Impact of Road Proximity and other Determinants of Air Quality along Multi-use Trails in the National Capital Region

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Abstract

Active travel can provide short-term and long-term health benefits and has the ability to reduce the negative externalities of vehicular traffic, for example, congestion, land consumption, and air pollution. However, exposure to air pollution is higher for pedestrians and cyclists than other road users when considering inhalation rate and travel distance. Route choice for active travel is a potential strategy to reduce the adverse impact of exposure to air pollution. Multi-use trails could be an effective way to reduce health impacts as the pollutant concentration is typically lower on trails, however, proximity to nearby roadways can deteriorate the air quality in multi-use trails. The goal of this study is to investigate the air pollutant concentrations on multi-use trails adjacent to different roadway classification and identify the factors that influence air quality in multi-use trails. I collected pollutant concentrations of $PM_{2.5}$, particle number, and black carbon using mobile monitoring on an e-bike. I identified five trail routes that run parallel to an interstate highway, principal arterial, and local roads for this study and collected pollutant concentrations during morning, afternoon, and weekend afternoon peak hours.

The average concentration of $PM_{2.5}$, particle number, and black carbon was 15.62 $\mu g/m^3$, 9,857 pt/cc, and 595.36 ng/m^3 respectively among all the trail routes used for this study. I observed higher pollutant concentrations during morning peak hours than afternoon peak hours. Also, concentrations were lower on weekends than weekdays. The pollutant concentrations were different among multi-use trails based on their proximity and characteristics of nearby roadways.

The pollutant concentrations significantly declined when the trail segment was 50-100 meters away as compared to segments within 50 meters of nearby interstates, freeways, or collectors. Concentrations increased significantly for trail segments having a nearby road Annual Average Daily Travel (AADT) of more than 32,000. The regression models explain 65%, 59%, and 52% of variability in the $PM_{2.5}$, particle number, and black carbon concentrations respectively. Nearby road AADT and road density were found to be significant for $PM_{2.5}$, particle number, and black carbon concentrations. Cooking place (rest areas with barbeque grills) and construction sites were significant and positively associated with $PM_{2.5}$ concentrations. Airport and construction sites near trails showed a positive relation to the particle number concentration. Parking spaces near trails increase the concentration of black carbon along trails. This study shows the impact of roadway proximity on the air quality of trails which should be considered by municipalities while planning for multi-use trail network to mitigate health risks of pedestrians and bicyclists on trails.

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General Audience Abstract

Traffic related pollutants such as $PM_{2.5}$, particle number, and black carbon can cause short and long terms health impacts. Exposure to these pollutants varies by travel mode, duration, route selection, etc. People who bike or walk have higher exposure than other users when taking the inhalation rate and travel duration into account. Hence, route choice is important in active travel. Multi-use trails could be effective to reduce exposure as the pollutant concentrations are typically lower on multi-use trails. However, multi-use trails are often in close proximity to pollution sources (i.e. roadways). This study focuses on identifying the impacts of road proximity and other determinants of air quality along multi-use trails. I selected five multi-use trails based on the classification of adjacent roadway and collected air quality data. I found that air quality differs along trails based on the proximity of nearby roadway and the trail route along interstate highway had the highest concentration of pollutants. The concentrations of pollutants were higher during morning than afternoon and also, it was higher during the weekdays than weekends. Trail segments within 0-50m distance of a nearby interstate or freeway had the highest concentration which decreased as the distance from the interstate or freeway increased. Construction site, airport, and BBQ place along trails also worsened air quality on multi-use trails. This study demonstrates the importance of selecting trail locations when planning for the trail network to improve the air quality on multi-use trails that will further improve the benefits of active travel.

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Chapter 1: Introduction

Vehicular traffic can provide individuals with flexible transportation options to reach the destination easily and comfortably. However, the uncontrolled growth of automobile use in the world includes negative externalities such as traffic congestion, air pollution, noise pollution, etc. [1]. One alternative approach to reduce the adverse impacts of vehicular traffic is active travel [1, 2], i.e., utilizing non-motorized modes of travel such as cycling and walking to satisfy travel needs [3, 4, 5]. Shifting from motorized travel modes to active travel for trips under 3 miles can reduce around 20,000 to 46,000 tons of CO_2 daily [6]. Combining with public transport, active travel has the ability to cover most mobility needs [5]. Active travel can furthermore reduce the adverse impacts of motorized vehicles by land consumption, environmental impacts such as air and noise pollution [4, 1, 5]. Furthermore, active travel offers physical and mental health benefits for short and long-term [3] by reducing obesity, lowering blood pressure, improving lung function, reducing the risk of cardiovascular diseases and diabetes, etc. [1, 3] Despite numerous benefits, bicyclists are more exposed to air pollution and traffic collisions [7, 8, 9, 10]. However, the benefits of active travel and physical activity outweighs the negative impact of air pollution except for extreme pollutant concentrations [11, 12, 13]. Traffic related pollutants are the main sources of air pollution causing human exposure [14, 15].

There are many traffic related pollutants that present health concerns including: particulate matter, black carbon, carbon monoxide, nitrogen dioxide, volatile organic compounds, etc. [16, 17]. Particulate matter with a diameter less than or equal to 2.5 µm also known as $PM_{2.5}$ can cause cardiovascular and respiratory diseases as it can penetrate the respiratory system [18, 19]. Long-term exposure to $PM_{2.5}$ is estimated to cause between 4.1 and 8.9 million deaths globally, ranking it as the sixth most important risk factor for mortality [3]. Furthermore, $PM_{2.5}$ emitted from combustion is more detrimental to health than $PM_{2.5}$ generated without combustion [20]. Black carbon, a specific type of particulate matter, is emitted due to combustion and considered to be more specific to local combustion than $PM_{2.5}$ [21]. Short- and long-term exposure to black carbon can cause cardiovascular and cardiopulmonary mortality respectively and black carbon is considered to be a better indicator of detrimental particles emitted to environment due to combustion [22]. Ultra fine particles (UFP) have an aerodynamic diameter of less than 100nm and are produced due to combustion of fossil fuel. With a higher concentration near freeways, UFP is considered to have higher toxicity than larger particles [17, 14]. However, exposure to air pollutants near roadways depends on various factors including the travel mode, type of fuel, meteorology, engine type, etc. [14].

Previous studies found that personal exposure to pollutant concentrations was lower for bicyclists than other modes of commuting to work. However, the exposure to pollutants was the highest for bicyclists after taking the inhalation rate (two-times higher than other motorized modes) and travel duration into consideration [14, 23, 24]. A study in California found that exposure to air pollution was higher when cycling on a high traffic route than a low traffic route [6]. Similarly, choosing a route with lower air pollution reduced the exposure to pollutants but slightly increased the travel duration [25]. Thus, route choice has an impact on exposure to pollutants for active travel. The concentrations of pollutants were lower while commuting on a multi-use trail than on-street bicycling facilities [2, 14, 26]. Although the air pollution concentration is lower on dedicated trails, there are no such studies that have investigated the air pollution concentration on trails due to its proximity to different types of roads. To fill this research gap, this study identified five multi-use trail routes running parallel to the interstate highway, principal arterial, minor arterial, and local streets and conducted a mobile air quality monitoring within the National Capital Region, USA.

1.1 Objective of the Study

To investigate the air pollutant concentration on multi-use trails adjacent to different roadway classification and identify the factors that influence air quality in multi-use trails.

1.2 Research Questions

i. Do the pollutant concentrations ($PM_{2.5}$, particle number, black carbon) differ among multi-use trails based on the proximity to different roadway classifications?

ii. How does the distance from different pollutant sources including roadway and land-use impact the air quality on multi-use trails?

iii. What are the factors that influence the pollutant concentrations on multi-use trails?

Chapter 2: Methodology

In this chapter, I will describe the methodology that includes- (1) equipment setup, (2) site selection and data collection, (3) post processing of the air pollution data, (4) variable preparation and model development.

2.1 Equipment Setup

For the mobile data collection, I have followed the equipment set up developed by Hankey and Marshall [2] and Dixit. K. K [27]. I have used a Specialized Turbo E-bike with a rear rack to carry the equipment. Using an e-bike for mobile air quality monitoring has its own advantage as it is a zero-emission mode and it can be helpful for personal exposure assessment [28]. To avoid the shocks due to bumpy roads, I have used a two layered foam base attached to the rear rack of the bike. All equipment was tightly attached to the base with straps to avoid equipment falling from the bike and reduce the impact of shocks. The bike comes with a 75mm front shock absorber that also helps reduce the mechanical shock. I used the following equipment during the mobile air pollution monitoring: (1) Sidepack AM520, (2) Condensation Particle Counter 3007, (3) Mircro-aethalometer AE-51, (4) GPS (BU-353 and GPS Logger app), (5) Raspberry Pi, (6) 2 Go Pro cameras.

2.1.1 Sidepack AM520

The TSI Sidepack Personal Aerosol Monitor operates with a battery and uses laser photometer for measuring mass-concentration of airborne particles [29]. It can be used to estimate $PM_{1.0}$, $PM_{2.5}$, PM_5, and PM_{10} using different impactor inlets. For the purpose of this study, I have used the $PM_{2.5}$ inlet. The instrument was factory calibrated. The Sidepack includes three types of modes: survey mode, manual mode, and program logging mode. The survey mode shows real time aerosol concentration but does not store the data. I have used manual mode for data logging while adjusting the date and time manually before each run. I have selected 1-s logging interval for data collection. I have zero calibrated the Sidepack once every two weeks to check for issues with the equipment. I cleaned the impactor inlet and applied oil to it prior to the study.

2.1.2 Condensation Particle Counter 3007

The TSI Condensation Particle Counter 3007 measures the submicron particle matter concentration and operates through AA sized batteries or AC power for portable use. Isopropyl alcohol is the operating fluid of this equipment [30, 31]. With the upper and lower limit of 10^{5} cm^{-3} and 10 nm, the CPC 3007 can count single particles [31]. However, it has some limitations as mobile monitoring equipment. One of them is the coincidence error [30]. It occurs when several particles enter the particle counting optics after reaching the maximum detection capacity making the data unreliable [30, 31]. Also, tilting the equipment may result in the damage of the optics [28].

The CPC 3007 takes 600s to start the operation. Before starting the equipment, the alcohol cartridge was mounted to the device. The alcohol cartridge was always inside the alcohol fill capsule with the marked level of isopropyl alcohol. I changed the wick prior to the study. Once I mounted the alcohol cartridge, I turned on the CPC 3007 before reaching the study route to avoid delay. Also, I connected the air inlet with the conductive tube. The conductive tube inlet was at human breathing height after sitting on the bike. CPC 3007 starts showing the real time particle number once started. To start logging the data, I had to select the log mode. I used 1-s logging interval to match with the other equipment. The CPC 3007 tilt alarm was disabled prior to the study.

2.1.3 Mircro- aethalometer AE-51

I used a micro-aethalometer AE-51 to measure the Black Carbon (BC) level during the study. The equipment has an internal battery for portable use. However, the micro-aethalometer AE-51 is vibration sensitive resulting in negative and positive excursion in the estimated BC reported by the equipment [28, 32]. Another limitation of the equipment is that the BC estimate may have negative BC values when the BC value is too low [32]. A fibrous filter that has been filled with aerosols is used to assess the attenuation of light (ATN) emitted from an LED source [32]. Unlike the CPC and sidepack, the micro-aethalometer does not include a built-in display to show the real time BC estimates. Once the equipment is ready to use, the green LED beeps continuously. When the memory is full, or it is malfunctioning the red LED blinks regularly. To set up the 1-s interval data logging, I connected the equipment to the microAethCOM app on the computer. Also, I adjusted the time regularly to avoid time offset. Once started it logged data automatically. The air inlet of micro-aethalometer was connected with the conductive tube and avoided the blocking of the air outlet of the equipment to avoid malfunctioning.

2.1.4 GPS

To record the co-ordinate system for every one second interval, I have used the BU-353 GPS device and the GPS Logger app on android device. To avoid interruption in the satellite signal, I mounted the BU-353 on the top of the rod that held the conductive tubes. BU-353 requires an outside power source to operate and it was connected to the Raspberry Pi (described in the following section) as a power source and store the co-ordinates. The mobile app included the option to add annotations. I annotated the location whenever passed through a tunnel, cooking area with smoke, etc.

2.1.5 Raspberry Pi

The Virginia Tech Center for Geospatial Information Technology (CGIT) team developed an app for the raspberry pi [27]. The application can log the real time reading of the GPS, micro-aethlometer AE-51, and CPC 3007 at one second interval. To log the data from the devices, I had to connect them to the USB ports in the following sequence- GPS, microaeth, and CPC 3007. The application has some limitations, for example, it cannot connect with the device when the log interval is different than 1-s, it does not detect the device if the sequence is not maintained, and it is highly shock sensitive as the USB connection gets displaced. Once the USB connection gets displaced, it freezes and stops recording data. Hence, I had to stop after every 10 minutes or whenever there is a heavy shock during the data collection to check if the application has stopped working. Due to this limitation, I used the mobile GPS app to avoid losing data. The raspberry pi requires an outside power source for which I used a 10000-watt power bank made by Anker. Due to the mechanical shocks the raspberry pi may get disconnected from the power source. I wrapped the USB power source of the raspberry pi with the power bank using tape to avoid this issue. The raspberry pi application does not work with the sidepack. Hence, it was important to avoid any time offset in the sidepack device. Later I merged the sidepack data with BC, CPC, and GPS data in the post processing stage.

2.1.6 Go Pro Setup

I used two GoPro HERO9 Black to record every mobile air quality monitoring run mounted on the front and back of the bike. I captured videos at 2.7K resolution with the frame rate of 24 per second. I always turned the horizon lock on to avoid the disturbance of video recording due to shock at maximum video mode. The maximum video mode to cover a wider field of view. I mounted the front camera on the handlebar close to the middle of the handlebar to get a better view. For the rear camera, I mounted it on the rod of conductive air tubes at the similar height of the front camera and similar settings. Before starting the recording, I always connected the cameras with GoPro Quik app to update the dates and times after I changed the batteries or shut down the cameras. I ensured the field of view was not blocked with any obstacles during the recording period.

