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Preliminary Assessment of Personal Time Activity Patterns and Change of Traffic Pollutant Exposure: *A multi-month cohort and panel based study*

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Bachelor of Science

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Thesis Committee Chair: Jeremy Sarnat, Sc.D.

An abstract of

A thesis submitted to the Faculty of the
Rollins School of Public Health of Emory University

in partial fulfillment of the requirements for the degree of
Master of Public Health
in Environmental Health

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Abstract

Preliminary Assessment of Personal Time Activity Patterns and Change of Traffic Pollutant Exposure: *A multi-month cohort and panel based study*

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Introduction: The evaluation of time-activity patterns is important in estimating personal exposure to air pollution, especially since the pollution levels may vary by location and the person has different temporal and locational patterns. Past studies have used traditional surrogate methods that were focused on data collected from centralized monitoring locations, which did not accurately characterize the pollutant variability we see nowadays. Recent studies have shown a trend in measuring personal exposure at the individual level by focusing on the microenvironment of each subject. Our study evaluated the usage of such methods in a small cohort and validated the association between personal exposure and background concentrations.

Methods: Data was collected from 51 subjects at the Georgia Institute of Technology campus. We collected particulate matter ($PM_{2.5}$), nitrogen oxide (NO_x), and black carbon (BC) concentrations over a 48-hr data collection cycle. At the same time weekly geospatial and activity data was collected using geospatial trackers. The statistical analysis was conducted to evaluate and validate the association between personal exposure and time-activity patterns.

Results: The data showed the subjects spent a majority of their time within an indoor microenvironment and showed bimodal patterns in terms of distance from the pollutant source. Concentrations also were different by week during the data collection period and seemed to be associated with background levels, but not at a statistically significant level. We also found that there were significant associations between personal pollutant exposure and indoor microenvironments, background pollutant concentrations measured at centralized location, and for $PM_{2.5}$ the distance from the Connector.

Discussion: Our study did have certain limitations that became evident during the analysis due to mechanical and instrumental errors that occurred during the data collection process. The similarity in the subjects' time-activity patterns and microenvironment emphasized the importance of personal monitoring compared to the traditional methods. As a part of a multi-tiered study we hope to further investigate the relation personal exposure data has with other factors that are related to exposure and health, such as metabolomics data.

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Contents

Acknowledgements

First and foremost I would like to thank my advisor and mentor, Jeremy Sarnat Sc.D. for providing me with the opportunity to work on the study and research team. He has always been there to provide me with sound advice and guide me through this process, and I would not have been able to be who I am today without him. I would also like to thank Donghai Liang (RSPH) and Seung-hyun Cho (RTI) for providing me with their time and support throughout this entire project. I was able to learn so much from working with them and although every day was a challenge it has taught me so much. Lastly I would like to thank my family and friends, for I could not have been able to do this without their support and care. Rain or shine they have always been there for me and I am eternally grateful for being able to have them in my life.

Introduction

Globally, air pollution is one of the main risk factors impacting public health in urban areas. In 2012, the World Health Organization (WHO) estimated that 3.7 million premature deaths were caused by ambient (outdoor air pollution) worldwide (WHO, 2012). In 2013, the WHO concluded that air pollution (e.g. Particulate Matter) was carcinogenic to humans heightening concern as a major environmental health risk.

Although air pollution is particularly burdensome in low- and middle-income countries, it does not eliminate the fact that it is associated with health effects on populations not necessarily belonging to those countries. In the United States, the Environmental Protection Agency (EPA) estimated that greater than 45 million people lived within a “near” distance from major roadways during 2009 (EPA, 2014). This number has increased over the past couple of years, as urban areas have become more densely populated. Recent demographic trends also point to increases in urban traffic activity, development, and industrialization resulting in higher pollutant emissions and increased levels of potential hazard exposures to the population (EPA, 2014).

Previous studies have shown that people who live, work, or have activities in an environment with elevated air pollution levels are at increased risk from a range of acute and chronic health effects. In particular, an extensive amount of research has been published linking elevated risks of lung cancer, cardiovascular disease, and hospital admissions for asthma with traffic related pollution (Byrd *et al.*, 2016; Jinsart *et al.,* 2002*;* Langrish *et al.,* 2012*;* Puett *et al,* 2014). Although susceptibility to air pollution health effects varies considerably, exposure to air pollution affects the entire population and is difficult to control given it complex fate in the atmosphere.

Most near road air pollution studies, especially in an urban environment, use outdoor ambient air pollution levels and centralized monitoring stations as surrogates of personal exposure (McCreddin, Alam, and McNabola, 2015; Steinle, Reis, and Sabel, 2013; Van Roosbroeck *et al.*, 2008). Depending on the study design, the traditional surrogate method may introduce a wide array of errors into an epidemiologic analysis associated with exposure misclassification. Other studies have used land use regression or distance decay regression strategies as a means of estimating personal exposure to pollutants (Montagne *et al.*, 2013*;* Su *et al.*, 2009). But with high spatial variability and reactivity of individual pollutants, it is also likely that these spatiotemporal modelling approaches are also subject to various exposure errors, and may not accurately capture pollutant hotspots, including those associated with dense traffic patterns and population levels (Yunesian *et al.*, 2006). The findings from these studies point to considerable remaining uncertainty regarding how best to measure and assign exposure to traffic pollutants in air pollution epidemiologic studies.

In order to assess air pollution exposure, especially at the personal and at an increased spatiotemporal resolution, several crucial aspects must be evaluated and estimated. Of these, time spent in various microenvironments, including indoors, outdoors, at work or school, serves as one of the most critical predictors of exposure to outdoor pollution. The lack of data on microenvironments can contribute uncertainty and bias to quantifying personal exposure and risk estimation (Breen *et al.*, 2014). Previous studies have utilized global positioning system data to obtain time-activity patterns within distinct microenvironments as a means of addressing this limitation (Dias and Tchepel, 2014).

The Dorm Room Inhalation to Vehicle Emissions (DRIVE) study was designed to evaluate which components of heterogeneous traffic primary pollutant mix predominately at near road sites and the suitability of using near road indicators as primary traffic surrogates in small cohort epidemiological studies. The study was conducted in a traffic pollutant hotspot in Atlanta, Georgia, the Georgia Institute of Technology (GIT) campus in the Downtown Connector area.

The present analysis is a preliminary assessment of the personal exposure data and its association with other measures of traffic pollution. Specifically, the analysis focuses on utilizing a small cohort and distinct microenvironments, which will be the campus and surrounding structures, to characterize pollution both using personal monitors and centralized monitoring stations. In order to do so the current analysis aims to examine differences in activity patterns and personal exposure when stratified by dormitory and evaluate the association between personal pollutant exposure levels as well as other exposure factors that may affect exposure to pollution in this near road setting. At the same time our main goal was to evaluate the near road setting, by determining if proximity and location from a roadway was a good proxy of exposure to pollution and to estimate how well central monitoring stations reflects corresponding personal exposures.

Methods

Data collection for DRIVE was conducted at and around an emission hotspot in Atlanta, GA. The study was conducted on the GIT campus, which is located within the geographic core of Atlanta, adjacent to the Downtown Connector. The Connector consists of two major interstate highways, the I-75 and I-85 that run along the GIT campus perimeter, and thus represents an ideal near road emission setting. According to the Georgia Department of Transportation, an average of 320,370 vehicles pass through the Connector on a daily basis, including approximately 16,000 trucks.

