health outcomes (i.e., respiratory disease (Giles and Koehle, 2014; Andersen et al., 2015)).

We present results from a mobile, bicycle-based particulate air pollution measurement campaign in Minneapolis, MN. Previous studies have used primarily motor vehicles to collect mobile measurements (Fruin et al., 2008; Larson et al., 2009; Su et al., 2013; Westerdahl et al., 2005; Hudda et al., 2014) and are disproportionately focused on or near freeways (Aggarwal et al., 2012; Patton et al., 2014). Some exploratory studies have measured air pollution on targeted bicycle routes in urban areas (Boogaard et al., 2009; Hatzopoulou et al., 2013; Hong and Bae, 2012; Van Poppel et al., 2013; Zuurbier et al., 2010; Van den Bossche et al., 2015). We designed our measurement campaign to assess three factors of on-bicycle exposure that have not been addressed in the literature: (1) estimating the contribution of near-traffic vs. regional emissions, (2) assessing how concentrations correlate with street functional class and proximity to major roads, and (3) quantifying acute increases in concentrations attributable to instantaneous traffic counts in close proximity to a cyclist.

We measured concentrations of PN, BC, and $PM_{2.5}$ as well as particle size along 3 routes (~100 km total) repeatedly during morning and afternoon rush-hours. We developed an approach to control for temporal variability in background concentrations; thus, we were able to pool measurements among monitoring days to explore patterns of exposure while cycling. Our dataset represents one of the largest bicycle exposure datasets to date (and for on-roadway measurements in general); our approach to systematically design routes and account for background concentrations to isolate the effect of traffic patterns and spatial distribution of emissions on exposure makes our study distinct when compared to previous studies of on-bicycle exposure.

2. Material and methods

We developed a custom, mobile monitoring platform using a bicycle and a modified bicycle trailer to measure on-road

concentrations of particulate air pollution. We sampled 3 prescribed routes during a consistent time of day to control for hourly variability in traffic patterns and emissions. Routes were sampled on a rotating basis; we completed 42 monitoring runs during morning (7–9am; n = 12) and afternoon (4–6pm; n = 30) rush-hours on weekdays (8/14/12-10/16/2012). As such, the measurements presented in this paper are representative of rush-hour concentrations during late summer and fall in Minneapolis. In total we cycled 1426 km to collect 85.3 h (for each instrument: 3×10^5 individual 1-s measurements) of on-road data.

2.1. The bicycle-based monitoring platform

We modified a commercial bicycle trailer to carry air pollution instrumentation that measures concentrations of four aspects of particulate air pollution: (1) TSI CPC 3007 (PN concentration; >10 nm), (2) AethLabs AE51 micro-aethalometer (BC mass concentration), (3) TSI DustTrak 8530 ($PM_{2.5}$ mass concentration), and (4) TSI NanoScan (particle size distribution; 10–420 nm). The first three instruments record measurements at 1 s intervals; the NanoScan completes one scan per minute. Temporally-resolved measurements of particles gives information on small-scale changes in concentrations attributable to acute exposure events such as vehicles passing in close proximity, crossing over a busy freeway, or waiting at a stoplight in traffic. Our sampling intake (~1.7 m above the ground; stainless steel and conductive tubing) is approximately at the breathing height of a cyclist. The bicycle and trailer were also equipped with a GPS device, odometer and speedometer, rear- and forward-facing video cameras, and temperature and relative-humidity data loggers (see Figs. S1 and S2; Table S1).

2.2. Instrumentation and data processing

Post-processing the data, to account for known measurement-artifacts, for each instrument is described below. The NanoScan did not require adjustments; instead this instrument was checked against a laboratory-based reference instrument at TSI, Inc. (R^2: 0.99; Fig. S3). Flow and zero checks were performed daily on all instruments before monitoring. We corrected for differential lag times among instruments (Fig. S4; Table S2).

For micro-aethalometer data, we removed spurious spikes due to mechanical shock using the method of Apte et al. (2011) and applied the Kirchstetter and Novakov (2007) correction for particle loading. The former algorithm resulted in 1% (morning) and 2% (afternoon) of the data being removed as spurious. DustTrak data were real-time corrected for relative humidity (Both et al., 2011; Chakrabarti et al., 2004). We created and applied a mass calibration using filter measurements (Casella Apex Pro pump, BGI cyclone, PTFE filters with pore size of 2.0 μm) to account for the local optical properties of particles at the study site (mass calibration R^2: 0.82; Fig. S5). For the 1.2% of on-road measurements greater than the manufacturer-specified maximum concentration of 100,000 particles cm^{-3}, we applied the correction from Westerdahl et al. (2005).

2.3. Monitoring route selection

We selected 3 monitoring routes (~32 km each) in the City of Minneapolis (Figs. S6–S9). Routes were chosen to cover many land uses and many neighborhoods, to sample at multiple distances from common emission-sources (e.g., major roads; the central business district), and to cover all street classifications while oversampling bicycle facilities (e.g., bike lanes or off-street trails). Routes were sampled repeatedly during morning and afternoon

rush-hours; routes were sampled in both forward and reverse directions.