2.1.7 Summary

All the equipment used for this study was portable. I was always careful using them to avoid equipment malfunction since they have their limitations. **Table 1** includes the equipment name, manufacturer, sampling interval, flow rate, range, and aerosol measurement-

Table 1: Equipment Description

Equipment	Manufacturer	Sampling Interval	Flow Rate	Range	Measurement
Sidepack AM520	TSI, Inc.	1-s	0-0.18 /min	0.001-100 mg m^{-3}	$PM_{2.5}$ Mass concentration
Condensation Particle Counter 3007	TSI, Inc.	1-s	700 mL/min	0-100,000 pt/cc	Particle number concentration
Micro-aethalometer AE-51	AethLabs	1-s	100-200 mL/min	0-1 mg m^{-3}	Black carbon concentration
BU-353	GlobalSat WorldCom Corp.	1-s	-	-	GPS coordinates
HERO 9 Black	GoPro	24 frames/s	-	-	Video Recording

Figure 1: E-bike for air quality monitoring

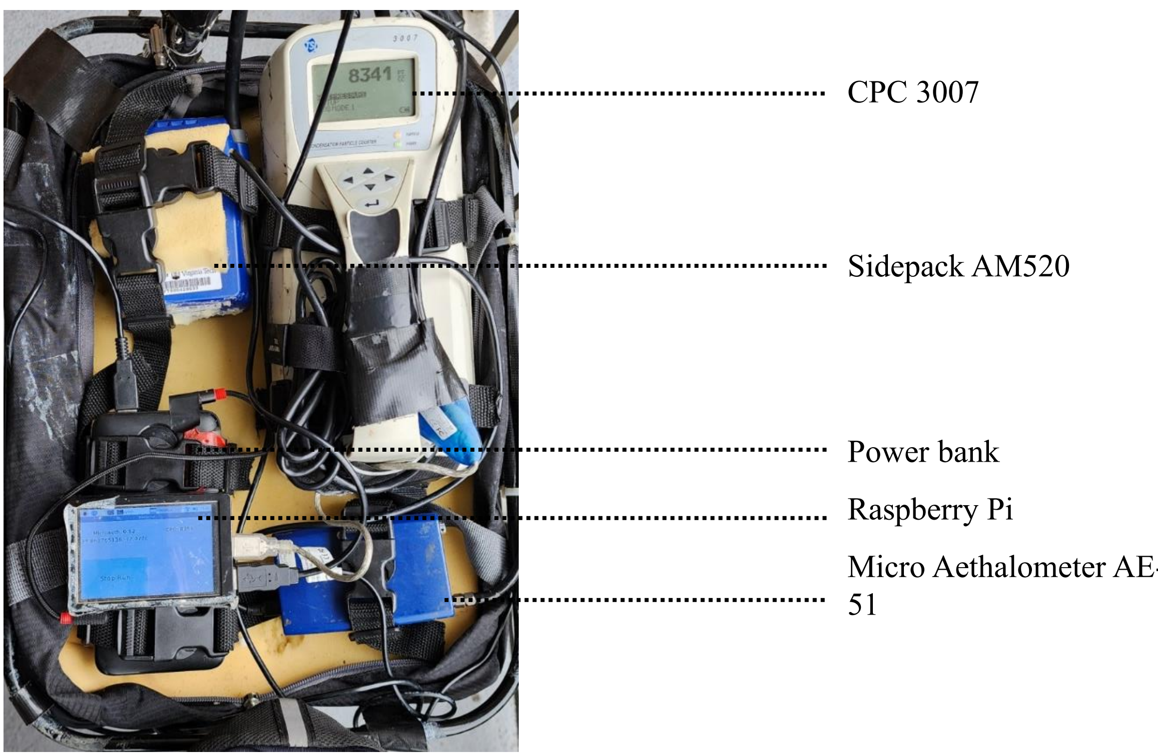

Figure 2: Equipment setup on bike rack

2.2 Site Selection and Data Collection

This section elaborates on the trail route selection and data collection schedule during the study period.

2.2.1 Route Selection

For the purpose of this study, I primarily focused on selecting bicycle routes on the bicycle trails in the National Capital Region. Rock Creek Trail, Chesapeake and Ohio (C&O) Canal Towpath, Capital Crescent Trail, Metropolitan Branch Trail, National Mall Trail, Anacostia River trail, Piney Branch Trail, Oxon Run Trail, Marvin Gaye Trail are located in Washington D.C. and Maryland- mostly within national parks [33]. C&O Canal Towpath, Capital Crescent Trail, Anacostia River Trail, Oxon Run Trail, Marvin Gaye Trail, Piney Branch Trail are located at the outskirts of Washington D.C. and Maryland. On the other hand, Metropolitan Branch Trail and Rock Creek Trail stretch from the D.C. city center to the outskirts and National Mall Trail is located at the city center [33]. Trails located in Virginia are- Custis Trail, Mount Vernon Trail, Four Mile Run Trail, Washington and Old Dominion (W&OD) Trail, 110 Trail, Bluemont Junction Trail, Ballston Connector Trail. Custis Trail, Mount Vernon Trail stretched out from the city center to the outskirts of Arlington and Alexandria. Bluemont Junction Trail, Ballston Connector Trail are located at the core of the city. On the other hand, Four Mile Run, W&OD Trail, 110 Trail are located on the outskirts of Arlington, VA.

To identify the routes, I focused on trail proximity to a roadway and its functional classification. The selected trails were the Custis Trail and W&OD Trail, Mount Vernon Trail, W&OD Trail, Capital Crescent Trail, and Rock Creek Trail. The Custis Trail route started from Rosslyn near the intersection of Langston Boulevard and N Fort Myer Drive. Custis Trail ended at the Bon Air Park where I got onto the W&OD trail towards North-West direction. This route always ran parallel to the Custis Memorial Parkway which is the Interstate-66 toll free roadway classified as major arterial. The Mount Vernon trail also had the same start point as Custis Trail but in the opposite direction towards East. At the beginning of this route, it runs parallel to I-66. From the beginning of Theodore Roosevelt Island, it runs parallel to the George Washington Memorial Parkway classified as a minor arterial. Some portions of this route run beside the Ronald Reagan Washington National Airport. This route ended near the intersection of E Abingdon Drive and Slaters Lane. The W&OD trail route is the shortest among all routes of this study. It starts from the intersection of W&OD trail and Columbia Pike and ends at Bon Air Park at the intersection of W&OD trail and Custis Trail. This segment is mostly adjacent to the neighborhood or local roads. The Rock Creek Trail route starts at the North-East end of the Theodore Roosevelt Memorial Bridge and runs parallel to the Rock Creek and Potomac Parkway NW, a principal arterial, till the intersection of Rock Creek and Potomac Parkway NW and Shoreham Drive. After that it runs alongside Beach Drive NW which is a minor arterial. At the intersection of Beach Drive NW and Broad Branch Road NW, this route ends. Some portion of this route is alongside the Smithsonian National Zoological Park. Finally, the Capital Crescent Trail route starts at the end of Water St NW at Washington D.C. and ends near the crossing of River Road at Maryland. The Washington D.C. portion of the Capital Crescent Trail runs alongside the Canal Road NW- a principal arterial. The Maryland side of the trail is nearby local roads. Although the D.C. segment has a road near it, the road is not visible from the trail and also has an elevation difference.

Figure 3 shows the routes selected for the study purpose. Among the five selected routes, Mount Vernon Trail route was the longest which was 10.3 kilometers followed by the Capital Crescent Trail that was 9.2 kilometers long. Custis and W&OD trail route was 9 kilometer in length whereas the Rock Creek Trail segment was 8.7 kilometer. The shortest trail route was the W&OD

trail route with a length of 3.7 kilometers.

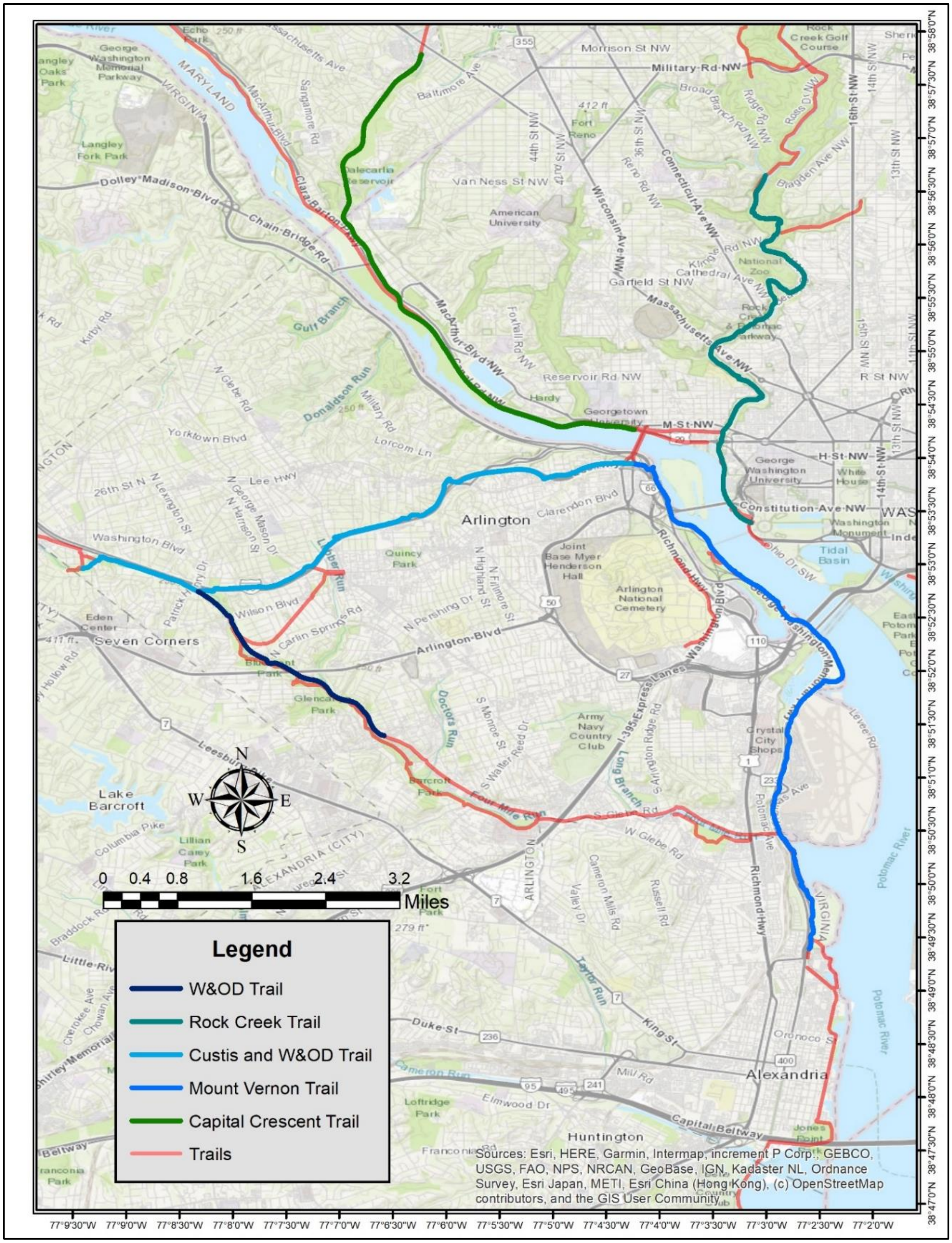

Figure 3: Sampling routes for mobile air quality measurements.

2.2.2 Sampling

I collected data on weekday and weekend peak hours to have similar characteristics of traffic patterns during the sampling period. During weekdays, I collected data on the morning and afternoon peak hours. Morning peak hours were 6 AM to 9 AM. On the other hand, afternoon peak hours included 3:30 PM to 7 PM. On the weekends I collected data only during the afternoon peak which is similar to Weekday afternoon peak hours. During the morning or afternoon peak time, I collected data from each route twice in the opposite direction. I avoided rainy days and cold weather days to avoid malfunction of the equipment. Table 2 to 4 indicate the data collection map at morning, afternoon, and weekend peak hours respectively.

Table 2: Data collection schedule during morning peak hours

Month	**October 2023**			**November 2023**		
Trail Name	**13**	**17**	**23**	**14**	**27**	**30**
Capital Crescent Trail						
Custis and W&OD Trail						
Mount Vernon Trail						
Rock Creek Trail						

Table 3: Data Collection schedule during afternoon peak hours

Month	**October 2023**		**November 2023**		
Trail Name	**17**	**19**	**16**	**23**	**30**
Capital Crescent Trail					
Custis and W&OD Trail					
Mount Vernon Trail					
Rock Creek Trail					
W&OD Trail					

Table 4: Data collection schedule during weekend peak hours

Month	October 2023				November 2023		
Trail Name	**15**	**21**	**22**	**27**	**11**	**12**	**19**
Capital Crescent Trail							
Custis and W&OD Trail							
Mount Vernon Trail							
Rock Creek Trail							
W&OD Trail							

Table 5 shows the number of sampling runs completed on each route during afternoon and morning of weekday, and weekend peak hours. I completed at least 10 sampling runs for all the trail routes except for the W&OD trail route which I sampled 8 times excluding the morning peak hours.

Table 5: Number of samples collected by trail and weekday

Trail Name	Afternoon	Morning	Weekend
Capital Crescent Trail	4	2	6
Custis and W&OD Trail	4	2	4
Mount Vernon Trail	4	4	4
Rock Creek Trail	4	4	4
W&OD	4		4

2.3 Post Processing of Data

Once the mobile air quality data collection was completed, I had to further process it to mitigate instrument-based limitations before using the data for analysis. This chapter elaborates on the instrument specific post processing of data.

2.3.1 Background Adjustment

I collected the $PM_{2.5}$ concentrations using the Sidepack AM520. Background concentration of air pollutants vary from day to day compared to the annual average. To make spatial comparisons, it is important to adjust the pollutant concentration to account for the day-to-day variability [28]. For this study, I did not have a central site for background data collection. As a result, I used the EPA hourly and annual average data of $PM_{2.5}$. I used the multiplicative background adjustment to account for the variability of the background air pollution concentration similar to Hankey et al [34]. I collected the hourly and monthly average $PM_{2.5}$ concentration. From the monthly average $PM_{2.5}$ concentration, I obtained the annual average $PM_{2.5}$ concentration. The correction factor I developed was the ratio of hourly concentration and annual concentration. Once I developed the correction factor for each mobile data collection hour, I multiplied the correction factor with the $PM_{2.5}$ mobile measurement.

2.3.2 CPC 3007 Measurement Correction

I used CPC 3007 for condensation particle number count. As mentioned earlier, the CPC 3007 has a limitation once it exceeds the maximum concentration capacity. Particles start to coincide once the equipment at its maximum detectable capacity. Hence, the measurement does not include the actual concentration of particle number. For monitoring location with concentration more than 10^5 pt/cm^3, I used the following correction equation developed by Westerdahl et al. [35]-

$$PNC_{corr} = 38456 * \exp(PNC * 0.00001)$$

Here, PNC_{corr} indicates the corrected particle number concentration after applying the correction equation, PNC indicates the particle number concentration recorded by the CPC 3007.

2.3.3 60-s Averaging of Black Carbon Concentration

I used Micro-aethalometer AE-51 for black carbon measurement where I logged the measurement at 1 second interval. However, the equipment is sensitive to mechanical shock which results in spurious spikes. To smoothen these spikes, I have calculated a 60-s average of the black carbon measurements before using the estimated black carbon concentration.

2.4 Variable Preparation and Model Development

To identify the variable that influences the air pollution and to estimate pollutants ($PM_{2.5}$, Black Carbon, Particle Number) on trails, I developed regression models. For that purpose, I used Google Street View imagery data, distance variables, density variables, and dummy variables. In this chapter, I will discuss the method of dependent and independent variable preparation and model development.