For this present study there are two exposure tiers of interest: personal exposures (including student participants from two dormitories on campus) and outdoor measurements (i.e., roadside monitoring station). The dorms were chosen based on their proximity to the Downtown Connector. Similar to many of the GIT student dormitories, the Perry-Matheson dormitory, is located in 20 meters from the Connector and served as an ideal location for characterizing and quantifying near road emissions. A second dorm, Woodruff, is located on the West end of the campus and is approximately 1400 meters from the Connector. Lastly, we collected measurements from roadside monitoring stations, situated in a mobile trailer, located on the edge of the Connector, roughly 10 meters from the Connector. Another central monitoring location site was located 2300 meters away from the Connector, which we referred to as the Jefferson Street site.

Participant Recruitment

For the entire study a panel of 62 students living in the two dorms were recruited, 27 from Perry-Matheson and 35 from Woodruff. Recruitment occurred on-site at the dorms by researchers in accordance to pre-established protocols and the Biomedical Institution Review Board at Emory University. Before finalizing enrollment, potential subjects had to undergo a preliminary health screening and were given an informed consent procedure for participation. Enrolled subjects were offered compensation for completing the 12-week data collection process and participating in the study. Once enrolled the subjects were given a baseline questionnaire to establish demographical information, preliminary health, and time-activity patterns. Subjects were then informed of the weekly personal exposure participation and were able to volunteer through a schedule system that was distributed via electronically. Of the 62 participating student subjects, 51 students chose to participate in the personal exposure sampling (Table 1).

Table 1.
Demographical information of the subjects that participated in the personal exposure sampling session over the data collection period.

Variable	Overall (n = 51)	Perry-Matheson (n = 23)	Woodruff (n = 28)
Age, Mean (SD)	19.3 (0.85)	19.2 (0.9)	19.4 (0.8)
BMI (SD)	23.3 (3.0)	22.7 (3.1)	23.9 (2.9)
Gender, n (%)			
Female	24 (47.1)	11 (47.8)	13 (46.4)
Male	27 (52.9)	12 (52.2)	15 (53.6)
Grade, n (%)			
Freshman	29 (56.9)	16 (69.6)	13 (46.4)
Sophomore	14 (27.5)	2 (8.7)	12 (42.9)
Junior	7 (13.7)	4 (17.4)	3 (10.7)
Senior	1 (2.0)	1 (4.3)	0 (0.0)
Health Status, n (%)			
Fair	5 (10.0)	1 (4.3)	4 (14.8)
Good	17 (34.0)	9 (39.1)	8 (29.6)
Very Good	22 (44.0)	9 (39.1)	13 (48.1)
Excellent	6 (12.0)	4 (17.4)	2 (7.4)
Medical Conditions, n (%)			
Yes	37 (74.0)	15 (65.2)	22 (81.5)
No	12 (24.0)	7 (30.4)	5 (18.5)
Refused	1 (2.0)	1 (4.3)	0 (0.0)
Time Spent Outdoors (Daily Average), n (%)			
Less than 1 hour	4 (8.0)	2 (8.7)	2 (7.4)
1-2 hours	21 (42.0)	11 (47.8)	10 (37.0)
3-4 hours	18 (36.0)	8 (34.8)	10 (37.0)
5 hours or more	7 (14.0)	2 (8.7)	5 (18.5)
Time Spent in Vehicle (Daily Average), n (%)			
Less than 1 hour	20 (40.0)	8 (34.8)	12 (44.4)
1-2 hours	27 (54.0)	14 (60.9)	13 (48.1)
3-4 hours	2 (4.0)	1 (4.3)	1 (3.7)
5 hours or more	1 (2.0)	0 (0.0)	1 (3.7)
Sleep (Daily Average), n (%)			
Less than 6 hours	1 (2.0)	0 (0.0)	1 (3.7)
6-8 hours	30 (60.0)	14 (60.9)	16 (59.3)
9-12 hours	19 (38.0)	9 (39.1)	10 (37.0)
Work/Employed, n (%)			
Yes	41 (82.0)	20 (87.0)	21 (77.8)
No	9 (18.0)	3 (13.0)	6 (22.2)

Outdoor and Roadside Monitoring

The outdoor sampling measurements provided an opportunity to characterize pollutant gradients across campus and were collected from a highly instrumented stationary roadside site located 10 meters from the Connector and the Jefferson Street monitoring site (JST), located 2300 meters away from the Connector. JST has been used to generate population exposure estimates in previous studies (Edgerton *et al*., 2005; Solomon *et al*., 2003), which focused on longitudinal associations and is broadly representative of Atlanta's urban background pollutant levels. Samples collected from the stationary sites include $PM_{2.5}$ mass, elemental carbon (EC), BC, and NO_x, NO2, and a wide array of other organic compounds.

Prior to the 12-week sample collection period, the DRIVE field staff collected EC concentrations over a 1-month period. Results showed that the EC concentrations at the stationary site were approximately 3.8 times higher on average than the JST site and was consistent with previous findings (Yan *et al.,* 2009). The EC concentrations over the 24-hour period also validated the location as a traffic pollutant hotspot throughout the day and that it was the most ideal location for a roadside monitoring station. Standard measurements along with advanced instrumentation components, were placed within the stationary roadside trailer during the sample collection period. $PM_{2.5}$ mass was collected using semi-continuous measurements (TEOM). BC samples were collected using the Magee Scientific Aethalometer and was logged using the WinWedge Pro software. Since the aethalometer measures BC concentration using aerosol-related light absorption, attenuation was defined as $-\ln(I/I_0)$, where I_0 is the light intensity of incoming light and I is the light intensity after passing through the filter. Continuous NO_x measurements were sampled via TAPI NOx 200A (Thermo-Scientific) and were adjusted for sampling time (via Cell Phone Eastern Standard Time). Once data was collected, offset correction and calibration was applied to the NO and NO_2 data.

Personal Exposure

Personal exposure data was collected from a total of 51 different student subjects; 23 from Perry-Matheson and 28 from Woodruff (Table 1). The sampling sessions were scheduled over the 12-week long data collection period. During each sampling week between 3 and 6 student subjects participated in an intensive personal exposure sampling session. For each subject, two 48-hour integrated personal $PM_{2.5}$, EC and NO_2 exposures were collected starting Monday morning and continuing until Friday morning (Monday AM – Wednesday AM; Wednesday AM – Friday AM). Subjects were given a personal exposure pouch (≈ 3 lbs) on Monday morning; on Wednesday, field staff met with subjects to replace filters and batteries for the second 48-hour sampling period.