The monitoring routes were distributed more equally among road types (arterial: 33%, collector: 19%, local: 19%, and off-street trails: 29%) than the City as a whole (arterial: 14%, collector: 14%, local: 64%, and off-street trails: 7%; see Table S5). We selected routes so that 53% of the total distance is on a bicycle facility (i.e., off-street trail, on-street lane or marking; 14% for the City). Land uses that may influence concentrations had good spatial coverage among our routes. For example, land uses within 25 m of the routes included retail (35%), industrial (16%), and open space (34%).

2.4. Reference site measurements and adjusting for background concentrations

To record day-to-day differences in background concentrations we collected measurements at a reference site for 30 min before and after each monitoring run (we did not have the necessary equipment to maintain a permanent reference site). The reference site was a 15 ha park on the Mississippi River ~300 m from the nearest major road (Fig. S10).

As a second estimate of background concentrations, we developed instrument-specific underwrite functions that identify the cleanest concentrations measured on-road (specifically, the 1st percentile concentration within a moving 30-min window; see Table S7). This approach aims to capture times when we sampled from air parcels with as little impact as possible from nearby sources, i.e., the closest to "background" one can find on-roadway during those 30 min.

The two approaches (measurement at a clean urban reference site; underwrite function to identify clean on-road air parcels) allow for correction for differences in daily background concentrations. We then apply the temporal (i.e., daily background) correction, as follows: (1) the underwrite function was generated for each time-series (i.e., monitoring run), (2) for each data point the corresponding underwrite concentration estimate was subtracted from the instrument-reported measurement, (3) a "typical" background concentration was calculated by averaging reference site measurements among all runs, and (4) that value was then added to all underwrite-adjusted measurements from the second step. This process was performed separately for morning and afternoon monitoring runs. (See Fig. S11 for an example monitoring run with corresponding underwrite functions; see Fig. S12 for a comparison of trip-averaged on-road, reference site, and underwrite estimate concentrations.)

2.5. Statistical analyses

2.5.1. Pollutant averaging time

We explored two aspects of time-averaging the mobile monitoring data: (1) correlations among pollutants, and (2) how those correlations depend on averaging-time. The former question sheds light on potential similarities or differences among pollutants in emission sources, transport and transformation in the atmosphere, and proximity to and density of emission sources. The latter question is important in part because specific instruments or specific monitoring campaigns might use different averaging times; to our knowledge, the influence of averaging time on pollutant correlations is unexplored in the literature.

2.5.2. Share of concentrations attributable to near-traffic emissions

We estimated the share of the instrument-reported concentration that is attributable to near-traffic emissions (as compared to regional sources); following Apte et al. (2011), we calculated the "φ" parameter using trip-averaged concentrations:

$$\varphi = (C_{onroad} - C_{ambient})/C_{onroad} \tag{1}$$

where C_{onroad} is the instrument-reported, on-road mobile measurement and $C_{ambient}$ is the underwrite estimate of background concentration.

2.5.3. Particulate concentrations, street functional class, and proximity to major roads

One strategy to reduce exposure to air pollution on bicycle networks is to locate facilities (e.g., bike lanes or shared spaces) where concentrations are relatively low. We summarized our measurements by two characteristics of the road network: (1) street functional class and (2) distance from a major (i.e., high-traffic) road. We explored how those two characteristics of the road network impact exposure while cycling. For this analysis, we used a 60 s time average for PN, PM$_{2.5}$, and particle size; we used a 180 s time average for BC to minimize negative BC values when applying the underwrite function (see the Supplemental material and Table S7).

2.5.4. Regression models of video-derived traffic counts and particle concentrations

We collected a total of 4.5 h of video (5.3% of the total on-road monitoring time) during four monitoring runs (2 morning [10/10/2014 & 10/15/2014] and 2 afternoon [10/10/2012 & 10/11/2014]). We randomly selected 118 on-street locations (~1% of the available video data) to manually count instantaneous traffic volumes for three vehicle-types: passenger vehicles, trucks, and buses. To be counted, vehicles had to be operating and located within one city block of the measurement location (traveling in either direction). At some high traffic locations it was difficult to count vehicles from the instantaneous screenshot of the video alone due to various obstructions. For those locations, video footage near the randomly selected timestamp (approximately ±10 s) was used to estimate the number of vehicles that would be in the screenshot had the view not been obstructed. Counts of each vehicle type (i.e., passenger vehicles, trucks, buses) were used as independent variables in regression models to estimate particulate concentrations.

Regressions were performed using the "on-road" (i.e., instrument-reported minus "background" [underwrite] estimates) pollutant concentrations as the dependent variables. Since measurements were pooled from mornings and afternoons (and among 3 different monitoring days) we aimed to remove the effect of day-to-day changes in background concentrations from this analysis. As a sensitivity analysis, we instead used uncorrected instrument-reported values; results were similar for PN and BC but regressions performed poorly for particle size and PM$_{2.5}$. We report results for the on-road component of pollutant concentrations in our base case models; as such our results should be interpreted as the "local" or on-road component of concentrations.

3. Results and discussion

We collected a total of 127.3 h of measurements (on-road: 85.3 h; reference site: 42 h), covering a total of 1426 km. The average cycling speed during the monitoring runs was 16.4 kmph (4.6 m/s). During morning monitoring runs mean (interquartile range [IQR]) weather parameters were: 8.3 °C (6.1–10.6 °C), 70% (63–77%) relative humidity, and 9.0 kmph (4.8–11.2 kmph) wind speed; during afternoon monitoring runs weather parameters were: 24.4 °F (20–30.5 °C), 31% (25–36%) relative humidity, and 14.5 kmph (9.7–20.9 kmph) wind speed. Table 1 gives descriptive statistics for the background-adjusted concentrations (1 s, i.e., no time averaging). (Unadjusted concentrations are in Table S8.)