2.4.1 Dependent Variable Preparation

Before using the point $PM_{2.5}$, particle number, and black carbon data, I had to merge them together based on the time. The Raspberry Pi creates a file combining the reading of particle number, black carbon, longitude, latitude, time, and date. However, I did not use the data file from Raspberry Pi as it had stopped numerous occasions during the data collection which could result in data loss. Instead, I collected the date and time information using the GPS logger app and used the Raspberry Pi data as a reference point for the merge to avoid any time offset between the equipment. I always updated the date and time of Sidepack as the Raspberry Pi app can be connected with Sidepack. I collected pollutant data at 1-s which I have spatially aggregated at 100m interval. The GPS logger app provided the gpx file for each route which I converted to a GIS shapefile using ArcMAP. Once I retrieved the route polyline, I split the route at 100m segments which I later used for spatial aggregation. The W&OD had the lowest number of segments which was 37 where the Mount Vernon Trail route had the highest number of segments-103. Once I identified the segments, I created a 25m buffer for each segment to assign each data point to a segment similar to Jason et al. [36]. I used the intersect tool in ArcMAP to assign data points to each segment. Once I assigned the data points to each segment, I used a python script where I used the pivot table to calculate the average pollutant reading for each segment of each trail route.

2.4.2 Independent Variable Preparation

As independent variables, I used GSV image, distance from land use, density variable, traffic related variable, trail specific dummy variable, etc. In this section, I will describe the process of independent variable preparation-

2.4.2.1 Variable Extraction from GSV Image

I used the GSV imagery data prepared by Meng. Q et al. [37] for the Washington D.C. region and Montgomery County, Maryland. GSV imagery can better capture the built and natural environment characteristics around the street which can be effective to predict the street-level air pollution [38]. The dataset for Washington D.C. included GSV image data from 2007 to 2020 where the other dataset of Maryland was only for 2019. The dataset contained geographic co-ordinates of each point which was the centroid of each 100m*100m grid, year of the image captured, and 150 variables. For full list of the 150 variables, refer to Meng. Q et al [38]. Among the 150 variables, only 47 variables were theoretically related to air pollution [37].

I created 50, 100, 200, 300, 400, 500, and 1000 meter buffer for each segment of each trail route using ArcMAP buffer tool as these buffer distances were found to be significant in Land Use Regression (LUR) models for pollutants [36]. To assign variables to each segment I intersected all the buffer segments with the GSV datasets. I used the intersect of a buffer and GSV dataset to calculate the mean of the individual variables for each trail route segment and followed the same process for all buffer distances [38]. Later, I further aggregated the 47 variables into 7 composite variables for each buffer distance using another python script by calculating the mean of variables in each composite variable and the composite variables were built environment, transport network, transport vehicles, nature, vegetation, water, and human. For the composite variables, I used the sub-group of variables defined by Meng et.al [37]. **Table 6** shows the 7 composite variables and variables that were aggregated.

Table 6: Composite variables with the aggregated variables for each composite variable

Composite variables	Variables aggregated
Built environment	Building, canopy, house, hovel, pier, skyscraper, swimming pool, wall
Transport Network	Bridge, dirt track, path, road, runway, sidewalk, streetlight, traffic light
Transport Vehicles	Airplane, boat, bus, car, minibike, ship, truck, van, signboard
Nature	Animal, earth, hill, land, mountain, rock, sand, sky
Vegetation	Field, flower, grass, palm, plant, tree
Water	Fountain, lake, river, sea, water, waterfall
Human	Person, bicycle

2.4.2.2 Distance from Land Use Variable Preparation

To identify how the relative location of each trail segment to land use impacts the trail air quality, I have calculated the distance from each land use using the near tool in ArcMAP. Before that I collected the land use data of Virginia (Arlington County, City of Alexandria), Washington D.C., and Maryland (Montgomery County) from the open data portal of each jurisdiction. The land use features included- recreational, park, industrial, commercial, agricultural, and residential land uses. Since there is limited heavy industry in the study area, I did not calculate the distance from industrial land use. Also, I did not calculate the distance from agricultural land use due to lack of agricultural land use around the study area as it is a highly urban setting. I extracted the individual land use features for each jurisdiction and merged them together using the Merge tool in ArcMap. Later, I calculated the shortest distance from each landuse at 1-s sampling points.

I categorized the distances into 0-50m, 50-100m, 100-200m, 200-300m, 300-400m, 400-500m, 500-1000m, 1000-1500m, and above 1500m. I used these categories to generate a boxplot to know how the average of trail air pollution changes when the distance increases [2].

To create the independent variables, I used Intersect tool in ArcMap to assign the distance of each point to a trail route segment and calculated the average distance of different land use features for each trail route segment.

2.4.2.3 Density Variable Preparation

For density variables, I calculated the building density [39, 36, 40], road density [41, 42, 43], and weighted population [39] for 50m to 1000m buffer distance of each segment.

I collected the building data, road polygon as ArcGIS shapefile from the open data source of Arlington County, City of Alexandria, Fairfax County, City of Falls Church at Virginia; Washington D.C. and Montgomery County at Maryland. I merged all the shapefiles of building data and road polygon. I also calculated the area of each feature inside the building data and road data in square kilometers. To calculate the building density and road density, I calculated the total area in square kilometers of each buffer distance for every segment. I intersected the buffer area of each segment with the merged shapefiles of building and road polygon using the Intersect tool in ArcMap. I divided the area of individual features by the area of each buffer segment and finally summed them to obtain the building density and road density for each trail route segment.

I collected the ACS 5-year population data of 2020 for each census tract from the open data source of the jurisdiction mentioned in section 2.4.2.2 except for the City of Falls Church and Montgomery County which I collected from the census website. Also, I collected the census tract shapefile of Montgomery County from data.imap.maryland.gov website and added the population data of 2020. Once I processed different population shapefiles, I merged them together and calculated the area of each census tract. After that I intersected each census tract with the buffer shapefiles and calculated the weight of each census tract dividing the area of each census tract by the area of each buffer distance. To obtain the weighted population, I multiplied the weight of each census tract with the population and summed them together for each segment buffer.

2.4.2.4 Traffic Related Variable Preparation

I considered the AADT of the nearest road from the trail route to know about the impact of high traffic route on the air quality of trail. Despite having the recording of all mobile monitoring runs, it was not possible to extract the vehicular count during the time of mobile monitoring as the traffic was not visible from the trail due to elevation difference, wall barrier, distance from the roads, etc. I collected the AADT of Montgomery County, Maryland from MDOT website and Washington D.C. from the opendata website. For Virginia, I collected the AADT from the VDOT website as an ArcGIS shapefile. I used the AADT of 2019 for Maryland, 2020 for Washington D.C. The AADT of Virginia started from 2010 till 2022. I calculated the nearest road of each data collection point using Near tool in ArcMap and intersected the shapefile with trail route segment shapefile. Later I calculated the average AADT for each trail route segment using pivot table in Python.

2.4.2.5 Dummy Variable

I used dummy (binary 1 or 0) variables such as- cooking place beside the trail, parking lot alongside the trail, tunnel/bridge underpass, airport, wall between the trail and roadway, and construction site visible during the data collection. I went through the video recordings of one sample collection and recorded the start and end time of each facility to match it with the sample run and each trail route segment. I assigned 1 to all the segments with the facilities mentioned above except for the wall. For a segment which had wall length of at least 50% of the segment, I assigned 1 to them for Custis and W&OD Trail route as it was the trail route with wall between the road and trail. There was a construction site beside the W&OD Trail route. A portion of the Mount Vernon Trail runs alongside the airport. The Capital Crescent Trail, Custis and W&OD route and W&OD Trail route had cooking places beside the trail that were places for people to rest with barbeque grills.

2.4.3 Distance from Roadway

Similar to the distance from each mobile measurement point and landuse discussed in 2.4.2.2, I calculated the distance from each mobile measurement point to the nearest roadway considering the functional classification of roadway. Hence, I calculated the distance from interstate, freeway, principal arterial, minor arterial, major collector, minor collector, and local road. I collected the roadway functional classification data of Virginia, Maryland, and Washington D.C. from VDOT, MDOT, and opendata portal of Washington D.C. respectively. However, the VDOT data did not include local roadways. I used open data portal of Arlington County, City of Alexandria to get the shapefile of local roadway near to the trail routes. Once I calculated the shortest distance from all roadway classifications, I aggregated the interstate and freeway, principal arterial and minor arterial, major collector and minor collector and calculated the shortest distance based on the minimum distance calculated earlier among the two roadway classifications. Also, I spatially aggregated the shortest distance to specify the shortest distance to nearest roadway according to the classification for each trail route segment. I categorized the roadway distances to less than 50m, 50-100m, 100-200m, 200-300m, 300-400m, 400-500m, 500-1000m, 1000-1500m, and above 1500m. I generated the boxplot for each air pollution measurement for each trail for morning and afternoon period using JMP Pro Graph Builder.

2.4.4 Summary Statistics of All Variables

Table 7 shows the summary statistics for all the variables along with the unit of each variable-

Table 7: Summary statistics of all variables

	Unit	Mean	std	Min	25%[a]	50%[a]	75%[a]	Max
Dependent Variables								
$PM_{2.5}$	µg/m^3	15.83	5.92	5.93	12.81	15.05	17.59	42.13
Particle number	pt/cc	10051.79	4682.11	3332.43	6088.17	9694.26	12928.23	33480.34
Black carbon	ng/m^3	602.79	236.67	-111.08	423.56	599.30	779.52	1274.36
Independent Variables								
Commercial	meter	416.21	292.82	6.85	187.50	368.61	566.60	1454.34
Parks	meter	55.98	107.29	0.00	0.00	0.81	46.33	547.76
Recreational	meter	810.18	450.04	7.20	454.83	738.79	1184.97	1741.86
Residential	meter	268.21	419.38	1.42	48.76	93.78	238.79	1757.23
AADT		37309.68	32174.60	0.00	13929.35	28357.00	58062.02	138465.21
Building Density100		0.04	0.06	0.00	0.00	0.03	0.07	0.38
Building Density1000		0.13	0.06	0.01	0.08	0.13	0.16	0.31
Building Density200		0.07	0.06	0.00	0.02	0.06	0.10	0.29
Building Density300		0.09	0.06	0.00	0.04	0.08	0.13	0.29
Building Density400		0.10	0.06	0.00	0.05	0.09	0.14	0.28
Building Density50		0.03	0.05	0.00	0.00	0.00	0.05	0.39
Building Density500		0.10	0.06	0.00	0.06	0.10	0.14	0.30

Built Environment 100	percentage	0.01	0.01	0.00	0.00	0.00	0.01	0.04
Built Environment 1000	percentage	0.01	0.01	0.00	0.01	0.01	0.01	0.03
Built Environment 200	percentage	0.01	0.01	0.00	0.00	0.01	0.01	0.03
Built Environment 300	percentage	0.01	0.01	0.00	0.00	0.01	0.01	0.03
Built Environment 400	percentage	0.01	0.01	0.00	0.00	0.01	0.01	0.03
Built Environment 50	percentage	0.01	0.01	0.00	0.00	0.00	0.01	0.07
Built Environment 500	percentage	0.01	0.01	0.00	0.00	0.01	0.01	0.03
Human 100	percentage	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Human 1000	percentage	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Human 200	percentage	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Human 300	percentage	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Human 400	percentage	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Human 50	percentage	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Human 500	percentage	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Nature 100	percentage	0.03	0.02	0.00	0.02	0.04	0.04	0.08
Nature 1000	percentage	0.03	0.01	0.01	0.02	0.03	0.04	0.06
Nature 200	percentage	0.04	0.02	0.00	0.02	0.03	0.05	0.08
Nature 300	percentage	0.03	0.02	0.00	0.03	0.03	0.04	0.08
Nature 400	percentage	0.04	0.02	0.00	0.03	0.03	0.04	0.08
Nature 50	percentage	0.03	0.02	0.00	0.02	0.04	0.05	0.08
Nature 500	percentage	0.03	0.02	0.00	0.03	0.03	0.04	0.08
Transport Network 100	percentage	0.04	0.01	0.00	0.04	0.05	0.05	0.06
Transport Network 1000	percentage	0.05	0.01	0.01	0.04	0.05	0.05	0.06
Transport Network 200	percentage	0.04	0.01	0.00	0.04	0.05	0.05	0.06
Transport Network 300	percentage	0.04	0.01	0.00	0.04	0.05	0.05	0.06
Transport Network 400	percentage	0.04	0.01	0.00	0.04	0.05	0.05	0.06
Transport Network 50	percentage	0.04	0.02	0.00	0.04	0.05	0.05	0.07
Transport Network 500	percentage	0.04	0.01	0.00	0.04	0.05	0.05	0.06
Transport Vehicles 100	percentage	0.00	0.00	0.00	0.00	0.00	0.01	0.01
Transport Vehicles 1000	percentage	0.01	0.00	0.00	0.01	0.01	0.01	0.01
Transport Vehicles 200	percentage	0.00	0.00	0.00	0.00	0.00	0.01	0.01

Transport Vehicles 300	percentage	0.01	0.00	0.00	0.00	0.01	0.01	0.01
Transport Vehicles 400	percentage	0.01	0.00	0.00	0.00	0.01	0.01	0.01
Transport Vehicles 50	percentage	0.00	0.00	0.00	0.00	0.00	0.01	0.01
Transport Vehicles 500	percentage	0.01	0.00	0.00	0.00	0.01	0.01	0.01
Vegetation 100	percentage	0.05	0.02	0.00	0.04	0.05	0.07	0.11
Vegetation 1000	percentage	0.05	0.01	0.02	0.04	0.05	0.06	0.08
Vegetation 200	percentage	0.05	0.02	0.00	0.04	0.05	0.07	0.10
Vegetation 300	percentage	0.05	0.02	0.00	0.04	0.05	0.06	0.10
Vegetation 400	percentage	0.05	0.02	0.00	0.04	0.05	0.06	0.09
Vegetation 50	percentage	0.05	0.02	0.00	0.04	0.05	0.07	0.12
Vegetation 500	percentage	0.05	0.02	0.01	0.04	0.05	0.06	0.09
Water 100	percentage	0.00	0.01	0.00	0.00	0.00	0.00	0.03
Water 1000	percentage	0.00	0.00	0.00	0.00	0.00	0.01	0.01
Water 200	percentage	0.00	0.01	0.00	0.00	0.00	0.00	0.03
Water 300	percentage	0.00	0.01	0.00	0.00	0.00	0.00	0.03
Water 400	percentage	0.00	0.01	0.00	0.00	0.00	0.01	0.02
Water 50	percentage	0.00	0.01	0.00	0.00	0.00	0.00	0.03
Water 500	percentage	0.00	0.01	0.00	0.00	0.00	0.01	0.02
Weighted Population50		2912.13	1943.51	0.00	1484.25	3219.58	4592.80	6450.86
Weighted Population100		2948.55	1880.08	1.00	1709.52	3234.87	4377.92	6487.00
Weighted Population200		3001.82	1786.45	1.00	1799.48	3284.37	4193.53	6459.12
Weighted Population300		3045.32	1715.84	3.86	2062.65	3311.85	4212.29	6696.05
Weighted Population400		3084.98	1653.42	9.34	2329.24	3326.77	4174.26	6878.32
Weighted Population500		3125.97	1600.56	28.07	2443.69	3354.45	4128.51	7011.90
Weighted Population1000		3250.76	1522.07	55.67	2683.95	3545.46	4347.23	7236.92
Road Density100		0.13	0.09	0.00	0.07	0.13	0.19	0.39
Road Density1000		0.18	0.14	0.00	0.11	0.14	0.16	0.74
Road Density200		0.16	0.19	0.00	0.07	0.10	0.18	1.06
Road Density300		0.23	0.28	0.00	0.09	0.18	0.23	1.83
Road Density400		0.13	0.06	0.00	0.09	0.14	0.17	0.27
Road Density50		0.15	0.10	0.00	0.07	0.16	0.21	0.41
Road Density500		0.13	0.06	0.00	0.09	0.14	0.17	0.25
Cooking Place		0.01	0.09	0.00	0.00	0.00	0.00	1.00
Parking		0.04	0.21	0.00	0.00	0.00	0.00	1.00

Tunnel	0.03	0.18	0.00	0.00	0.00	0.00	1.00
Airport	0.03	0.18	0.00	0.00	0.00	0.00	1.00
Noise wall	0.11	0.31	0.00	0.00	0.00	0.00	1.00
Construction Site	0.01	0.11	0.00	0.00	0.00	0.00	1.00

[a] percentile

2.4.5 Variable Selection from Multiple Buffer Distance

The processed independent variables included variables with multiple buffer distance from the trail route segment. I examined the Pearson's correlation co-efficient of each buffer distance of variables to identify the buffer distance that has higher correlation with the dependent variable [7].