Each individual pouch consisted of three data collection components and were easily attachable to the strap of a backpack or bag, corresponding to the breathing zone of the student subject with minimal discomfort or alteration to their daily activity. $PM_{2.5}$ was collected using a personal nephelometer (μPEMs)(MicroPEM v 3.2A, RTI), which also contained a 25mm Teflon filter (37mm Teflo, Gelman Sciences) to facilitate gravimetric mass measurements. The μPEMs collected particles through a sampling inlets at a 0.5 liter per minute (LPM) flow rate. Particle mass was collected onto the filters, which were used for the gravimetric analysis of personal $PM_{2.5}$ exposure. Continuous measurements of particle mass concentrations was also collected using the nephelometer within the μPEMs, at 10 second sampling intervals. All collected data was compiled using the μPEMs docking station program and transferred onto a secured study database. At the end of each individual sampling session, the μPEMs were cleaned and batteries along with the filters were replaced. Filter particle mass was measured within a temperature (18° – 24° C) and humidity (RH: 40±5%) controlled weighing room by a trained DRIVE lab technician. The gravimetric filter mass was then used as a correction factor for the nephelometer data and zero-shifted to take into account instrument offset. Personal NO_2 exposures were collected using a passive sampler that contained cellulose filters coated with triethanolamine (Ogawa & Company, 1998), which were analyzed using spectrophotometric methods.

Geospatial patterns were collected through portable global positioning system (GPS) trackers that were attached to the side of the sampling pouch. GPS data tracked locations continuously over the two consecutive 48-hour cycles. Locations or stationary points were defined as points where a given subject stayed for more than five minutes, were marked with their corresponding longitudinal and latitudinal inputs, and labeled as 'waypoints'. We chose to use GPS trackers instead of diaries or questionnaires to analyze time-activity patterns to eliminate any recall bias that may have occurred. Past studies have shown success with monitoring time-activity patterns using GPS, over traditional survey methods (Glasgow *et al.*, 2014; Nethery *et al.*, 2014; Wu *et al.*, 2010). Distance from the waypoints to the Connector were calculated using the ArcGIS program and were quantified as the shortest linear distance from a given waypoint to the Connector. Batteries in each of the GPS units were exchanged between each cycle to ensure maximum collection duration. Once the collection cycle was complete, data was downloaded and converted using the Past-Track 10 software, which allowed the creation of datasets containing temporally-resolved spatial locations for each subject during their personal sampling period. The logged GPS data was then utilized to aid in quantifying time spent in various microenvironments and proximity to traffic sources as potential modifiers of personal exposures. Specifically, each GPS location was categorized into an indoor or outdoor environment and into a campus area (near, center, far, or other) using ArcGIS.

Data and Statistical Analysis

Data that was collected during the sampling period was stored in a locked location until transferred and copied into a secure database that could only be accessed by authorized study staff. All continuous data was evaluated using temporal averages of all measures (e.g., 1-hr, 24-hr average for pollutant concentrations and mass). The baseline questionnaire and spatiotemporal data that was collected from the GPS were processed and used to calculate the time spent in different microenvironments (e.g. indoor and outdoor) within the GIT campus, along with establishing any preliminary health conditions or factors that may have effected outcome. For the present study the main aim was to evaluate how well traffic indicators measured at a centralized stationary site reflects personal exposure measurements. Therefore, factors that affected the strengths of association including time activity patterns and locational proximity to the roadway were evaluated. Once data was collected using the individual programs for each method, calculations and analysis were conducted using R Statistical Computing Program (Ver 3.2.2).

The establishment of dormitory stratification data was examined and estimated by calculating the individual time weighted average distance for the subjects at each waypoint location. Validation and comparison of the means of subsets of the data were conducted using t-tests. We used multivariate linear regression models for the analysis of the associations between personal exposures and exposure factors of interest, including roadside concentrations. All linear regression modelling was conduct using the R statistical platform. The primary regression model focused on spatiotemporal covariates that were determined, *a priori*, and personal exposure concentrations were modeled as the dependent variable. Within the model, roadside and JST concentrations were included as dependent variables:

$$\chi_{sti} = \alpha_s + \beta Z_{sti} + \theta_{JST} + \varepsilon_{ST}$$

where α_s is the intercept, χ_{sti} denotes the corresponding measurement for the i^{th} participant, and β is the coefficient of interest that describes the influence of predictor or factor Z_{sti}. The factors of Z_{sti} that will be examined include: indoor microenvironments, locational microenvironments, and distance from Connector. The θ_{JST} represents the background pollutant concentration measured from the JST site and ε_{ST} denotes random normal error.

Results

In total, 116 48-hour integrated $PM_{2.5}$ and NO_2 samples were collected from a total of 51 subjects for each pollutants. GPS data was collected from 40 subjects, 20 subjects from each dorm, over the course of 11 weeks. During the collection period one of the GPS devices malfunctioned and was not able to record data, therefore there were less GPS samples compared to the $PM_{2.5}$ and NO_2. Each cycle was on average 2,873 minutes long (weekly was 5746.22 minutes) and was collected every week during the sampling period, excluding Fall Break (October 13th – October 17th, 2014) and Thanksgiving (November 26th – November 28th, 2014).

GPS Results

Figure 1. ArcGIS output of all waypoints within the GIT campus proximity. The green points represent stationary waypoints from Perry-Matheson subjects, whereas the blue points represent waypoints from Woodruff subjects.

A total of 503 stationary waypoints were collected from the 40 subjects over the sampling period, resulting in an average of 12.6 waypoints/student with 214.5 minutes spent at each waypoint. There were 268 waypoints from the 20 Woodruff subjects, resulting in an average of 13.4 waypoints/student with 264.0 minutes spent at each waypoint. In contrast, the 20 Perry-Matheson students logged 235 waypoints, resulting in an average of 11.8 waypoints/student with 158.0 minutes spent at each stop. We observed high concentrations of points near Perry-Matheson and near Woodruff dormitories (Figure 1), and at scattered points around the center of campus (250 to 1000 meters from the Connector). The central area of campus had the most waypoints, which was 178 (35.38%) of total waypoints. When assessing the time-weighted data, stationary time was greatest in the Woodruff dorm area (39.4% of total stationary time).

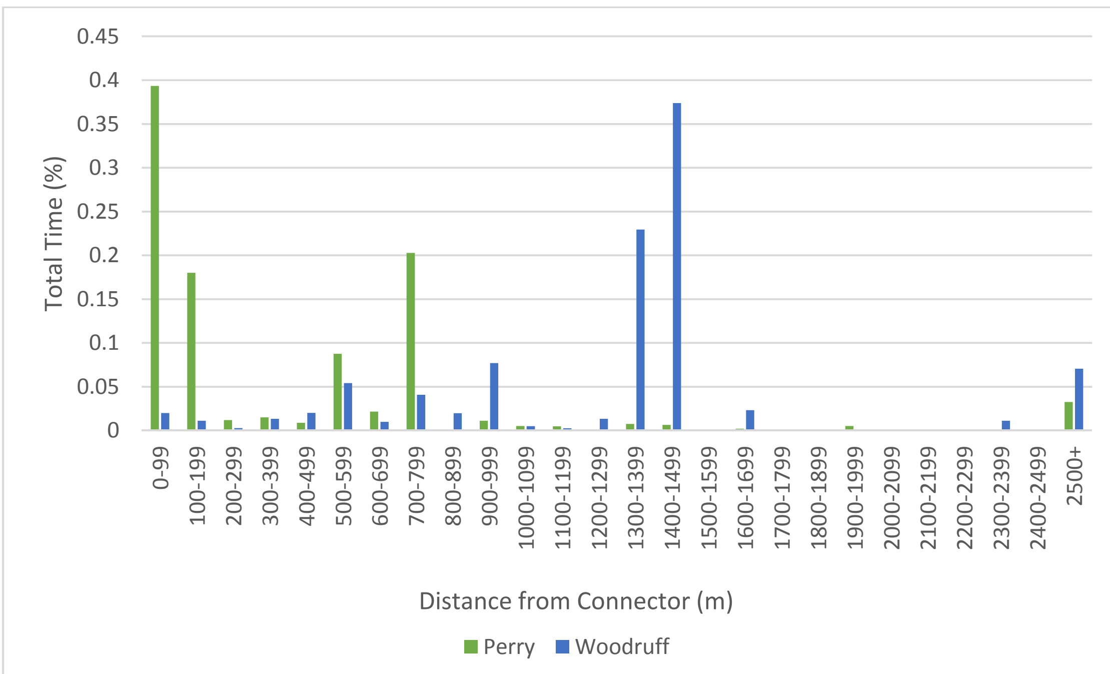

Figure 2. Total time percentage spent at 100 meter increment distances by dormitory.