Table 1
Summary statistics of on-road concentrations.[a]

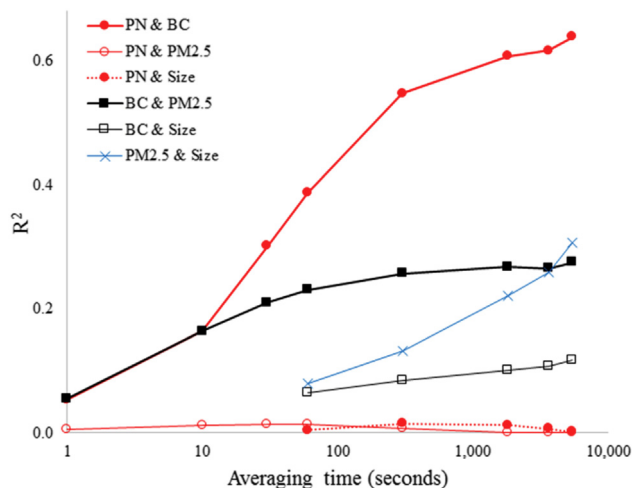| Pollutant	n	Arith. mean	Geo. mean	Std. dev.	Geo. std. dev.	P10	P25	P50	P75	P90
Morning (n = 12 monitoring runs, 24.2 h)										
PN (pt cm^{-3})	86,983	35,003	28,924	37,677	1.7	17,252	19,801	25,347	37,068	56,318
BC (µg m^{-3})	86,951	2.7	2.5	1.4	1.4	1.7	1.9	2.3	3.0	4.0
PM$_{2.5}$ (µg m^{-3})	86,983	10.9	10.5	4.8	1.3	8.6	9	9.8	11.4	14.2
Size (nm)	86,983	43.2	8.0	42.6	1.2	35.8	39.9	42.6	45.4	50.4
Afternoon (n = 30 monitoring runs, 61.1 h)										
PN (pt cm^{-3})	220,097	18,401	16,534	16,374	1.4	12,458	13,141	14,678	17,961	25,318
BC (µg m^{-3})	147,681	0.8	0.7	0.6	1.6	0.4	0.5	0.7	0.9	1.4
PM$_{2.5}$ (µg m^{-3})	211,234	9.4	9.1	6.3	1.2	8.1	8.1	8.6	9.5	10.4
Size (nm)	213,687	40.1	39.5	7.6	1.2	34.5	37.7	39.3	41.1	45.6

[a] All values are 1s measurements. Particle size values were assigned to each 1s location during 60 s scans resulting in a sample size for analysis that is equal to the datasets based on 1s measurements. BC values are reported using a 180 s time average to reduce inherent noise in data from the micro-aethalometer.

3.1. Correlations between measurements as a function of averaging time

We applied two approaches to calculate time-average values from the instruments: (1) moving averages (here, the size of a dataset remains unchanged) and (2) interval averages (since the original data are at 1 s, here the sample size is reduced by a factor equal to the averaging time in seconds). Trends in between-pollutant correlations were similar using both methods; the moving average method results are presented in Fig. 1.

Overall, PN and BC exhibited the strongest correlation (R^2: 0.05–0.64); this outcome is likely because PN and BC are indicators of traffic-related air pollution and thus are elevated near traffic emissions. BC's correlations with PM$_{2.5}$ and particle size were modest (R^2: 0.06–0.28). PM$_{2.5}$ and particle size showed moderate correlation as averaging time increased (R^2: 0.26 for 1 h time average). PN correlated with neither particle size nor PM$_{2.5}$ (R^2: 0.001–0.02).

Correlation between parameters generally increased with averaging time until about 1–5 min; for averaging times greater than 5 min, correlations did not noticeably increase (exception: moderate increases between particle size and PM$_{2.5}$). This finding suggests that smoothing the time-series data to greater than 60–300 s will not yield significantly greater insight into how these parameters interact (yet would sacrifice temporal and spatial resolution).

3.2. Estimating share of exposure due to near-traffic emission sources

We estimated the share of instrument-reported concentrations attributable to near-traffic emission sources (φ). Fig. 2 shows the distribution of trip-averaged φ values by pollutant and time of day.

As expected, φ was higher for the traffic-related pollutants (BC and PN) than for PM$_{2.5}$. PN and PM$_{2.5}$ had lower φ values in the afternoon than in the morning; this result is presumably attributable to the increased dilution that occurs in the afternoons owing to increases in mixing height and surface wind speeds. However, for BC, φ was higher in the afternoon than in the morning. This result is perhaps explained by the changes in background concentrations of BC during the course of the day as compared to the other pollutants. PM$_{2.5}$ and PN background concentrations decreased modestly over the course of the day (PM$_{2.5}$: 8.0 µg m^{-3} [morning], 7.8 µg m^{-3} [afternoon]); PN: 15,000 particles cm^{-3} [morning], 12,000 particles cm^{-3} [afternoon]). BC background concentrations decreased more drastically (1.5 µg m^{-3} [morning], 0.3 µg m^{-3} [afternoon]). Since BC background concentrations approached zero during the afternoon, any spike in instrument-reported concentrations would be attributed to near-traffic emissions, thus overall increasing the value of φ