Table 8: Correlation coefficient of building density with $PM_{2.5}$, Particle Number, and Black Carbon (highest correlation coefficients highlighted with grey)

Buffer Distance (meter)	$PM_{2.5}$	Particle Number	Black Carbon
50	0.155	0.154	-0.002
100	0.239	0.206	0.036
200	0.294	0.304	0.138
300	0.313	0.362	0.194
400	0.320	0.371	0.219
500	0.315	0.339	0.225
1000	0.328	0.225	0.232

There is a positive correlation between the building density and $PM_{2.5}$ concentration, particle number, and black carbon concentration but the magnitude varies by buffer distance. The building density also denotes the development density of that individual buffer distance. A positive correlation indicates that increasing development would result in increasing exposure to $PM_{2.5}$ due to the increase in activity [36]. For $PM_{2.5}$, I found building density at 1000 meter had the highest correlation coefficient of 0.328. For particle number and black carbon, development density at 400 meter and 1000 meter had the highest correlation coefficient of 0.371 and 0.232 respectively.

Table 9 shows the correlation coefficient of GSV variables that are related to the built environment.

Table 9: Correlation coefficient of built environment, nature, vegetation, and water with $PM_{2.5}$, Particle Number, and Black Carbon (highest correlation coefficients highlighted with grey)

Composite Variable	Buffer Distance (meter)	$PM_{2.5}$	Particle Number	Black Carbon
Built Environment	50	0.264	0.223	0.065
	100	0.258	0.207	0.003
	200	0.216	0.177	-0.071
	300	0.200	0.315	-0.026
	400	0.198	0.311	-0.034
	500	0.185	0.298	-0.037
	1000	0.191	0.312	-0.001
Nature	50	0.199	0.419	0.018
	100	0.207	0.425	0.035
	200	0.200	0.420	0.019
	300	0.166	0.380	-0.007
	400	0.158	0.371	-0.011
	500	0.171	0.380	0.000
	1000	0.245	0.440	0.062
Vegetation	50	0.141	0.031	0.197
	100	0.105	-0.021	0.207
	200	0.138	-0.008	0.242
	300	0.212	-0.033	0.282
	400	0.237	-0.016	0.303
	500	0.231	-0.022	0.290
	1000	0.148	-0.150	0.194
Water	50	-0.043	-0.068	-0.238
	100	-0.042	-0.069	-0.229
	200	-0.165	-0.159	-0.298
	300	-0.293	-0.228	-0.378
	400	-0.350	-0.277	-0.405
	500	-0.343	-0.280	-0.402
	1000	-0.296	-0.193	-0.394

There is a positive correlation of the build environment with $PM_{2.5}$ concentration and particle number. However, the relation was negative for black carbon concentration. Built environment at 50m and 300m buffer included the highest correlation coefficient of 0.264 and 0.315 for $PM_{2.5}$ concentration and particle number respectively. On the other hand, built environment at 200m buffer exhibited the highest negative correlation coefficient of -0.071 with the black carbon concentration.

I found nature at 1000m buffer of each trail route segment had the highest positive correlation with $PM_{2.5}$, particle number, and black carbon concentration. Vegetation was positively correlated with $PM_{2.5}$ and black carbon concentration. The highest positive correlation of $PM_{2.5}$ and black carbon concentration with vegetation was found at 400m buffer distance and the correlation coefficients were 0.237 and 0.303 respectively. Particle numbers had a negative correlation with vegetation at 1000m buffer distance which had the highest correlation coefficient of -0.15.

Water was negatively correlated with $PM_{2.5}$, particle number, and black carbon concentration. I found the strongest negative correlation of water with $PM_{2.5}$ and black carbon concentration at 400m buffer distance. For particle numbers the highest coefficient was found at 500m buffer distance.

Table 10: Correlation coefficients of human, transport network, and transport vehicles group at multiple buffer distance with $PM_{2.5}$, Particle Number, and Black Carbon (highest correlation coefficients highlighted with grey)

Composite Variable	Buffer Distance (meter)	$PM_{2.5}$	Particle Number	Black Carbon
Human	50	-0.075	-0.075	-0.243
	100	-0.065	-0.071	-0.234
	200	-0.157	-0.133	-0.315
	300	-0.245	-0.158	-0.338
	400	-0.303	-0.206	-0.374
	500	-0.293	-0.202	-0.385
	1000	-0.216	-0.103	-0.405

Composite Variable	Buffer Distance (meter)	$PM_{2.5}$	Particle Number	Black Carbon
Transport Network	50	0.559	0.548	0.458
	100	0.565	0.555	0.470
	200	0.613	0.589	0.473
	300	0.622	0.620	0.456
	400	0.631	0.624	0.450
	500	0.630	0.626	0.439
	1000	0.596	0.611	0.396
Transport Vehicles	50	0.479	0.364	0.272
	100	0.462	0.371	0.279
	200	0.308	0.230	0.117
	300	0.376	0.327	0.179
	400	0.330	0.264	0.162
	500	0.297	0.216	0.125
	1000	0.311	0.254	0.134

The human variable group was negatively correlated with all the pollutants. For $PM_{2.5}$ and particle numbers, the correlation coefficient was high at 400m buffer distance. For black carbon concentration, the highest correlation coefficient was found at 1000m buffer distance.

I found the transportation network variable to be positively correlated with all pollutants. Among all these variable groups, transportation network showed the strongest correlation with $PM_{2.5}$, particle number, and black carbon concentration. The highest correlation was found at 400m buffer distance for $PM_{2.5}$ concentration, 500m buffer distance for particle number, and 200m buffer distance for black carbon concentration.

Transportation vehicles also demonstrated positive correlation while the strongest positive correlation was found at 100m buffer distance for particle number and black carbon concentration. For $PM_{2.5}$, I observed the highest correlation coefficient of 0.479 at 50m buffer distance.

Table 11: Correlation coefficients of weighted population and road density group at multiple buffer distance with $PM_{2.5}$, Particle Number, and Black Carbon (highest correlation coefficients highlighted with grey)

Composite Variable	Buffer Distance (meter)	$PM_{2.5}$	Particle Number	Black Carbon
Weighted Population	50	0.107	-0.212	0.228
	100	0.121	-0.208	0.240
	200	0.139	-0.195	0.252
	300	0.150	-0.185	0.258
	400	0.159	-0.181	0.266
	500	0.163	-0.185	0.283
	1000	0.185	-0.182	0.318
Road Density	50	0.508	0.388	0.209
	100	0.477	0.353	0.242
	200	0.014	0.104	-0.188
	300	0.101	0.113	-0.098
	400	0.481	0.280	0.182
	500	0.466	0.261	0.168
	1000	0.122	0.022	-0.015

Weighted population was positively correlated with $PM_{2.5}$ and black carbon concentrations and the highest correlation was found at 1000m buffer distance. However, it was negatively correlated with the particle number and the highest correlation was observed at 50m buffer distance. Road density was positively correlated with $PM_{2.5}$ and particle number. However, it showed a mostly positive correlation with black carbon concentration. Road density at 50m buffer distance was highly correlated with $PM_{2.5}$ and particles number where the correlation of black carbon and road density was highest at 100m buffer distance.

2.4.6 Multicollinearity

Before I ran the stepwise regression models for variable selection, I checked for multicollinearity for all the candidate variables selected for the three stepwise regression model. Multicollinearity could lead to a higher standard error in terms of coefficient estimate resulting in bias to interpret the significance due to the linear correlation among the explanatory variables [33, 44]. I used VIF to eliminate the multicollinearity issue considering a VIF value higher than 10 would demonstrate multicollinearity and excluded variables with VIF higher than 10 [33].

Table 12: VIF of all candidate variables for modelling $PM_{2.5}$ (variables with VIF>10 highlighted with grey)

All candidate variables		Eliminating variable with VIF>10	
Variable Name	**VIF**	**Variable Name**	**VIF**
Commercial	3.36	Commercial	2.95
Parks	2.28	Parks	2.05
Recreational	1.85	Recreational	1.64
Residential	8.24	Residential	6.35
AADT	1.81	AADT	1.51
Building density 1000m	5.95	Building density 1000m	2.73
Built environment 50m	1.32	Built environment 50m	1.27
Human 400m	13.17	Transport Vehicle 50m	1.48
Nature 1000m	14.87	Vegetation 400m	1.83
Transport Network 400m	15.38	Weighted Population 1000m	4.71
Transport Vehicle 50m	2.06	Road Density 50m	2.17
Vegetation 400m	4.22	Cooking place	1.59
Water 400m	13.38	Parking	1.28
Weighted Population 1000m	5.41	Tunnel	1.09
Road Density 50m	2.26	Airport	1.58
Cooking place	1.61	Wall	1.80
Parking	1.31	Construction Site	1.44
Tunnel	1.10		
Airport	1.81		
Wall	1.85		
Construction Site	1.48		

Table 12 shows that human at 400m buffer, nature at 1000m buffer, transport network at 400m buffer, and water at 400m buffer had VIF value more than 10. The candidate variables for the stepwise regression model had VIF value less than 10 where the highest VIF value was observed for distance from residential land use which was the only variable with VIF value higher than 5. Other than that, all variables had a VIF value less than 5.

Table 13: VIF of all candidate variables for modelling particle number (variables with VIF>10 highlighted with grey)

All candidate variables		Eliminating variable with VIF>10	
Variable Name	**VIF**	**Variable Name**	**VIF**
Commercial	3.52	Commercial	2.87
Parks	2.07	Parks	1.92
Recreational	1.76	Recreational	1.66
Residential	7.74	Residential	5.09
AADT	1.83	AADT	1.55
Building density 400m	5.81	Building density 400m	4.14
Built environment 300m	3.80	Built environment 300m	2.86
Human 400m	10.52	Transport Vehicle 100m	1.80
Nature 1000m	12.50	Vegetation 1000m	1.88
Transport Network 500m	12.37	Weighted Population 50m	3.24
Transport Vehicle 100m	2.36	Road Density 50m	1.97
Vegetation 1000m	4.88	Cooking place	1.60
Water 500m	12.76	Parking	1.27
Weighted Population 50m	3.66	Tunnel	1.06
Road Density 50m	2.18	Airport	1.59
Cooking place	1.61	Wall	1.55
Parking	1.28	Construction Site	1.44
Tunnel	1.07		
Airport	1.98		
Wall	1.60		
Construction Site	1.47		

Table 13 shows similar VIF values with human at 400m buffer, nature at 1000m buffer, transportation network at 500m buffer, and water at 500m buffer distance having VIF value more than 10. After eliminating these variables, only distance from residential land use had a VIF value higher than 5. So, there was no serious multicollinearity issue.

Table 14 shows VIF values for all the candidate variables of black carbon were less than 10 indicating no serious multicollinearity among the variables. Distance from residential land use had the highest VIF of 7.56 followed by transport network at 200m buffer distance. Nature at 1000m buffer distance also included VIF more than 5.

Table 14: VIF of all candidate variables for modelling black carbon concentration

Variable Name	VIF	Variable Name	VIF
Commercial	3.34	Transport Vehicle 100m	2.34
Parks	2.13	Vegetation 400m	3.36
Recreational	1.86	Water 400m	3.74
Residential	7.56	Weighted Population 1000m	5.21
AADT	1.91	Road Density 100m	2.28
Building density 1000m	5.64	Cooking place	1.60
Built environment 200m	2.28	Parking	1.30
Human 1000m	4.66	Tunnel	1.11
Nature 1000m	7.38	Airport	1.82
Transport Network 200m	7.55	Wall	1.81
Construction Site	1.52		

2.4.7 Stepwise Regression Model

Once I identified the candidate variables for the estimation of $PM_{2.5}$, particle number, and black carbon concentration, I used stepwise regression model for variable selection for the Ordinary Least Square regression model. I conducted the forward stepwise regression model in JMP Pro and selected variables which had a p-value less than 0.1 [45, 46]. The forward selection model started with the intercept term only and added variables to the model by selecting the variable with lowest p-value one at a time. The model continues until it added all the variables with p-value less than 0.1.

Chapter 3: Data Analysis

This chapter includes the analysis of air quality on all the trails used for data collection in this study. The air quality for each trail section provides an in-depth analysis of $PM_{2.5}$, particle number, and black carbon concentration in the selected trail routes during two weekday peak hour and weekend peak hour. The distance from different types of streets and land uses show the change in air quality related to the change in distance. Finally, the regression model section focuses on the traffic related, built environment characteristics, trail specific factors that impact the air quality in trails.

3.1 Air Quality on Trails

The average concentration of $PM_{2.5}$ during the data collection period was 15.62 µg/m^3 where the average background concentration was 5.75 µg/m^3 which indicate a higher concentration along the trails. The average black carbon concentration estimate was 595.36 ng/m^3 and I found the average concentration of the particle number to be 9857 pt/cc. The average concentration varied by trail and also by the data collection at different peak hours. In general, the pollutant concentration was higher during the weekday, and it decreased around 43%, 57%, 57% for black carbon, $PM_{2.5}$, and particle number concentration respectively at the weekend. The background concentration changed around 18.5% from weekdays to weekends. Similarly, pollutant concentrations were higher during morning peak hours than the afternoon peak hours.