Figure 2 shows a clear bimodal pattern in time spent from the Connector, stratified between the subjects living in each of the two dormitories, indicating that a majority of the students' times were spent within or near their respective dormitories. Woodruff subjects spent a total of 37.4% of their time within or near the Woodruff dorm location (1.4 km from the Connector). Conversely, students from the Perry-Matheson dorm spent about 39.4% of their total time within or near the Perry-Matheson dorm location (10 m from the Connector). We also noted that a substantial fraction of time was spent near the central area of campus by the subjects, mainly due to the presence of academic and athletic facilities on this part of the GIT campus. Overall, between the two subject population approximately 10% of the total time was spent beyond the campus perimeter (farther than 1.6 km from the campus geospatial domain).

$PM_{2.5}$, NO_2, and BC Measurements

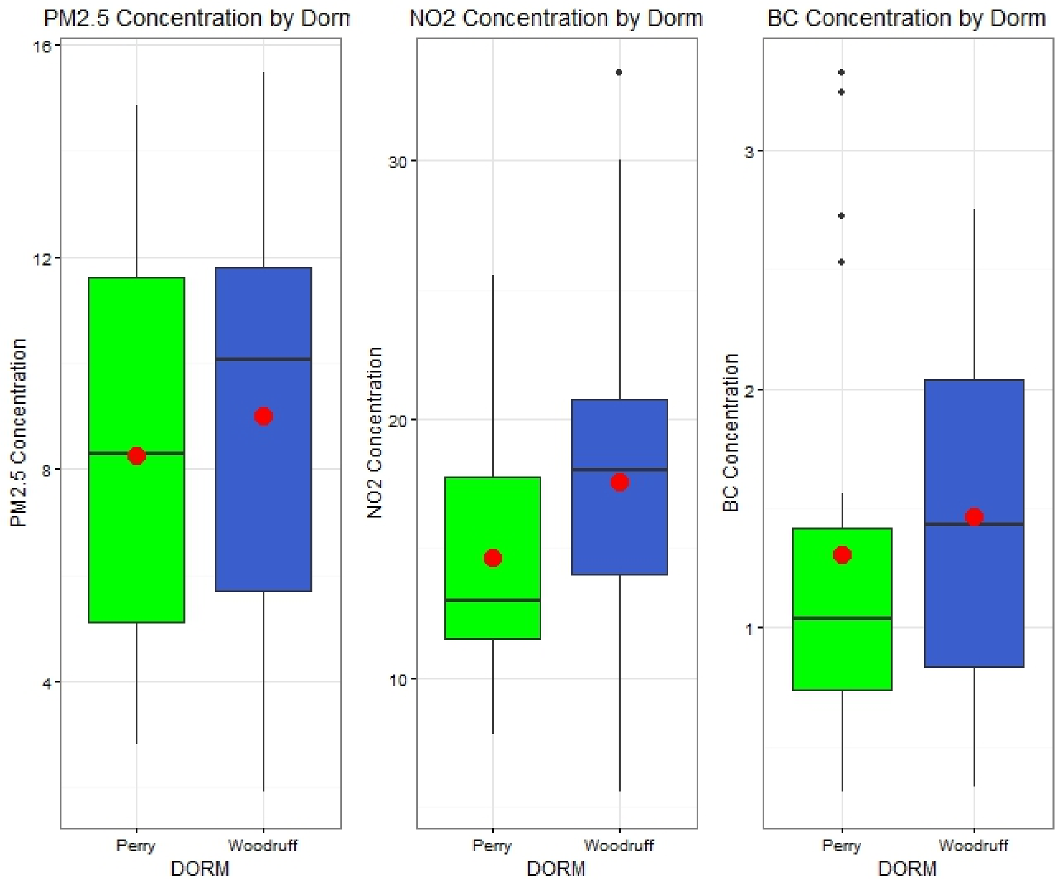

Figure 3. Overall boxplots of each pollutant concentration (µg/m^3) stratified by dorm. Black line indicates median and red dot indicates mean for each group.

Initial analyses were conducted assessing differences in exposure distributions for the pollutants of interest stratified by dormitory (Figure 3). We evaluated the difference between the groups by using the Welch two sample t-tests for each pollutant, with no pollutants showing significant difference ($p < 0.05$). Following this analysis, we conducted a time-series analysis on for each of the pollutants over the course of the data collection period as a function of corresponding JST site concentrations that were measured concurrently. Results are shown in Figures 4, 5, and 6, in which we observed changes in pollutant levels by week and the respective JST concentration measurements observed during that time.

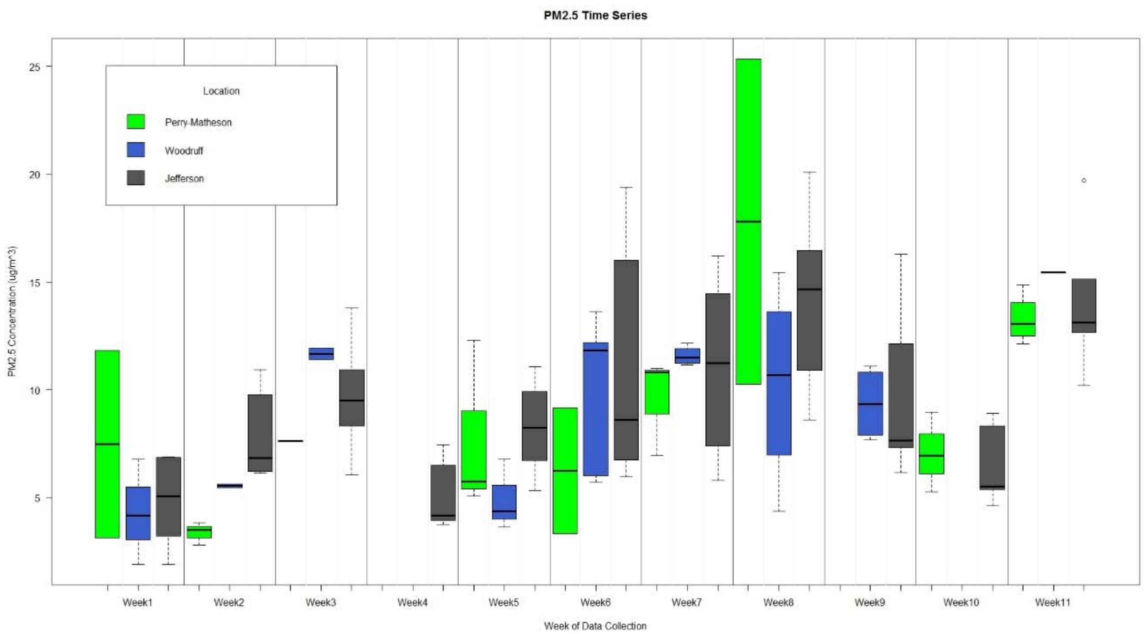

Figure 4. Time series boxplots of $PM_{2.5}$ concentrations with JST measurements.