Fig. 1. Correlations (R^2) of particulate matter parameters as a function of averaging time.
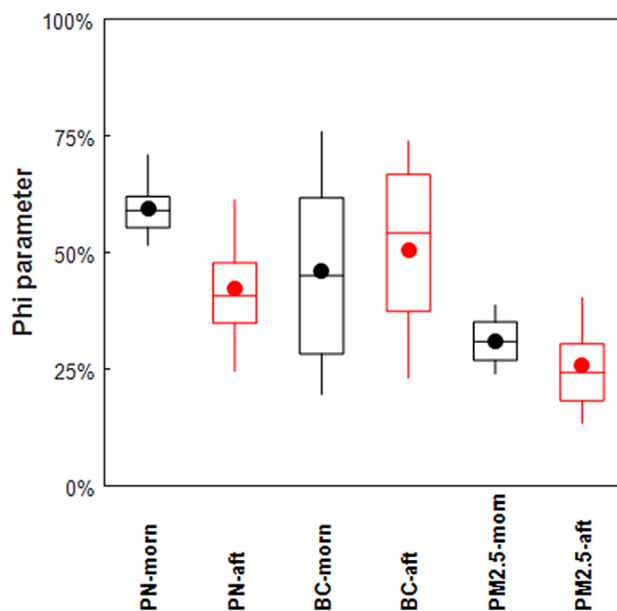
Fig. 2. Estimated proportion of instrument-reported, trip-averaged concentrations attributable to near-roadway emissions (dot: mean; line: median; whiskers: 5th and 95th percentile).

in afternoon relative to morning. Our φ parameter estimates are similar to those of Apte et al. (2011) (study site: New Dehli, India) for PM$_{2.5}$ (this study (Apte et al., 2011) mean φ: 28 [30]%) but smaller for BC (48 [68]%) and PN (51 [86]%). This difference could perhaps be a result of more roads in Minneapolis having near background-level concentrations, differences in the selection of routes in each study, or differences in vehicle fleets or fuels in each city.

3.3. Particulate concentrations and street characteristics

Road networks are designed in a hierarchal fashion to group streets into classes according to their desired service (typically, by expected motor-vehicle traffic volumes). We stratified our monitoring routes by four classes: arterial, collector, local streets, and off-street trails; Fig. 3 summarizes the mobile measurements by street functional class.

PN and BC were modestly elevated on arterials and collectors as compared to local streets and off-street trails. Particle size and PM$_{2.5}$ did not vary much by street classification. Concentrations were higher in mornings than in afternoons; the between-road type difference in concentrations was slightly more pronounced during mornings than afternoons for PN (morning [afternoon] arterial to local median ratio: 1.31 [1.20]) but the opposite for BC (morning [afternoon] arterial to local median ratio: 1.13 [1.36]). The upper ends of the distributions (i.e., 75th and 90th percentiles) showed larger between-road type differences than central

tendencies (i.e., mean and median) suggesting that short-duration exposures to elevated concentrations are more likely to occur on major roads.

Since concentrations are moderately elevated on major roads, a logical approach to building a bicycle network might be to locate routes (i.e., bicycle lanes or shared spaces) on local streets instead of arterials or collectors. Fig. 4 shows concentrations for two categories of roads: (1) major roads (i.e., arterials and collectors) and (2) local roads adjacent to major roads. The local roads are separated into 4 groups by distance from the nearest major road.

PN and BC concentrations on local roads decrease with increasing distance from a major road (changes are smaller for PM$_{2.5}$ and particle size). Similar to street functional class, these patterns were slightly more pronounced for mornings than for afternoons for PN (morning [afternoon] median major road to local road [101−200 m] ratio: 1.34 [1.18]) and the opposite for BC (morning [afternoon] median major road to local road [101−200 m] ratio: 1.15 [1.28]). Again, differences were larger for the upper ends of the distributions than for central tendencies.