3.1.1 Capital Crescent Trail

Among all the trail routes, Capital Crescent Trail had the lowest pollutant concentration. The average concentration of $PM_{2.5}$ was 8.66 µg/m^3 while the afternoon average was higher than the morning average. The afternoon average of $PM_{2.5}$ was 9.15 µg/m^3 and the morning concentration was 6.58 μg/m^3 -28% lower than the afternoon average. This could be due to the background concentration was lower for the morning data collection period (1.20 μg/m^3) comparing to the afternoon background concentration (4.98 μg/m^3). The weekend concentration was 8.54 μg/m^3 while the weekday concentration was slightly higher (8.71 μg/m^3). The background concentration during the weekend and weekday was also similar which were 4.24 and 4.31 μg/m^3 respectively. Similarly, the black carbon concentration was higher during the afternoon (436.55 ng/m^3) where the morning concentration was 33% lower. However, the opposite was found for the particle number concentration. The particle number concentration was 5946 pt/cc during the morning and 4940 pt/cc at the afternoon peak. The average particle number concentration was also higher during the weekend and lower on the weekdays.

Figure 4 shows the concentration of each pollutant for all the segments of the Capital Crescent Trail route. The segments with higher concentration of $PM_{2.5}$ were adjacent to parking lots, cooking places, near the Chain Bridge, and at the entrance of Dalecarlia tunnel while travelling towards North-West direction. The first few segments while travelling in North-West direction also had higher concentrations which could be due to the congestion at M Street NW while entering to the Key Bridge. Particle number concentration also showed a similar characteristic for parking, cooking areas, and congestion. The concentration was the lowest after crossing the Chain Bridge adjacent to freeway or expressway. This may also explain the higher black carbon concentration adjacent to Chain Bridge. Some trail routes with higher Black Carbon concentration were located adjacent to residential housing. Although, black carbon and $PM_{2.5}$ concentrations had similarities, the particle number concentration was lower near Chain Bridge as there was difference in elevation of the freeway and trail route [47].

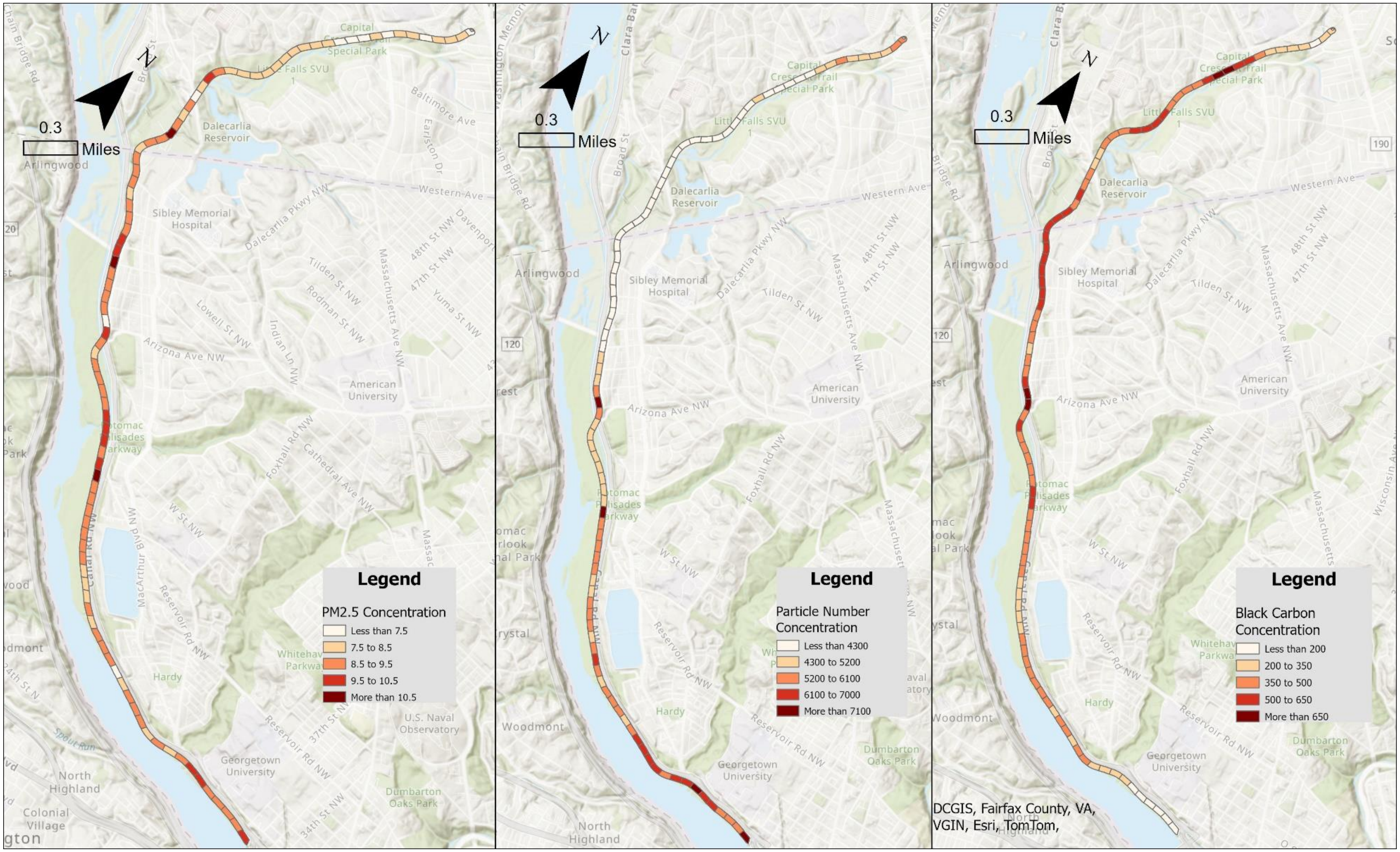

Figure 4: $PM_{2.5}$ ($\mu g/m^3$), Particle Number (pt/cc), and Black Carbon (ng/m^3) concentration at each segment along Capital Crescent Trail Route (from left to right)

3.1.2 Custis and W&OD Trail

Running parallel to the interstate highway this trail route had the highest pollutant concentration of $PM_{2.5}$, black carbon, and particle number which were- 23.66 μg/m^3, 842.74 ng/m^3, and 14155 pt/cc respectively despite the background $PM_{2.5}$ concentration was the second lowest among all trail routes. This may be related to the impact the interstate highway might have on trail air quality. Pollutant concentrations were also higher during the morning and lower during the afternoon data collection period. The average black carbon concentrations were 1860.69 and 610.92 ng/m^3, average $PM_{2.5}$ concentrations were 34.25 and 21.25 μg/m^3, average particle number concentrations were 31609 and 10181 pt/cc during morning and afternoon peak hours respectively. The morning background concentration of $PM_{2.5}$ was also higher than the afternoon concentration which was about 45.68% increase than the afternoon concentration. The weekday and weekend concentrations were also different where the weekday concentrations were higher than the weekday. Black carbon and $PM_{2.5}$ concentrations were around 3-fold and 4-fold higher respectively on weekdays than weekends. On the other hand, the weekday particle number concentration was also around 4-fold higher than weekend concentration. The background concentration of $PM_{2.5}$ was about 9-fold higher for weekdays than weekends.

Despite having noise walls separating the trail from the highway, this trail segment had higher concentrations of pollutants as this route was adjacent to the interstate highway. Previous studies also found higher air pollution concentrations adjacent to the interstate highway with having sound walls [7]. The segments with highest $PM_{2.5}$ concentrations were near to Bon Air Park at a cooking place and near Rosslyn at the intersection of multiple roads and frequent congestion. The particle number concentration was higher at the segments adjacent to the I-66 toll road with free traffic flow resulting in complete combustion increasing particle number [14].

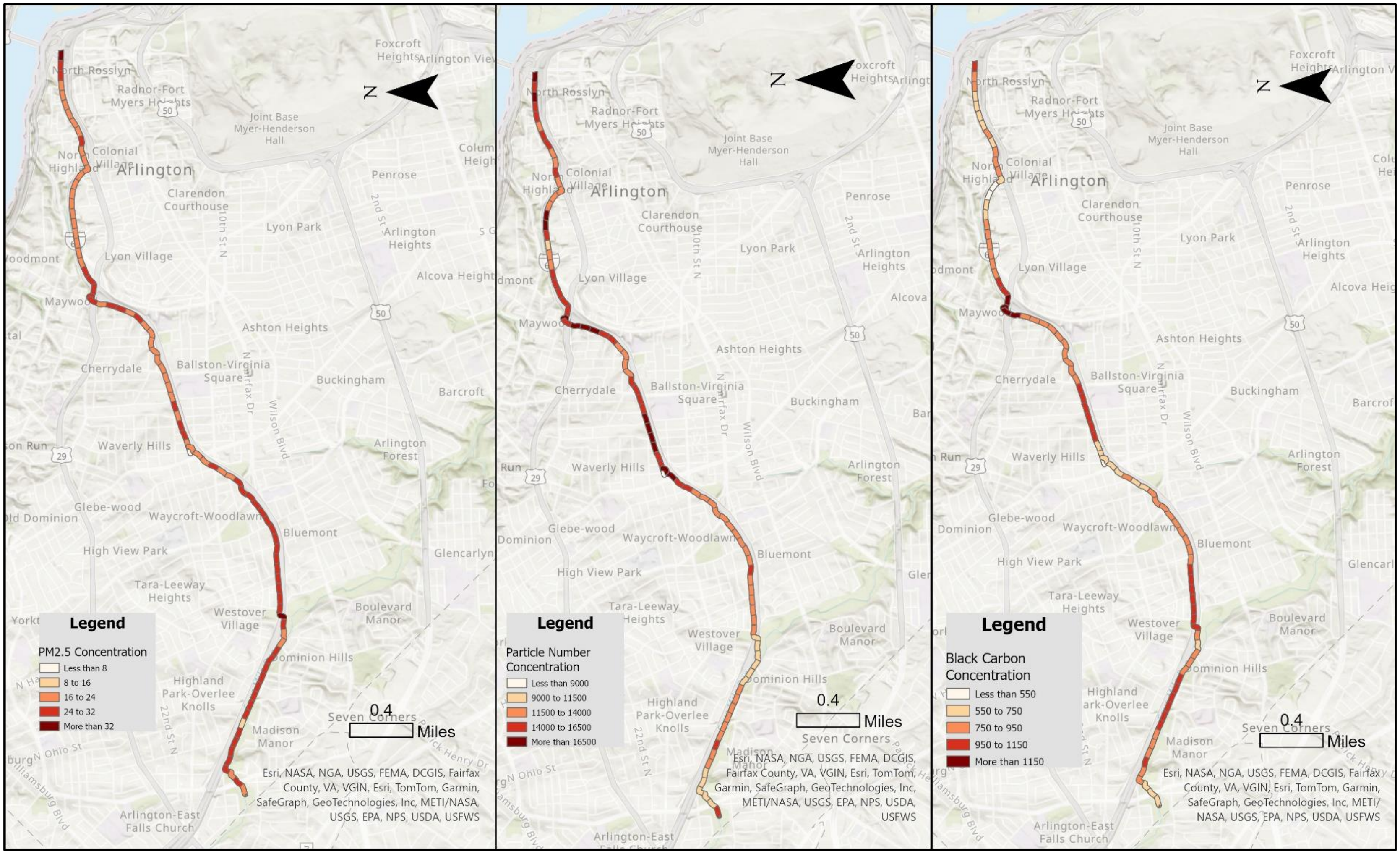

Figure 5: PM$_{2.5}$ (µg/m^3), Particle Number (pt/cc), and Black Carbon (ng/m^3) concentration at each segment along the Custis and W&OD Trail Route (from left to right)

3.1.3 Mount Vernon Trail

The Mount Vernon Trail runs parallel to the George Washington Memorial Parkway which serves the function of a freeway and major arterial had the second lowest concentration of pollutant concentrations. The average $PM_{2.5}$ concentration was 15.12 µg/m^3 and the background average concentration was 6.18 µg/m^3. The average black carbon and particle number concentrations were 557.6 ng/m^3 and 12163 pt/cc respectively. Similarity was found in terms of morning and afternoon average of pollutant concentrations. $PM_{2.5}$, black carbon, and particle number concentrations were 13.08 µg/m^3, 394.56 ng/m^3, and 8808 pt/cc respectively during the afternoon period. On the other hand, the morning time concentrations of $PM_{2.5}$, black carbon, and particle number were 20.17 µg/m^3, 961.98 ng/m^3, and 20487 pt/cc respectively. Besides that, the morning background concentration of $PM_{2.5}$ was also about 2-times higher than the afternoon average background concentration. I also found the weekday concentration of pollutants was higher than the weekend average concentration.

Mostly the trail segments with higher $PM_{2.5}$ concentrations as shown in **Figure 6** were at the parking lot of Theodore Roosevelt Island Bridge, the road crossing near the airport where vehicles came to a full stop at the stop sign, and near to the traffic signal at the end of the trail route near Alexandria. Particle number concentration was higher near to the airport and highest adjacent to the runway while other segments had a lower concentration for this trail route. Black carbon concentration was also higher adjacent to the airport and at the beginning of the trail route at Rosslyn could be the result of higher traffic concentration as found in previous study [6], and near to the parking lot of Theodore Roosevelt Island.