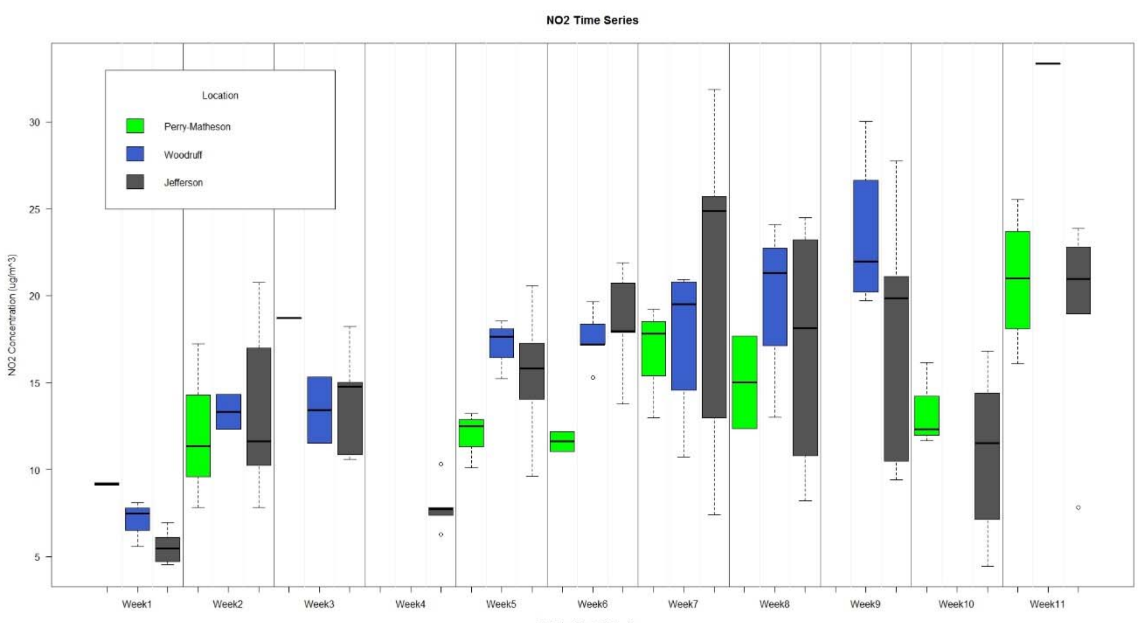

Figure 5. Time series boxplots of NO_2 concentrations with JST measurements.

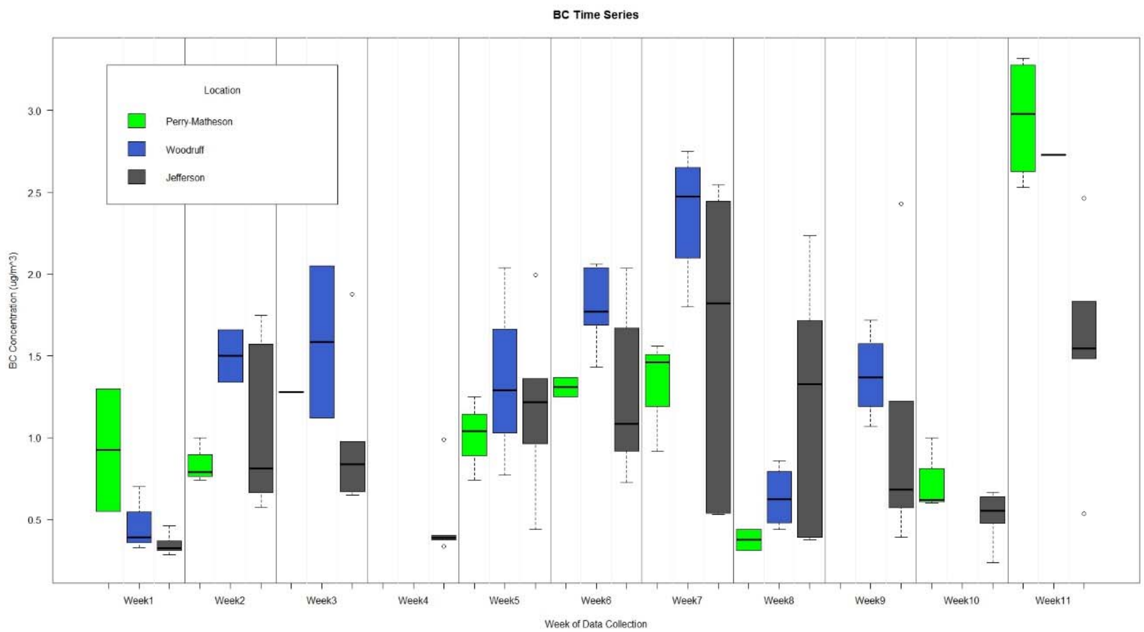

Figure 6. Time series boxplots of BC concentrations with JST measurements.

The JST site measurements correspond to the background pollutant concentrations measured 2.3 kilometers away from the Connector. Compared to the overall boxplots of pollutant concentrations, we observed a pattern between the dormitories and the JST measurements for each respective pollutant. As there were elevated levels of pollutant concentrations being measured at the JST site, subjects from Woodruff experienced increased levels of pollutant exposure. We were also able to display that during the data collection period the concentrations of each group varied on a weekly basis.

Pollutant concentrations were tested for distribution and skewness before proceeding with analysis. All pollutants of interest fell within the acceptable limits of normal univariate distribution (e.g. ±2 kurtosis). We then conducted univariate regression analysis for each individual pollutant with the corresponding variables of interest that were selected beforehand; time weighted average distance, indoor microenvironment (total time percentage), near Connector microenvironment, far Connector microenvironment, central campus microenvironment, and background pollutant levels in urban Atlanta (JST site measurements). Figures 7 through 9, and Tables 2 through 4 display the results of the univariate regression analysis.