Overall, these results suggest that moving bicycle traffic one block away from major roads has the potential to reduce exposure to PN and BC. For example, a typical block in Minneapolis is about 120 m; using that distance as a basis, mean exposure during morning rush hours would be reduced by 31% (16%) for PN (BC) and 90th percentile exposure would be reduced by 40% (24%) upon moving from a major road to a parallel local road.
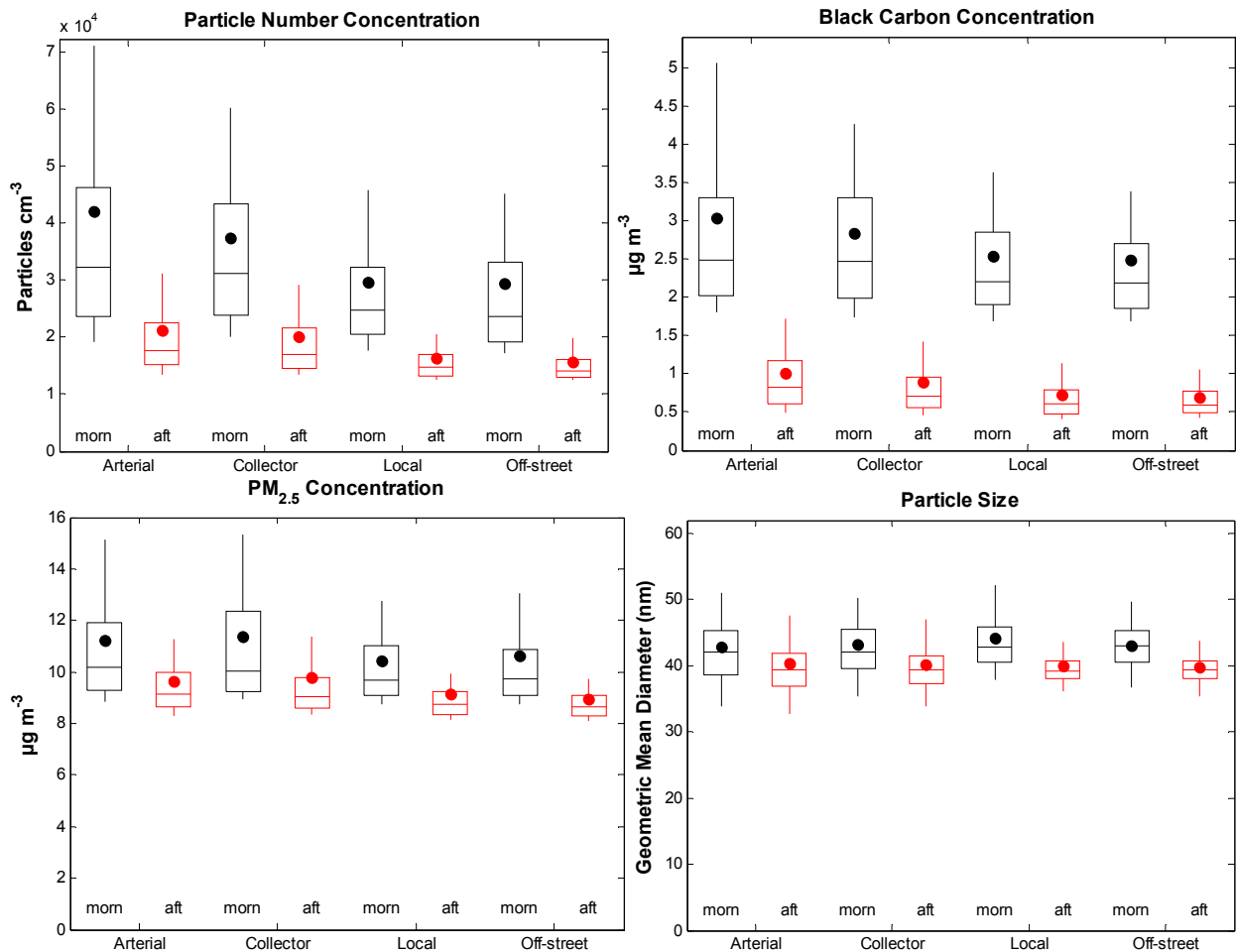

Fig. 3. Particulate concentrations (60 s time average for PN, PM$_{2.5}$, and particle size; 180 s time average for BC) by street functional class (dot: mean; line: median; whiskers: 5th and 95th percentile).
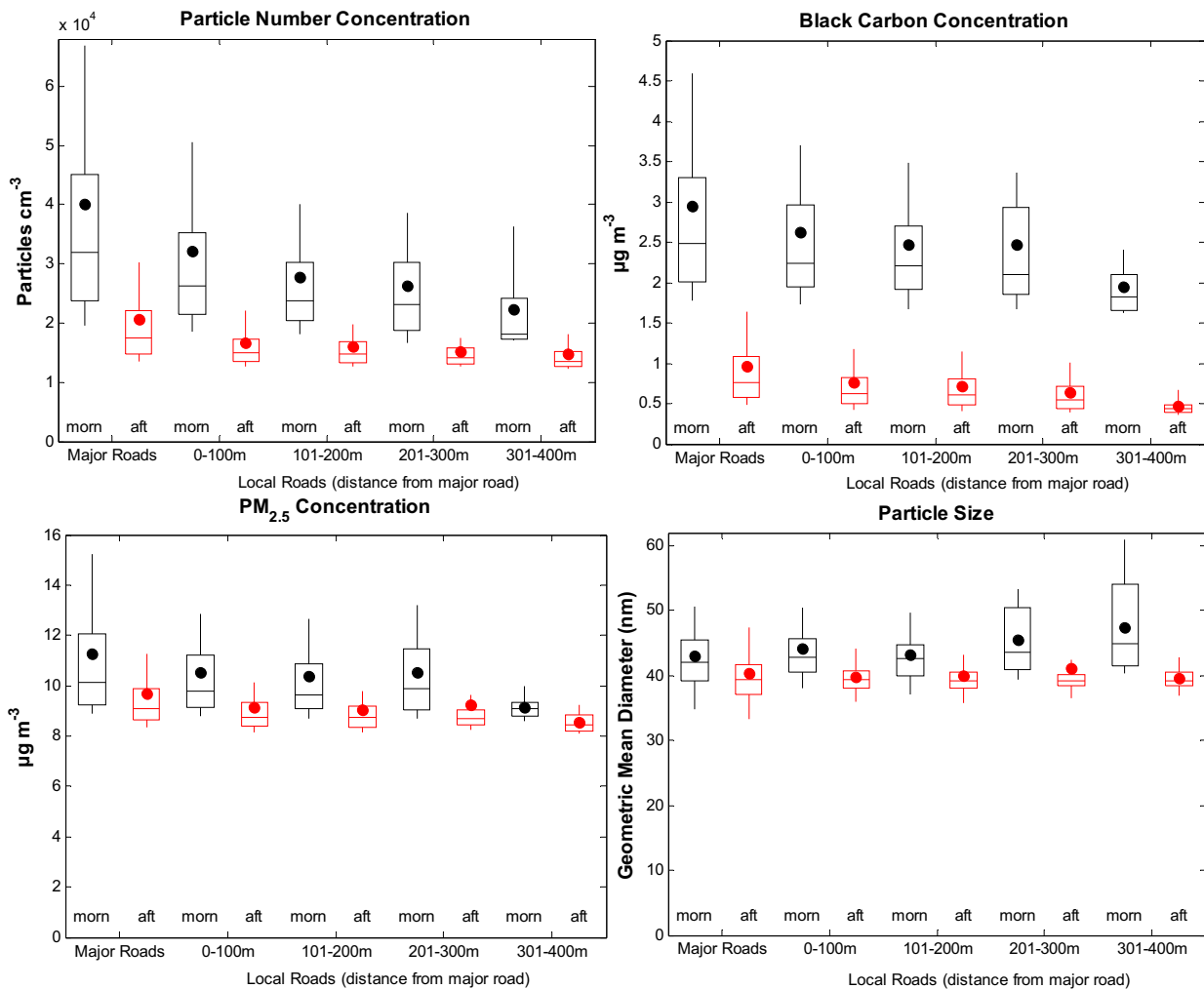
Fig. 4. Particlulate concentrations (60 s time average for PN, PM$_{2.5}$, and particle size; 180 s time average for BC) for major roads and local roads adjacent to major roads (dot: mean; line: median; whiskers: 5th and 95th percentile).