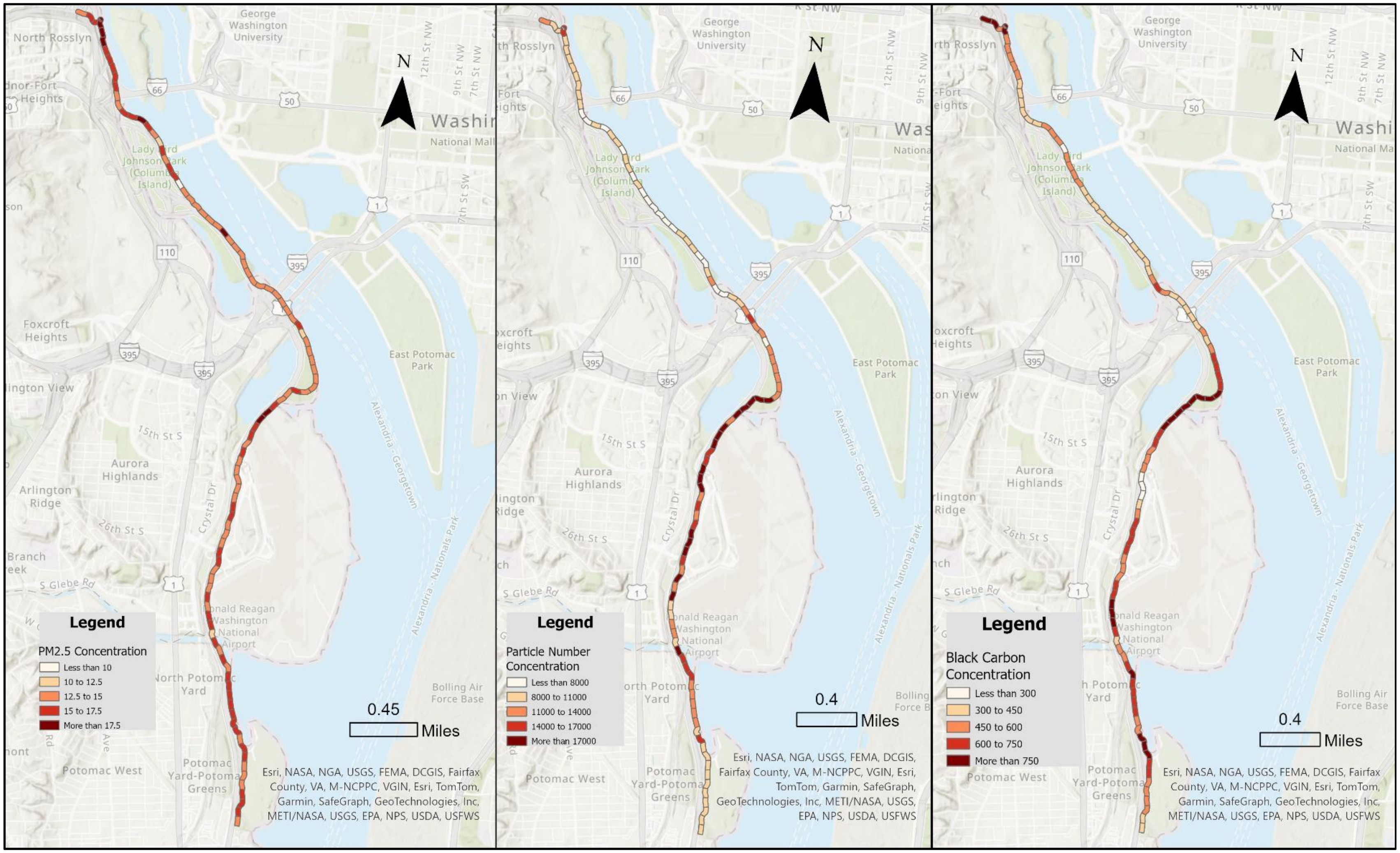

Figure 6: $PM_{2.5}$ ($\mu g/m^3$), Particle Number (pt/cc), and Black Carbon (ng/m^3) concentration at each segment along the Mount Vernon Trail Route (from left to right)

3.1.4 Rock Creek Trail

Rock Creek Trail had similarity with the Mount Vernon Trail as both of them mostly run inside the park with waterbody with a highway parallel to it. Unlike Custis Trail, both trails do not have any noise wall to separate the trail users from the roadway. The physical distance from the road was around 100 meters. The roadway running parallel to the Rock Creek Trail has functional classification of major arterial and minor arterial. However, few segments of Rock Creek Trail are further away from the roadway when the trail runs inside the national zoo. The average $PM_{2.5}$, black carbon, and particle number concentrations were 14.57 $\mu g/m^3$, 540.41 ng/m^3, and 8368 pt/cc. Similar to the general pattern of morning and afternoon concentration, the morning concentration of pollutants was higher than the afternoon concentration. However, the background average concentration of morning $PM_{2.5}$ was higher than the afternoon concentration. The average afternoon [morning] concentrations of $PM_{2.5}$, black carbon, and particle number were- 14.15 $\mu g/m^3$ [15.33 $\mu g/m^3$], 444.71 ng/m^3 [714.04 ng/m^3], and 8286 pt/cc [8517 pt/cc] respectively. The average concentration of black carbon and particle number was higher during the weekday than weekend. However, the weekend concentration (15.59 $\mu g/m^3$) of $PM_{2.5}$ was higher than the weekday concentration (14.11 $\mu g/m^3$). Also, the background concentration of $PM_{2.5}$ was higher during the weekend (7.24 $\mu g/m^3$) than weekend (5.55 $\mu g/m^3$).

Figure 7 shows the three segments of Rock Creek Trail where $PM_{2.5}$ concentration was higher, and these segments included the intersection of trail and roadway with higher traffic concentrations. The segments with the highest concentration of particle number were located adjacent to Rose Park in Washington D.C.

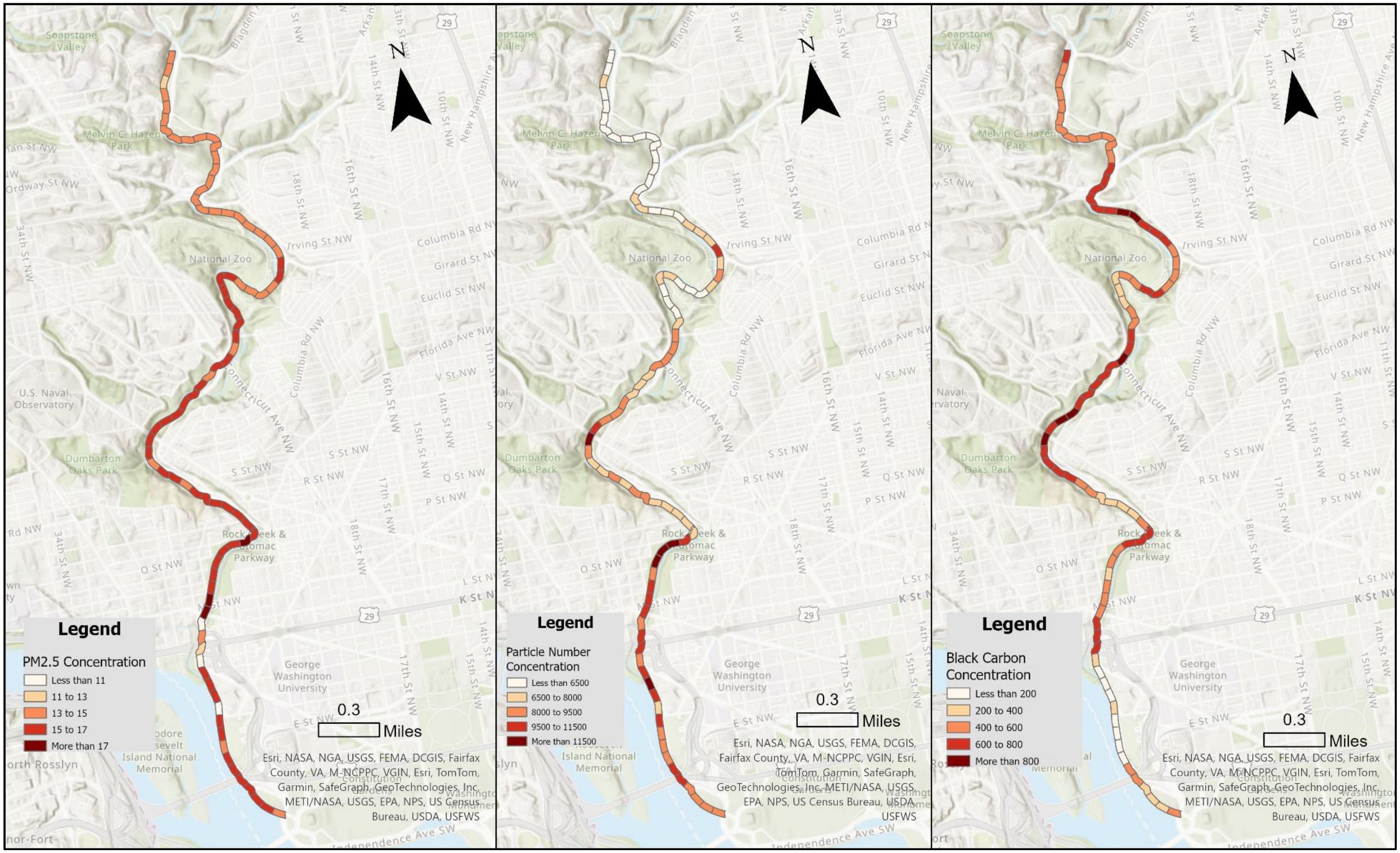

Figure 7: $PM_{2.5}$ ($\mu g/m^3$), Particle Number (pt/cc), and Black Carbon (ng/m^3) concentration at each segment along the Rock Creek Trail Route (from left to right)

3.1.5 W&OD Trail

The W&OD Trail route was the smallest among all trail routes identified for this study. This trail runs inside a park which has mostly local roads in proximity. However, there was an active construction site along the trail route during the study period. This trail route had the second highest concentration of $PM_{2.5}$ and black carbon among all trail routes which could be due to the construction site and frequent cooking spaces along the trail. The average concentrations of $PM_{2.5}$, black carbon, and particle number were 19.37 µg/m^3, 793.28 ng/m^3, and 9545 pt/cc respectively. The average weekday concentration was higher for black carbon and $PM_{2.5}$ but it was lower for particle number concentration than weekend.

Figure 8 shows the start and end point of the construction site. $PM_{2.5}$ concentration and particle number concentration were the highest adjacent to the construction sites which demonstrates the impact of construction site on the overall air quality to its proximity.

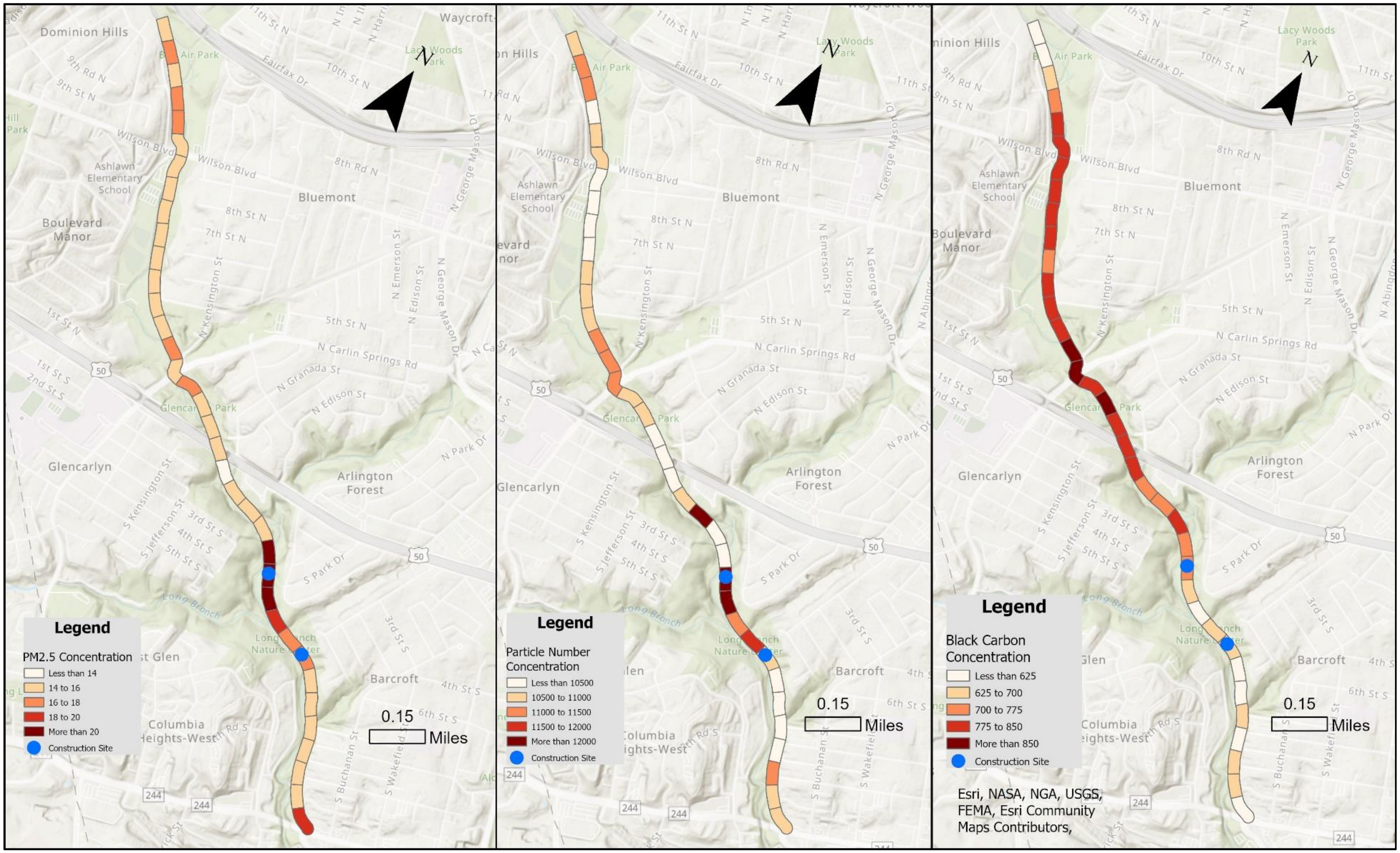

Figure 8: $PM_{2.5}$ ($\mu g/m^3$), Particle Number (pt/cc), and Black Carbon (ng/m^3) concentration at each segment along the W&OD Trail Route (from left to right)

3.1.6 Comparative Statistical Analysis

I checked the histogram and normal Q-Q plots of $PM_{2.5}$, particle number, and black carbon concentration and found that $PM_{2.5}$ and particle number did not follow a normal distribution, but these two concentrations closely aligned with a log-transformed distribution. However, the black carbon concentration aligned with the normal distribution. To check if the air quality along different trails varied with different trail settings, I conducted a nonparametric Kruskal-Wallis test for $PM_{2.5}$ and particle number concentration and a student *t*-test to compare the means of each trail route pair selected for this study.

3.1.6.1 Kruskal-Wallis Test

I used the 100-m spatially aggregated concentrations of $PM_{2.5}$ and particle number for this test. The hypotheses for the Kruskal-Wallis test were-

H_0: There is no difference in the pollutant concentration among the trail routes

H_A: The pollutant concentration differs for at least one of the trail routes

Table 15: Kruskal-Wallis test result for $PM_{2.5}$

Trail Route	Trail Route	Score Mean Difference	Standard Error Difference	Z	p-Value
Mount Vernon Trail	Capital Crescent Trail	96.42	8.10	11.91	<.0001
Custis and W&OD Trail	Capital Crescent Trail	89.01	7.81	11.40	<.0001
Rock Creek Trail	Capital Crescent Trail	88.95	7.75	11.48	<.0001
W&OD Trail	Capital Crescent Trail	64.48	7.28	8.86	<.0001
W&OD Trail	Mount Vernon Trail	19.32	7.77	2.49	0.0129

W&OD Trail	Rock Creek Trail	15.52	7.05	2.20	0.0278
Rock Creek Trail	Mount Vernon Trail	-0.08	8.01	-0.01	0.9915
W&OD Trail	Custis and W&OD Trail	-53.98	7.19	-7.51	<.0001
Rock Creek Trail	Custis and W&OD Trail	-85.89	7.70	-11.15	<.0001
Mount Vernon Trail	Custis and W&OD Trail	-91.93	8.06	-11.41	<.0001

Table 15 shows that there is no difference (p=0.99) in the $PM_{2.5}$ concentration of Rock Creek Trail and Mount Vernon Trail. This can be due to the similarity in the functional classification of adjacent street. Other than that, the $PM_{2.5}$ concentration was different for each trail route pair.