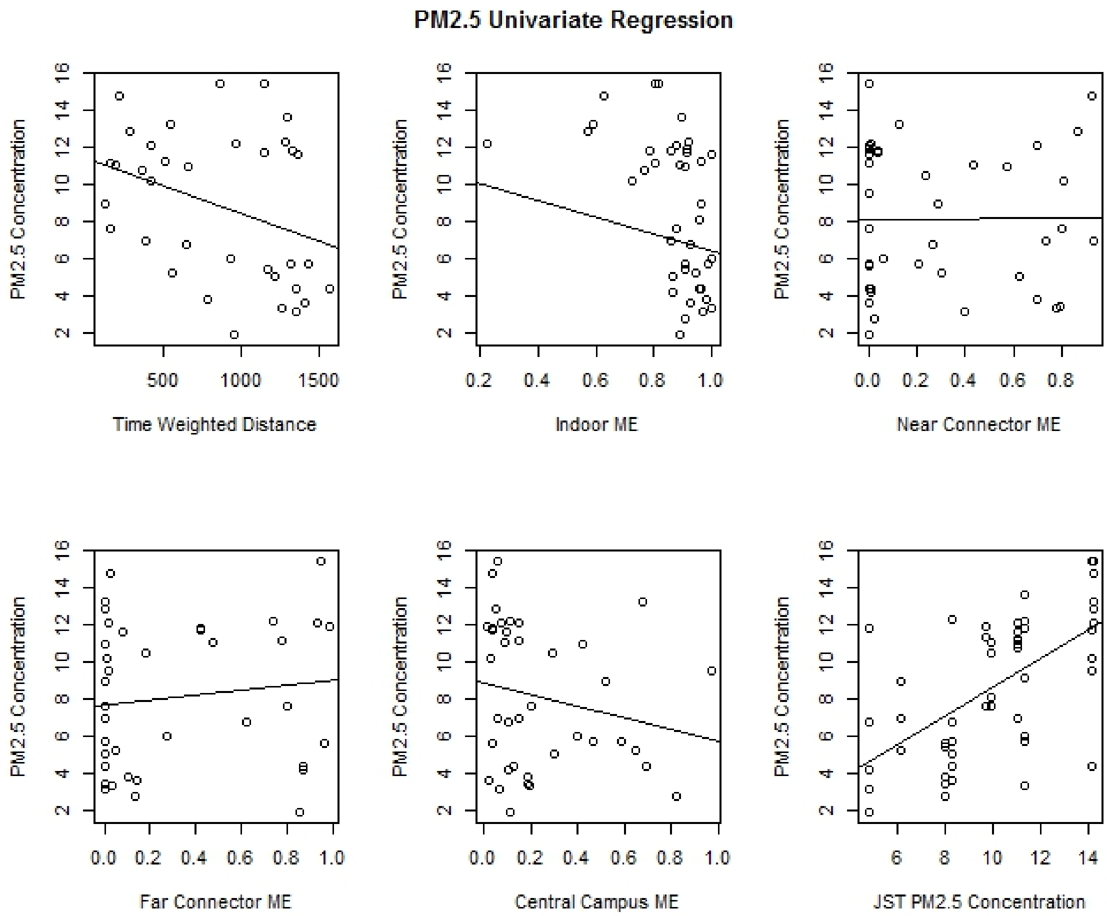

Figure 7. Univariate regression plots of the dependent variables and personal $PM_{2.5}$ concentration (μg/m^3).

Table 2.
Univariate linear regression coefficients and statistical values for $PM_{2.5}$. * symbolizes statistical significance (p = 0.05).

	Coefficient	Adjusted R2	p-Value	
Dorm	0.099	0.000	0.495	
Week	0.543	0.280	0.000	*
Time Weighted	-0.346	0.093	0.042	*
Indoor	-0.354	0.102	0.027	*
Near Connector	0.016	0.000	0.924	
Far Connector	0.128	0.000	0.438	
Central Campus	-0.206	0.017	0.208	
Outer Campus	0.006	0.000	0.972	
Jefferson Street	0.603	0.351	0.000	*

Time-weighted average distance from the Connector, indoor microenvironment, and background $PM_{2.5}$ concentrations were all shown to be statistically significant predictors of corresponding personal $PM_{2.5}$ exposures ($p < 0.05$) (Table 2). As shown in the univariate regression results, with the increase of time weighted average distance and time spent in an indoor microenvironment, we could expect a decrease in overall average personal $PM_{2.5}$ exposure. In contrast, an increase in background concentration at JST was shown to be associated with an increase in corresponding personal $PM_{2.5}$ exposures.

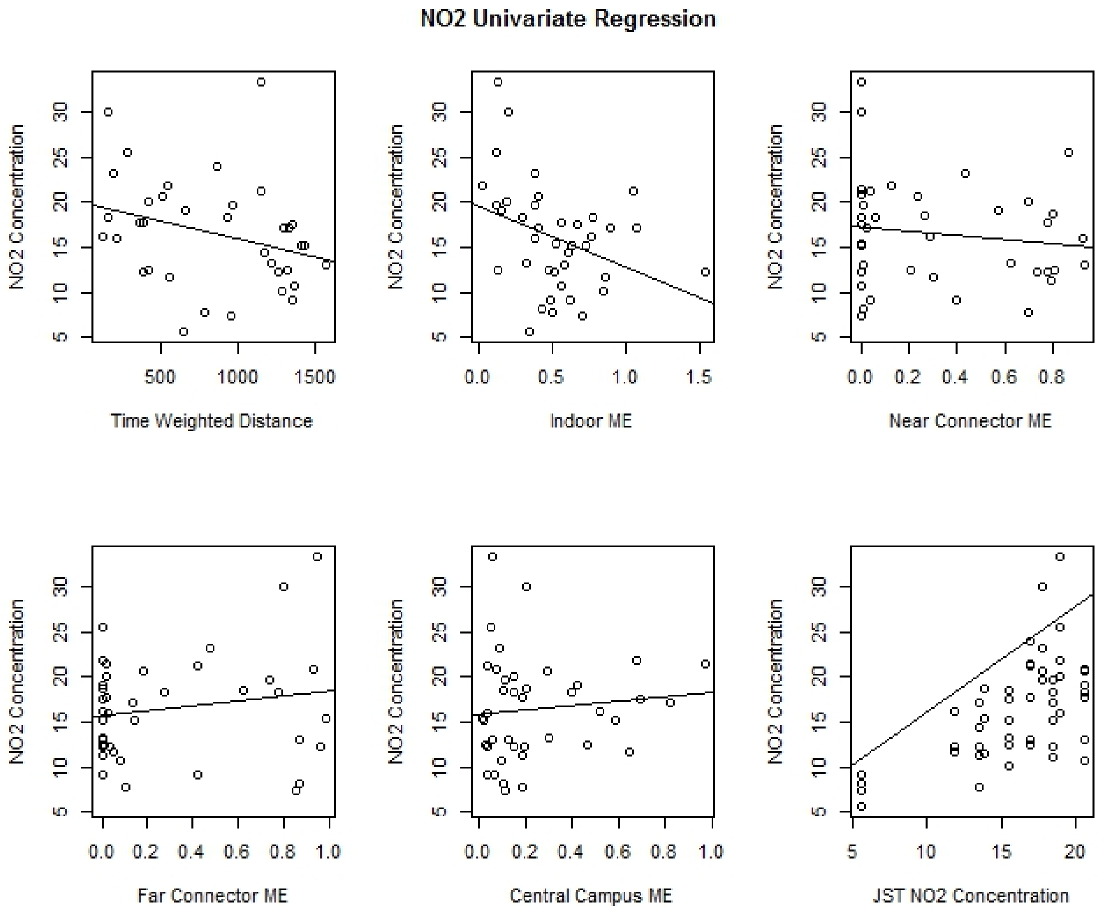

Figure 8. Univariate regression plots of the dependent variables and personal NO_2 concentration ($\mu g/m^3$).

Table 3.
Univariate linear regression coefficients and statistical values for NO_2. * symbolizes statistical significance ($p = 0.05$).