We tested if concentrations were lower on roads with bicycle lanes as compared to no facility. Differences in central tendencies were small (e.g., morning [afternoon] mean differences for no facility vs. a bike lane were −5% [2%] for PN and −7% [0.06%] for BC) with small differences for acute exposure, e.g., morning [afternoon] 90th percentile differences were −11% [−3%] for PN and −15% [−14%] for BC.

3.4. Regression models of video-derived traffic counts and particulate concentrations

Table 2 shows summary statistics for the video-derived vehicle counts for the 118 randomly selected locations (see Fig. S13 for spatial distribution of the locations and vehicle traffic volumes). As expected, passenger vehicles were most common (87% of vehicles); buses (12%) and trucks (1%) are rarer. Passenger vehicle counts

were correlated with street functional class (Table S9), with the highest counts on arterials (7.1) followed by collectors (3.7) and local roads (1.2).

We used counts of each vehicle type as independent variables in a regression analysis to assess changes in on-road concentrations associated with traffic. We ran models for various time averages (i.e., 1 to 1800 s) for each pollutant. In general we found smaller time averages (e.g., 1−60 s) performed better in regression analysis than longer time averages (likely owing to the fact that our vehicle counts are instantaneous). For averaging times larger than 60 s, model R^2 dropped rapidly (see Table S10). In all cases, small time averages (e.g., 10−30 s) performed better than 1-s measurements. This result is likely because the instantaneous air pollution measurements may or may not include the time when most of the vehicles in the video image are passing the monitoring platform (e.g., the bicycle may pass through the micro-plumes of the vehicles in the image 10−30 s before or after the image was recorded). For this reason we used slight temporal smoothing of the data (i.e., 30 s) for the models presented here.

Results for particle size were weak and in the opposite direction as expected (i.e., increased particle size with traffic); this may be a result of the relatively larger time resolution of the NanoScan (60 s) which may be too large to capture the instantaneous impact of traffic events. Table 3 shows regression results for the 30 s time average models of PN (model-R^2: 0.27), BC (R^2: 0.23), and PM$_{2.5}$ (R^2:

Table 2
Vehicle counts from the video (number of vehicles per image).

	Passenger vehicle count	Truck count	Bus count	Total count
Mean	4.8	0.1	0.7	5.6
IQR	1−7	0−0	0−1	1−8
P5−P95	0−15	0−1	0−3	0−15

0.14); results for particle size and all other averaging times are in Table S10.

Model coefficients were largest for trucks, moderate for buses, and relatively small for passenger vehicles. The impact of one additional car (within a city block) on concentrations was generally not statistically significant for PN and BC, but was significant for $PM_{2.5}$ ($p < 0.01$); for trucks, the impact was significant ($p < 0.01$ for PN and BC; $p < 0.05$ for $PM_{2.5}$) for all models. On average, each one truck increased 30 s average on-bicycle concentrations by 31,000 particles cm^{-3}, 1 $\mu g\ m^{-3}$ $PM_{2.5}$, and 1.6 $\mu g\ m^{-3}$ BC based on our regression results.

To better assess the impact of traffic counts on concentrations we multiplied the variable coefficients by the difference between the variable 95th and 5th percentile for each model. Since truck counts were infrequent it was necessary to use the difference between the 95th and 5th percentile rather than a smaller range (e.g., IQR) to include all independent variables. (The truck counts IQR is 0; see Table 2.) Fig. 5 shows plots of this parameter ($\beta \times$ 5th/95th percentile difference) as a function of averaging time for PN, BC, and $PM_{2.5}$.