Table 16: Kruskal-Wallis test result for particle number concentration

Trail Route	Trail Route	Score Mean Difference	Standard Error Difference	Z	p-Value
Mount Vernon Trail	Capital Crescent Trail	94.42	8.10	11.66	<.0001
Custis and W&OD Trail	Capital Crescent Trail	88.97	7.81	11.39	<.0001
Rock Creek Trail	Capital Crescent Trail	75.22	7.75	9.71	<.0001
W&OD Trail	Capital Crescent Trail	64.48	7.28	8.86	<.0001
W&OD Trail	Rock Creek Trail	48.23	7.05	6.84	<.0001
W&OD Trail	Mount Vernon Trail	-1.10	7.77	-0.14	0.8873
Mount Vernon Trail	Custis and W&OD Trail	-34.32	8.06	-4.26	<.0001
W&OD Trail	Custis and W&OD Trail	-50.21	7.19	-6.99	<.0001
Rock Creek Trail	Mount Vernon Trail	-56.72	8.01	-7.08	<.0001
Rock Creek Trail	Custis and W&OD Trail	-79.56	7.70	-10.33	<.0001

Table 16 shows that the p-value is greater than 0.05 for W&OD Trail and Mount Vernon Trail routes which shows that we fail to reject the null hypothesis and these there is no difference in particle number concentration for these two trail routes. The existence of a construction site and airport at these two trail routes could be the reason for similarity in particle number concentration. All other route pairs were different from each other.

3.1.6.2 Student *t*-test

The result of student *t*-test shows that the p-value was greater than 0.05 for Mount Vernon Trail and Rock Creek Trail. Hence, there is no difference in black carbon concentrations for these trail routes.

Table 17: Student *t*-test result for black carbon concentration

Trail Route	Trail Route	Difference	Standard Error Difference	p-Value
Custis and W&OD Trail	Capital Crescent Trail	451.92	25.66	<.0001
W&OD Trail	Capital Crescent Trail	332.52	33.69	<.0001
Custis and W&OD Trail	Rock Creek Trail	328.30	26.02	<.0001
Custis and W&OD Trail	Mount Vernon Trail	297.44	24.97	<.0001
W&OD Trail	Rock Creek Trail	208.90	33.97	<.0001
W&OD Trail	Mount Vernon Trail	178.04	33.17	<.0001
Mount Vernon Trail	Capital Crescent Trail	154.48	24.83	<.0001
Rock Creek Trail	Capital Crescent Trail	123.62	25.88	<.0001
Custis and W&OD Trail	W&OD Trail	119.40	33.80	0.0005
Mount Vernon Trail	Rock Creek Trail	30.86	25.20	0.2215

3.1.7 Summary

I found the highest average concentration of $PM_{2.5}$ along the Custis and W&OD Trail route followed by the Mount Vernon Trail route. The maximum concentration of $PM_{2.5}$ during the study period was along Custis and W&OD Trail routes during the afternoon time. The morning concentration of black carbon, particle number, and $PM_{2.5}$ was higher than the afternoon concentration. Capital Crescent Trail route showed the opposite where high concentration was found during the afternoon period, and I could not collect morning data for W&OD trail route. The higher concentration of pollutants during the morning period can be explained by the increased dilution at the afternoon time [2]. Another study found that the difference between background and roadside concentration is lower at night but starts to increase as the traffic volume and wind speed increase from early morning [48]. **Figure 9** shows the boxplot of pollutant concentration during morning and afternoon time for each trail route.

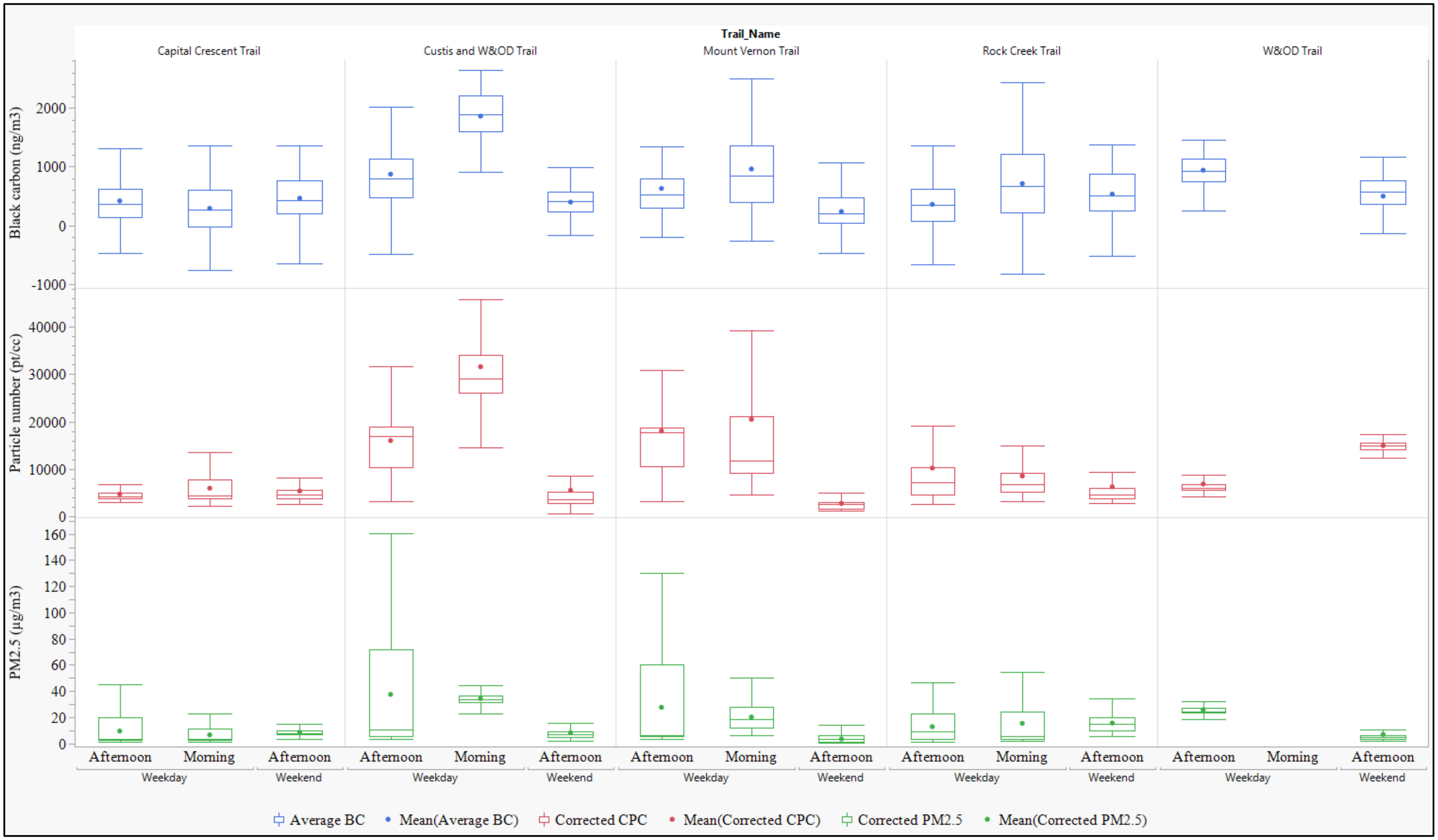

Figure 9: $PM_{2.5}$, particle number, black carbon (bottom to top) distribution along all trail routes

3.2 Trail Distance from Landuse, Street Characteristics and Particulate Concentration

To reduce the particulate matter concentration in multi-use trails, it is important to know how the concentration changes while distance from nearby traffic and other emission sources increases. This section highlights the change in particulate matter concentrations for change in distance from nearby land uses and roadway functional classification.

3.2.1 Roadway Functional Classification

Figure 10 shows the change in concentration of $PM_{2.5}$, particle number, and black carbon due to the increasing distance from different types of roadways. When the trail segment is within 50-m of an interstate or freeway the $PM_{2.5}$ concentration is 20.52 µg/m^3 and it decreases significantly (p= 0.002) to 15.88 µg/m^3 when the segment distance from nearby freeway or interstate is within 50 to 100m. But the change is not significant (p= 0.948) as the distance increases to 100-200m. However, the concentration tends to decrease till 300-400 m and increases after that but still lower than the mean and median concentration within the 100m proximity. Particle number distribution also followed a similar pattern as the distance from interstate or freeway increased. The particle number concentration changed significantly (p= 0.0102) from 0-50m bin to 50-100m bin. The median concentration decreased around 25% due to the change in distance. The median particle number concentration decreased was 1.3-fold and 2-fold higher at 0-50m bin than 200-300m bin and 300-400m bin respectively. These results support previous studies as the particle number concentration was higher at 0-50m bin and it was 1.5-folds higher than the 200-450m bin [17]. However, the black carbon concentrations did not change significantly (p= 0.2876) from 0-50m bin to 50-100m bin. A significant change was observed from 0-50m bin and 50-100m bin to 100-200m bin with p-values of <0.0001 and 0.0003 respectively. The increased concentration after 400-500m distance can be explained by the proximity to other roadways. 400-500m away from interstate or freeways trail segments were near to arterial (62.78m). The concentration was still lower than the 0-50m bin related to the AADT. Although the proximity to arterial increased, the AADT decreased resulting in lower concentrations than the 0-50m bin.

The distance of trail segment from arterial did not show variability similar to freeway or interstate. $PM_{2.5}$ and black carbon concentrations increased significantly from 0-50m bin to 400-500m bin ($p = 0.0003$ and <0.0001 respectively). This could be due to the AADT of the nearby road that was the highest among all the bins.

The concentration of $PM_{2.5}$, particle number, and black carbon decreased significantly ($p = 0.0211$, 0.0049, and 0.0018 respectively) as the distance from collector streets increased from 0-50m to 50-100m. The median concentration remains steady after that for $PM_{2.5}$. The black carbon median concentration slightly increases from 400-500m bin to 500-1000m bin.

Within the first 300m distance of local road the mean pollutant concentrations decreases for $PM_{2.5}$, particle number, and black carbon. The concentration decreases about 28%, 20%, and 30% for $PM_{2.5}$, particle number, and black carbon respectively from segments that are 0-50m away from local road to 200-300m.

The results show that moving a trail segment 100m away from different roadway would decrease the particle concentration, likely related to the increasing distance from nearby pollutant sources.

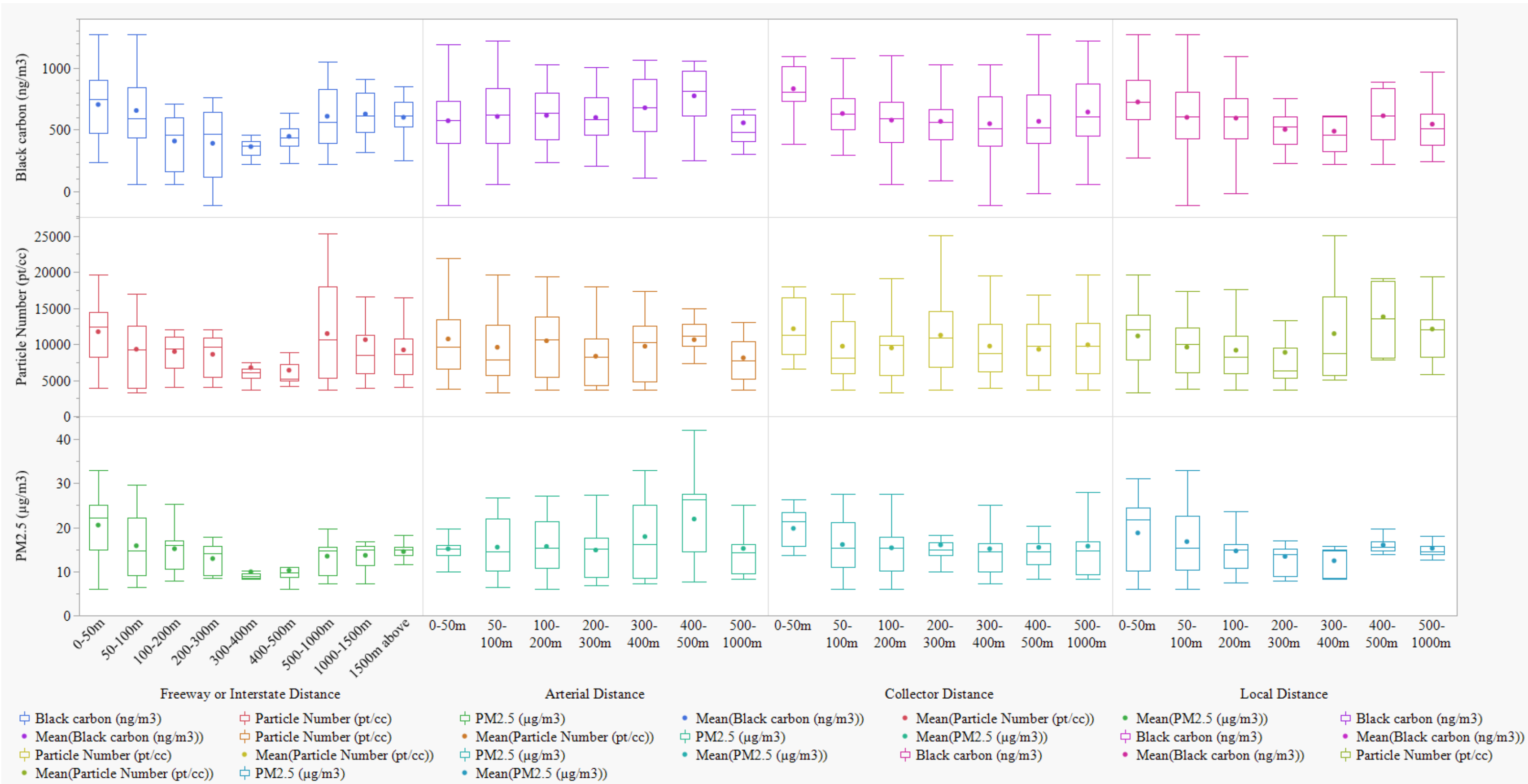

Figure 10: $PM_{2.5}$, particle number, and black carbon concentration (spatially aggregated at 100m) by functional classification of streets

3.2.2 Distance from Land Uses

Figure 11 shows the pollutant concentration as the distance from commercial, residential, park, and recreational land use increases from the trail segments. The mean and median concentration decreased gradually from 0-50m to 50-100m bin and the decrease followed to 200-300m bin for commercial land use. Initially the particle number concentration increased from 0-50m bin to 50-100m bin. However, the concentration continued to decrease from 50-100m bin to 200-300m bin. The lowest concentration was observed when the commercial land use distance was 1000 to 1500 meters. The $PM_{2.5}$ concentration decreased significantly (p=0.0055) from 0-50m distance to 50-100m distance to nearest residential landuse. The decrease in concentration was also significant (p= <0.0001) from 50-100m bin to 100-200m bin. The pattern was similar for particle number concentration where it continued to decrease until 300 to 400m. The highest particle number concentration was observed at 1000 to 1500m. This could be explained by the average AADT from nearby road which was highest when the trail segment was 1000 to 1500m away from residential land use. Black carbon concentration also decreased significantly (p=0.0439) from 0-50m bin to 50-100m bin and it followed for 100-200m bin as well. Similar to particle number concentration, 1000 to 1500m distance from residential land use had the second highest mean concentration of black carbon. Also, the $PM_{2.5}$ concentration decreased from 0-50m bin to 100-200m bin for recreational land use.