	Coefficient	Adjusted R2	p-Value	
Dorm	0.259	0.048	0.066	
Week	0.644	0.403	0.000	*
Time Weighted	-0.303	0.065	0.073	
Indoor	-0.355	0.103	0.026	*
Near Connector	-0.138	0.000	0.397	
Far Connector	0.179	0.006	0.270	
Central Campus	0.101	0.000	0.535	
Outer Campus	-0.198	0.014	0.221	
Jefferson Street	0.602	0.350	0.000	*

For personal NO_2 exposures, the univariate regression analysis displayed statistical significance ($p < 0.05$) for the indoor microenvironment and background NO_2 concentration predictors (Table 3). Similar to the personal $PM_{2.5}$ results, the personal NO_2 concentrations can be expected to decrease with an increase in time spent in an indoor microenvironment and increase with elevated background concentration.

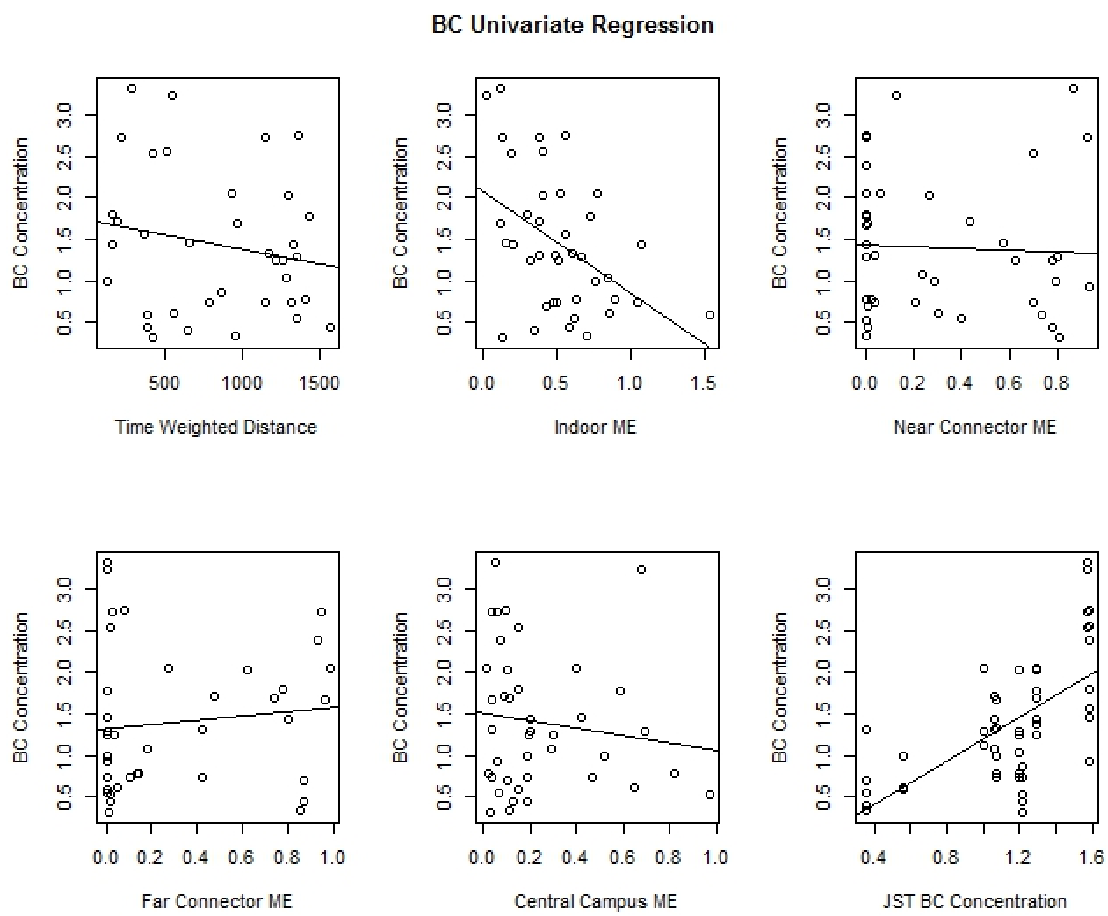

Figure 9. Univariate regression plots of the dependent variables and personal BC concentration ($\mu g/m^3$).

Table 4.
Univariate linear regression coefficients and statistical values for BC. * symbolizes statistical significance ($p = 0.05$).

	Coefficient	Adjusted R2	p-Value	
Dorm	0.103	0.000	0.474	
Week	0.402	0.145	0.003	*
Time Weighted	-0.190	0.008	0.267	
Indoor	-0.460	0.190	0.003	*
Near Connector	-0.039	0.000	0.813	
Far Connector	0.120	0.000	0.461	
Central Campus	-0.131	0.000	0.421	
Outer Campus	0.007	0.000	0.968	
Jefferson Street	0.623	0.376	0.000	*

For personal BC exposures, the results showed the week, indoor microenvironment, and JST predictors as significant ($p < 0.05$). Although the coefficients were different the trend was the same as well in the personal BC concentrations and NO_2 concentrations. We would expect an increase in concentration as the background BC concentration was elevated during that sampling cycle and a decrease in personal BC exposure the further the subject is away from the Connector. Week was also evaluated as a predictor for each individual pollutant due to the varying concentration we observed during each week. For all three pollutants the univariate regression of the week variable was significant and had a positive correlation. Then using the results from the univariate linear regression model we created a multivariate model that examined the association between time-activity varying predictors and personal pollutant exposures. Specific results are displayed in Table 5 and 6.

Table 5.
Multivariate linear regression of strong predictors with Personal PM2.5 concentration (μg/m^3). * symbolizes statistical significance (p = 0.05).

	Personal $PM_{2.5}$			
	Coefficient	*95% C.I.*	*p-value*	
Time Weighted	-0.315	(-0.005, 0.000)	0.024	*
Indoor	-0.001	(-3.580, 3.566)	0.997	
Jefferson	0.618	(0.424, 1.167)	0.000	*

Table 6.
Multivariate linear regression of strong predictors with Personal NO2 and BC concentrations (μg/m^3). * symbolizes statistical significance (p = 0.05)

	Personal NO_2				Personal BC			
	Coefficient	*95% C.I.*	*p-value*		*Coefficient*	*95% C.I.*	*p-value*	
Indoor	-0.189	(-8.703, 1.407)	0.152		-0.234	(-1.031, 0.057)	0.071	
Jefferson	0.590	(0.426, 1.106)	0.000	*	0.594	(0.692, 1.731)	0.000	*

For the multivariate linear regression analysis, measurements at the JST site were significant predictors of corresponding personal exposure for all three pollutants. As concentrations observed at the JST site increased, the personal pollutant levels also increased. Although not statistically significant, the negative coefficients for the indoor microenvironment predictor provides some anecdotal indication that decreases in personal pollutant exposures were associated with more time spent indoors. Unlike the other two pollutants, the personal $PM_{2.5}$ model proved that the time weighted average distance was a significant predictor and validated that with we would observe decreased personal $PM_{2.5}$ concentrations as we moved further away from the Connector.

Discussion

The personal exposure analysis that was conducted as part of the current analysis serves as a baseline and preliminary assessment of the larger DRIVE aims with the overall goal of evaluating the suitability of novel multipollutant traffic indicators. For the current analysis, focusing on the personal exposure components of the study, we were able to follow a unique panel residing in close proximity to the Connector, and who spent a majority of their time in a near road microenvironment. With this in mind, the current analysis aimed to characterize the spatiotemporal variability throughout the microenvironment, as well as the level of exposure each subject experienced during the multi-month study.