Several interesting results are shown in Fig. 5. First, trucks (although infrequent) seem to have a large impact on PN and BC. Trucks were the most important variable in the models for those pollutants for all averaging times. In both the PN and BC models, buses had the second highest impact followed by passenger vehicles. For $PM_{2.5}$, all vehicle types had a similar influence in the regression, which could potentially be a result of the more regional nature of $PM_{2.5}$ as compared to PN and BC. Fig. 5 also highlights that 10–60 s time averages are likely the appropriate time-scale of the impact of these passing vehicles.

To compare model results among pollutants we fully normalized the coefficients in the 30 s time average regression models. The model βs have units of dependent variable over independent variable (i.e., concentration/vehicle count). To compare among models we multiplied each β by this factor: difference between 95th and 5th percentile vehicle counts/difference between 95th and 5th percentile concentration. We performed this normalization for the 30 s time average models (Table 3; a particle size model was not available for that time resolution).

The fully normalized βs are 8.5 (PN) and 4.2 (BC) times higher for trucks than for passenger vehicles; normalized βs for buses are 1.9 (PN) and 2.1 (BC) times higher than for passenger vehicles. These results indicate the importance of buses and trucks (despite their infrequency relative to cars) in explaining variations in on-road concentrations. At the same time, they might also reflect that our results are confounded by other factors. For example, truck

traffic could be correlated with industrial land use or with higher vehicle traffic in general (thus capturing not only truck traffic but other co-located emission sources). To test those two ideas (i.e., whether we passed trucks more often in high traffic areas or in-dustrial areas), we divided the randomly selected measurements into two groups: locations with and without trucks. We then calculated the industrial area within a 50 m buffer of each location. There was no statistically significant difference in vehicle traffic between location types (passenger vehicle [bus] count p-value: 0.94 [0.22]); however, truck traffic was more likely to be located in industrial areas according to this dataset ($p < 0.01$; see Table S11). As a sensitivity analysis we included tempurature, relative hu-midity, wind speed, and industrial land use as independent vari-ables in the 30 s time average regression models (see Table S12). Inclusion of these variables increased model-R^2 slightly (average increase: 0.12). However, there were only slight changes in the magnitude (and significance) of the coefficients for vehicle counts; thus, we chose to report models including only vehicle counts here. Despite the possibility of confounding factors, larger diesel vehicles (e.g., buses and trucks) are heavier emitters than smaller gasonline vehicles (EPA, 2008) and are responsible for at least a portion of the elevated concentrations.

3.5. Implications for on-bicycle exposure and future research

We successfully collected a large, mobile monitoring dataset to assess on-bicycle exposure to particulate air pollution in Minne-apolis, MN. Our work builds on previous exploratory studies of on-bicycle exposure by systematically designing our mobile moni-toring dataset to control for temporal variability in concentrations. Our mobile monitoring approach allowed for quantification of various factors relating the spatial distribution of mobile emission sources to on-bicycle exposure.

We designed our measurement campaign to control for seasonal and time-of-day temporal variability in concentrations (i.e., we monitored only in the fall during rush-hours). By doing so we were able to explore how small-scale spatial shifts in cycling routes (e.g., moving away from high traffic roads) impact exposure. At the same time, we were not able to explore patterns of exposure during different seasons or during non-rush hour times-of-day. We found that particulate concentrations were relatively higher during morning rush-hour as compared to afternoons; that finding sug-gests both spatial location of cyling routes and decisions about when to cycle are important aspects of exposure.

Our study highlights several areas that could be explored in future research. For example, we did not have sufficient equipment

Table 3
Regression results (30 s time average) based on video-based vehicle counts.[a,b]

	Model β	95th/5th Independent variable	95th/5th dependent variable	Fully normalized β[c]
Particle number				
Passenger	243 pt cm^{-3} $vehicle^{-1}$	15 vehicles	50,848 pt cm^{-3}	0.07
Truck	30,607*** pt cm^{-3} $vehicle^{-1}$	1 vehicles	50,848 pt cm^{-3}	0.60
Bus	2284* pt cm^{-3} $vehicle^{-1}$	3 vehicles	50,848 pt cm^{-3}	0.13
$PM_{2.5}$				
Passenger	0.06*** $\mu g\ m^{-3}$ $vehicle^{-1}$	15 vehicles	4.13 $\mu g\ m^{-3}$	0.23
Truck	0.99** $\mu g\ m^{-3}$ $vehicle^{-1}$	1 vehicles	4.13 $\mu g\ m^{-3}$	0.24
Bus	0.21* $\mu g\ m^{-3}$ $vehicle^{-1}$	3 vehicles	4.13 $\mu g\ m^{-3}$	0.15
Black carbon				
Passenger	0.02 $\mu g\ m^{-3}$ $vehicle^{-1}$	15 vehicles	3.79 $\mu g\ m^{-3}$	0.10
Truck	1.57*** $\mu g\ m^{-3}$ $vehicle^{-1}$	1 vehicles	3.79 $\mu g\ m^{-3}$	0.42
Bus	0.26*** $\mu g\ m^{-3}$ $vehicle^{-1}$	3 vehicles	3.79 $\mu g\ m^{-3}$	0.21