Results from the GPS monitoring were consistent with our *a priori* expectations. The stationary points were scattered along campus but exhibited high densities at the two dormitory locations. Also, the duration at each point indicated that most of the participants spent a majority of their time at their respective dormitories and indoors (Figure 2). However, the findings do raise some concerns, especially with instrumental errors that occurred throughout the data collection period. When processed using ArcGIS, the GPS data appeared to lack spatial resolution in terms of accurately pinpointing waypoint locations and in some cases the movement of subjects. The waypoints that we had classified as "Red flag" during our analysis were those that seemed to lack the spatial precision were made a bit unclear of the microenvironment they were located. They consisted of approximately 38% of our total waypoints (193 in total). Previous studies have shown similar precision and data logging errors when compared to personal surveys or interviews, especially when working with personal GPS modules (Nethery *et al.*, 2014). But most are attributable to the device's capacity for positional accuracy in typical locations (indoor, outdoor, and in movement), factors that influence satellite reception (building material and type), acquisition time, battery life, and adequacy of memory for data storage (Wu, Fan, and Ohman-Strickland, 2010). Although the units that we had acquired for our study did not face a majority of the aforementioned issues, there is the potential that satellite reception and positional accuracy were the causes for our "Red flag" points.

The subjects that were recruited for the personal exposure data collection came from a specific sub-population, which eliminates the underlying inequalities (socioeconomic status and geography) we could have encountered with a more generalized population. Although there were the two subgroups, students living in both the Woodruff and Perry-Matheson dorms, within the entire subject population our results showed that broad time-activity patterns did not differ substantially on an individual basis. Most of the subjects, for example, spent a majority of their time within their respective dormitories and then spent the rest of their time either in class or moving through the GIT campus. Since the students showed similar time-activity patterns, the microenvironment variables did not significantly differ between the two groups, which may explain the lack of spatial variability other than the distance from the Connector between the two subgroups.

The predictors that were found significant do, however, support our and other previous expectations that being indoors reduces overall exposure to pollution generating outdoors, including traffic-related pollution and that spending time farther from a pollutant source also reduces overall levels of exposure. In our panel, this was particularly true for $PM_{2.5}$ exposures. For NO_2 and BC, there was less of a difference in exposure between the two student groups.

For all of the traffic pollutants that were measured at the personal exposure level, we found that none were significantly different in terms of overall concentrations between the two subgroups. The week-by-week variability in exposures showed that the two subgroups' personal pollutant levels were influenced most by the corresponding background pollutant levels measured at the JST location. Analysis also showed that the JST pollutants levels were positively and significantly associated and with corresponding personal exposure for each of the measured pollutants. These findings provide some degree of validation of the data quality for the personal exposure monitoring.

Unlike $PM_{2.5}$, the personal exposure results for NO_2 and BC did not exhibit a significant association with the distance (time-weighted distance) from the Connector. The findings for PM2.5 validated previous studies that distance does play a crucial role in the variability in exposure levels observed across campus. But the NO_2 and BC concentrations did not share the same results, which may have been due to the high background concentrations of the two pollutants being observed over the course of 11 weeks. Since all three pollutants were measured using different instruments, calibrated differently, and quantified using different methods there is the possibility that measurement error or unspecified contamination may have affected the outcomes of the two pollutants.

The characterization and quantification of the exposures of interest is useful to gain an improved and developed understanding of the spatiotemporal aspects of personal exposure and urban traffic pollution, which is why we designed the study to categorize the microenvironments into different groups. Of the microenvironment groups we assessed the near Connector, far Connector, central, and outer campus aimed to show a gradient and a quantified buffer zone for the pollutant variability. Although the time spent at each location varied along with the time weighted distances overall when associated with concentration there was no significant association with time spent in each of the microenvironments, indicating that the varied pollutant concentrations (coefficients from Tables 2,3, and 4) we see with the different microenvironments were not applicable with the respectable pollutant concentrations. This might be due to the high background concentrations we observed throughout the data collection period or from the fact that the distances that the perimeters that were established for each microenvironment were not sufficient to observe a clear pollution gradient. Overall, a further investigation is warranted to justify the role time spent in the various microenvironments on the GIT campus plays in predicting personal exposure.

Our study incorporates the diversity of microenvironments a person spends throughout the week and enables analysis of exposure in a realistic setting that includes everyday time-activity and location patterns. But despite the indoor microenvironment being significant we were not able to observe a major difference between the two subgroups in terms of personal exposure. This indicates that traditional measurement techniques that were mentioned above (centralized monitoring stations) may be insufficient in terms of quantifying levels of personal exposure. Especially for populations like the one included in the DRIVE study, who spend a majority of their time next to a well-defined traffic hotspot and pollutant source, a centralized monitoring station would not have been able to provide an accurate estimate of exposure levels and instead may have been biased. Similarly, use of a single roadside monitor failed to provide accurate indicators of differences in pollutant levels between the two subgroups.

Limitations

Throughout the course of our data collection some bias may have arisen from the questionnaires, which may have led to a change in life style or staying away from pollutant sources. This may have led to an increased duration in indoor microenvironments or stationary points in general, due to the subjects' concerns of being exposed to traffic pollutants. We are also faced with the potential challenge of having a convenience sample consisting of students. Although the spatial activities varied between the two dormitory subgroups, they still had similar temporal patterns and had a good amount of overlapping due to their schedules. There were indeed advantages of using such a focused population, since they are required to spend a majority of their time within the GIT campus environment therefore minimizing the effects of external factors that may have altered the pollutant levels. However, the similarity in lifestyles and the GIT campus possibly not being large enough to observe a clear concentration gradient may have been a reason why there was no overall significant difference between the two subgroups. Therefore an increased sample population, along with a more varied study population (faculty, students, and other nearby population) that spends a majority of their time near the pollutant source might have given us a better understanding of the spatiotemporal variability in a near road environment.

Overall the technological advancements provided us with the advantage of using small, efficient, and less time consuming personal measurement methods that did not interfere with each subject's lifestyle. But a major shortcoming of using such devices is the lack of power or high sensitivity resolution measurements that we find with larger devices. We were able to observe this pattern with some of the devices we used, especially with the µPEM and GPS modules. Due to instrumentation constraints and mechanical errors, we were not able to collect the expected amount of data cycles. There is also the possibility that the filter samples might have been contaminated during processing or the devices were not cleaned properly, which may have resulted in offsets and improper logging of data. It is evident that further diagnostic surveillance and control procedures should be implemented to help to alleviate traffic pollutant levels all across urban Atlanta.

Conclusion

In general, measuring personal exposure to air pollutants is a complex task requiring large amount of resources for personal monitoring, especially with such an active population that resides in close proximity to a pollutant source. The change in personal pollutant exposure was related to personal time-activity patterns among the 51 students. Our study showed that using a single centralized monitoring station and corresponding pollutant variability models to determine the exposure levels on a personal scale was not sufficient enough and in certain cases could be biased towards those that are closer to pollutant sources. The similarity in exposure between the subjects displays the importance of unconventional and innovative measurements techniques used to quantify pollutant exposure. Moreover, our study outlined the importance of multidisciplinary models and study designs when conducting research on heterogeneous air pollutant, like traffic pollutants, to deal with the complexity and dynamic nature they possess.

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