[a] Model-R^2: PN (0.27); BC (0.23); $PM_{2.5}$ (0.14). Constant: PN (7520); BC (0.62); $PM_{2.5}$ (1.19).
[b] *** denotes p-value <0.01; ** denotes p-value < 0.05; * denotes p-value < 0.10.
[c] Normalized βs are interpreted as the number of 95th/5th percentile interval increases of the dependent variable (i.e., concentrations) for each 95th/5th interval increase in each predictor variable.
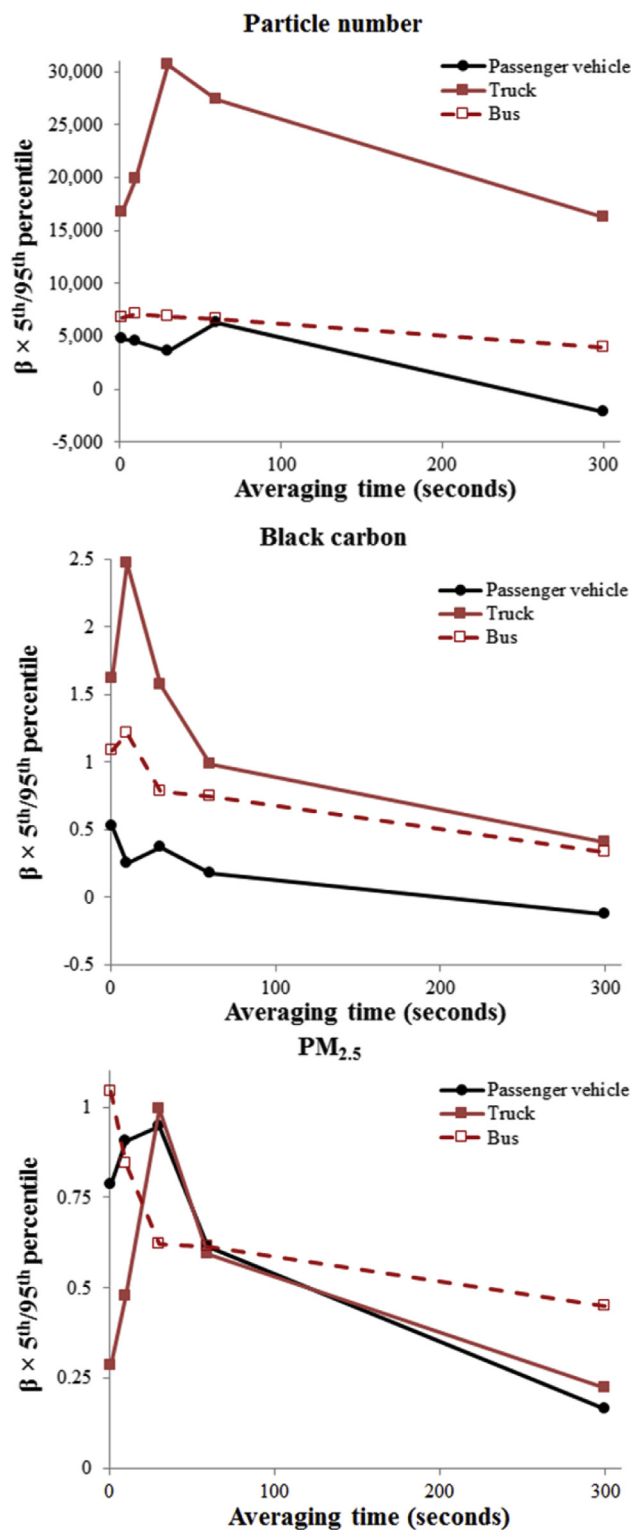
Particle number

Black carbon

PM$_{2.5}$

Fig. 5. Variables for the PN, BC, and PM$_{2.5}$ regression models shown as model $\beta \times$ 5th/95th percentile difference. Results show relative impact of truck traffic on small time scales as compared to other vehicles and time averages.

to deploy a permanent reference site. Instead we developed an approach involving reference measurements before and after monitoring runs and employing an underwrite function to estimate background concentrations; future research could test this method by comparing with fixed-site reference measurements. We used video-derived traffic counts to assess each passing vehicle's effect

on exposure; identifying publicly available data on instantaneous traffic patterns (e.g., designing monitoring routes to include automated traffic recorders) would provide a more comprehensive understanding of how traffic patterns influence acute exposure events.

4. Conclusions

We cycled 1426 km to collect 85.3 h (for each instrument: 3×10^5 individual 1s measurements) of on-road particulate concentrations (PN, BC, PM$_{2.5}$, particle size) during rush-hours (7–9am; 4–6pm) in Minneapolis, MN. We found that local (i.e., near-traffic) emissions were important contributors to exposure concentrations (e.g., local sources accounted for ~50% of the instrument-reported PN and BC concentrations). Particulate concentrations were generally elevated during morning rush-hour (as compared to afternoons) and were correlated with street functional class; on average, local roads slightly removed from major roads had lower particulate concentrations (e.g., PN and BC concentrations were ~20% lower on local roads 1-block from major roads). On-bicycle concentrations were correlated with instantaneous traffic patterns within 1 block of the mobile monitoring platform. Trucks were associated with significant acute exposure events; for example, each truck accounted for an average concentration-increase of 31,000 pt cm^{-3}, 1.0 µg m^{-3} PM$_{2.5}$, 1.6 µg m^{-3} BC). Our work yields insight into nuances of how a low-exposure bicycle network could be designed; for example, moving bicycle facilities from high-traffic roads to adjacent local roads or avoiding co-locating bicycle and truck traffic.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.atmosenv.2015.09.025.

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