The distance from residential land use seems to influence the air quality in trails and the quality improves for trail segments at 100-200m away from residential land use.

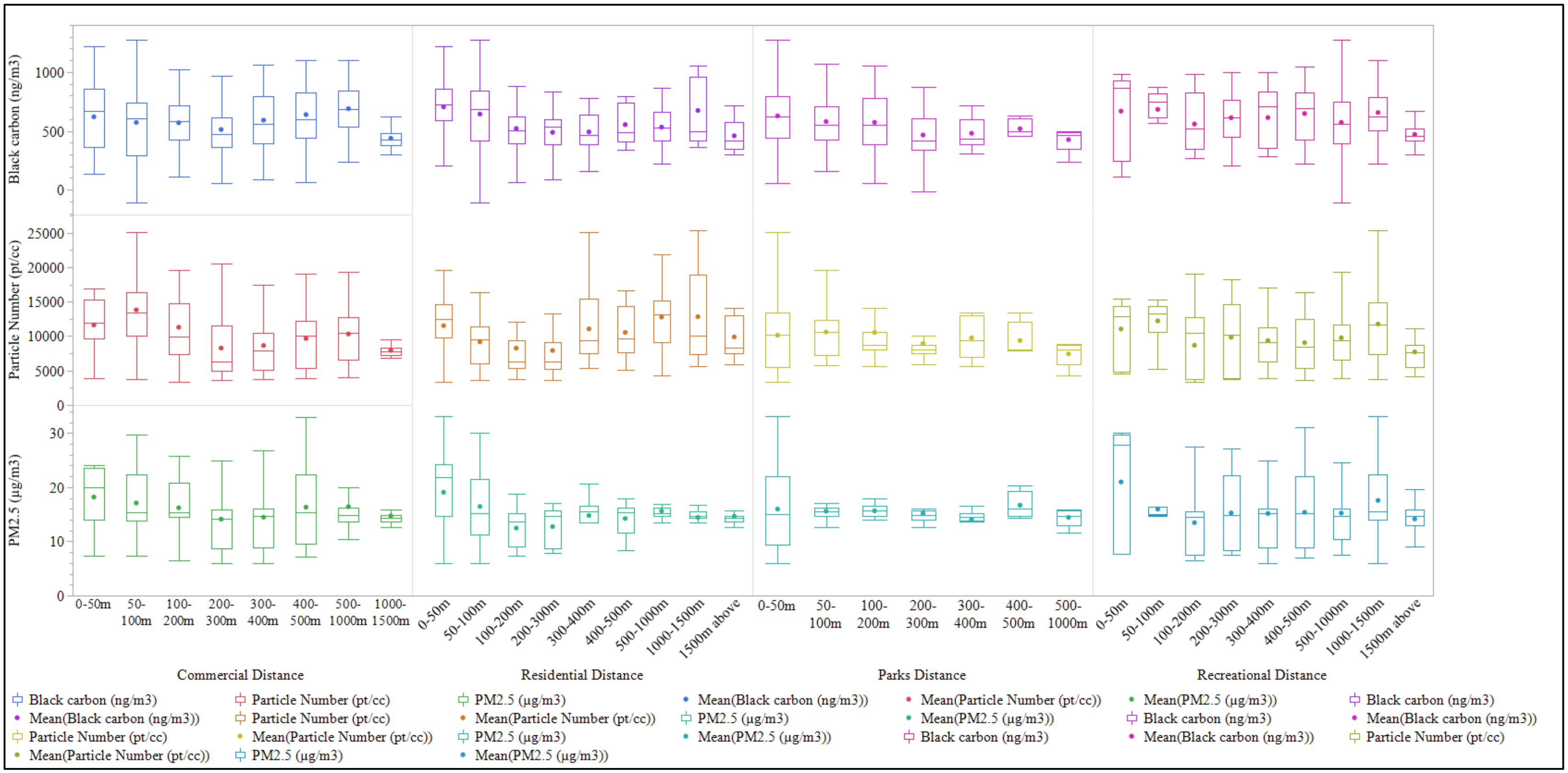

Figure 11: $PM_{2.5}$, particle number, and black carbon concentration (spatially aggregated at 100m) by distance from land use

3.2.3 Nearby Road AADT

Nearby road AADT **(Figure 12)** shows higher concentrations of pollutants for AADT under 8000 likely because of the proximity of local roads nearby (average of 115.6 meter). However, the highest concentration was found for the trail segments which had AADT more than 32000 for the nearest roadway. Previous studies also found higher concentration of ultra-fine particulate matter, carbon monoxide, and black carbon at high traffic routes [6].

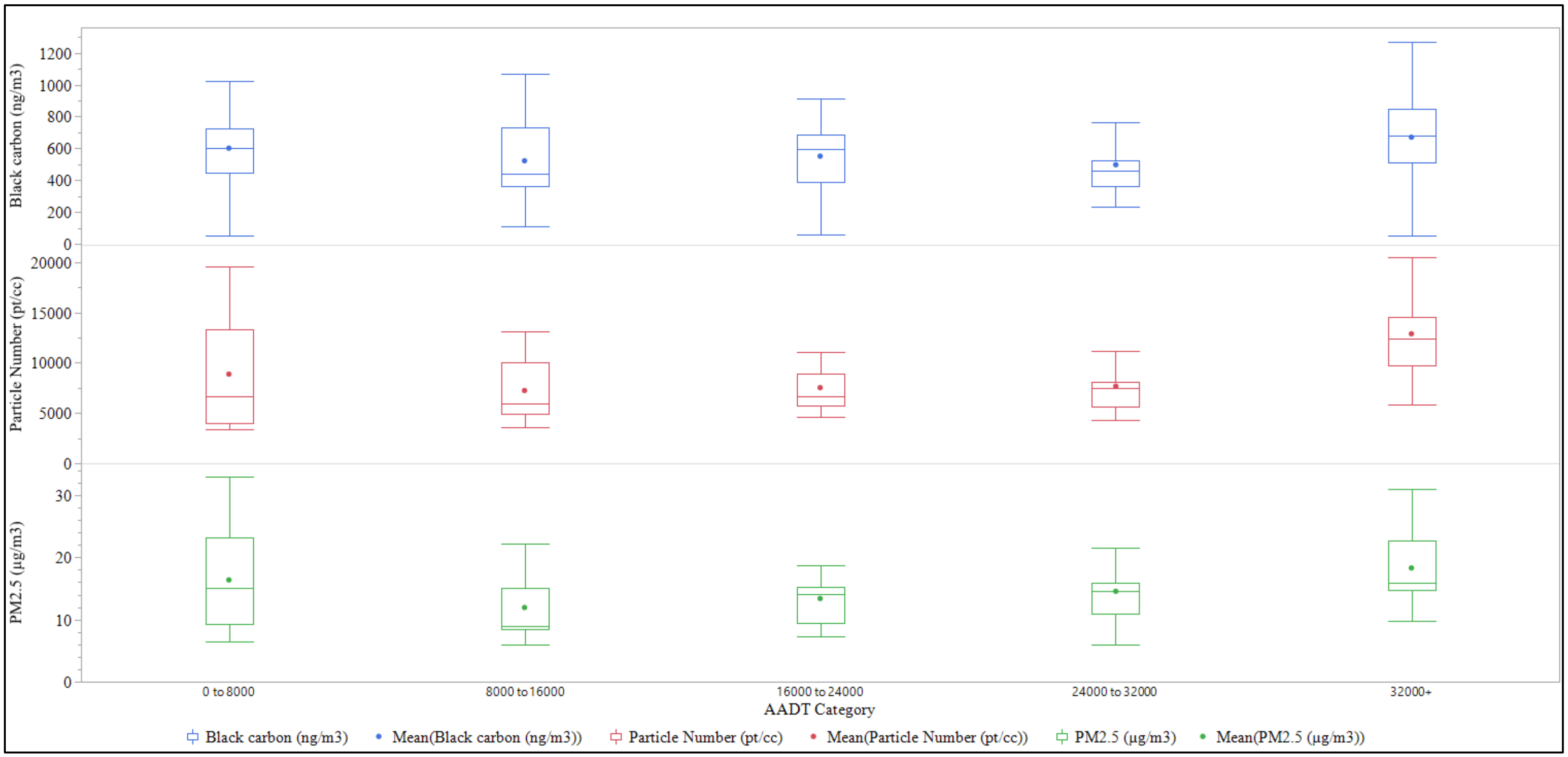

Figure 12: $PM_{2.5}$, particle number, and black carbon concentration (spatially aggregated at 100m) by road AADT

3.3 Factors Influencing Pollutant Concentrations

I used the Ordinary Least Square (OLS) regression model to know about the factors that influence the particle concentration in trails. I used the spatially aggregated particle concentrations as dependent variables. For black carbon concentration, I spatially aggregated (100 meter) the 60 second average concentrations to calculate the average concentration of black carbon for each segment. I ran three stepwise forward selection models to select the independent variables for $PM_{2.5}$, particle number, and black carbon. I also log transformed the $PM_{2.5}$ and particle number concentration as they followed log-normal distribution. **Table 18** shows the variables selected by the forward selection model-

Table 18: Variables selected by the forward selection model

$PM_{2.5}$	Particle number	Black carbon
Distance from commercial land use	Distance from recreational land use	Distance from residential land use
AADT	AADT	AADT
Building density at 1000m	Building density at 400m	Built environment at 200m
Transport vehicle at 50m	Transport vehicles at 100m	Human at 1000m
Vegetation at 400m	Vegetation at 1000m	Transport network at 200m
Road density at 50m	Weighted population at 50m	Weighted population at 1000m
Cooking place	Road density at 50m	Road density at 100m
Noise wall	Airport	Parking near trail
Construction site	Noise wall	Noise wall
	Construction site	

To facilitate comparison between coefficients of independent variables, I fully normalized the model coefficients by multiplying the co-efficient with the ratio of difference between 95th/5th percentile values of independent variable and difference between 95th/5th percentile of particle concentration [49].

3.3.1 $PM_{2.5}$ Model

The $PM_{2.5}$ had an adjusted r-squared value of 0.6473 indicating that 64.73% of the variation in the dependent variable ($PM_{2.5}$ concentration) can be explained by the independent variables. The model adjusted r-squared value aligns with previous studies that used Land Use Regression model [49]. Significant at 99%, the model shows that AADT, transport vehicles at 50m buffer, road density at 50m buffer, construction site, noise wall, vegetation at 400m buffer, building density at 1000m buffer, and distance from commercial land use were positively related to the $PM_{2.5}$ concentration. Most of the independent variables showed an expected sign. However, vegetation at 400m buffer distance shows a positive relation likely due to the vegetation near to the highways that GSV images captured. Similarly, a noise wall is always collocated at segments adjacent to the freeway or interstate where the $PM_{2.5}$ concentration is higher. Previous studies also found noise wall to be ineffective in terms of reducing $PM_{2.5}$ concentrations [7]. In section 3.1.5, a higher concentration of $PM_{2.5}$ was observed to the trail route segments adjacent to a construction site. Transportation vehicles and higher AADT indicate the increased in emission sources which could result in higher $PM_{2.5}$ concentration.

Table 19: Regression model results of $PM_{2.5}$ concentrations

Variables	β	95th and 5th percentile difference of independent variable	95th and 5th percentile difference of dependent variable	Normalized β[a]
Intercept	1.92***	-	-	-
Commercial	14.36E-5***	956.85	19.07	0.007
AADT	32.27E-6***	102537.25	19.07	0.017
Building Density1000	0.93***	0.22	19.07	0.011
Transport Vehicles 50.0	35.70***	0.008	19.07	0.015
Vegetation 400.0	2.64***	0.055	19.07	0.008
Road Density50.0	1.106***	0.31	19.07	0.018
Cooking Place	0.27**	-	-	-
Noise wall	0.32***	-	-	-
Construction Site	0.44***	-	-	-

R^2 : 65.51%
Adjusted R^2 : 64.73%

*** significant at 99%
** significant at 95%
a Normalized βs are interpreted as the number of 95th and 5th percentile difference increases of the dependent variable for each increase in difference of 95th and 5th percentile of the independent variable

3.3.2 Particle number model

The adjusted R-squared value of the particle number model was 59.37% indicating that the independent variables can explain 59.37% of the variability of the dependent variables. **Table 20** shows that distance from recreational land use and weighted population had a negative effect on the particle number concentration. As the distance from recreational land use increases, the particle number concentration would decrease. Although presence of an airport did not contribute to increase $PM_{2.5}$, airport increases the particle number concentration in its proximity [50]. Similarity was found for AADT, construction site, noise wall, road density, transport vehicle, vegetation that contributed positively to the particle number concentration.

Table 20: Regression model results of particle number concentrations

Variable	β	95th and 5th percentile difference of independent variable	95th and 5th percentile difference of dependent variable	Normalized β[a]
Intercept	8.56***	-	-	-
Recreational	-14.8E-04***	1503.56	14496.64	-1.53E-05
AADT	4.94E-06***	102537.25	14496.64	3.49E-05
Building Density400	1.29***	0.22	14496.64	1.91E-05
Transport Vehicles 100.0	62.97***	0.008	14496.64	3.51E-05
Vegetation 1000.0	3.06**	0.041	14496.64	8.74E-06
Weighted Population50	-5.11E-05***	6121.5	14496.64	-2.33E-05
Road Density50.0	0.49**	0.31	14496.64	1.06E-05
Airport	0.71***	-	-	-
Noise wall	0.19***	-	-	-
Construction Site	0.53***	-	-	-

R^2 : 60.37%
Adjusted R^2 : 59.37%

*** significant at 99%
** significant at 95%
a Normalized βs are interpreted as the number of 95th and 5th percentile difference increases of the dependent variable for each increase in difference of 95th and 5th percentile of the independent variable

3.3.3 Black Carbon Model

Distance from residential land use, AADT, transport network at 200m buffer, weighted population at 1000m buffer, road density at 100m buffer, parking adjacent to trail route, and noise wall was positively associated with the black carbon concentration in trail routes. Increased distance from residential land use would increase in the black carbon concentration. However, residential land use could increase the black carbon concentration due to burning biomass and wood [51]. In this case, the distance from residential land use could also indicate an increase in vehicular activity due to moving away from local roads, resulting in the increase in black carbon concentration. Transport related variables such as AADT, road density, transport network would increase black carbon concentration. Also, the location of a parking lot in the trail would increase the black carbon concentration. The adjusted R-squared value of 51.92% indicates that 51.92% of the variability of the dependent variable can be explained by the independent variables in this model.

Table 21: Regression model results of black carbon concentrations

Variable	β	95th and 5th percentile difference of independent variable	95th and 5th percentile difference of dependent variable	Normalized β[a]
Intercept	36.06	-	-	-
Residential	0.14***	1519.35	771.08	0.27
AADT	1.51E-3***	102537.24	771.08	0.20
Built Environment 200.0	-7835.11***	0.01744	771.08	-0.18
Human 1000.0	-105065.60***	0.001765	771.08	-0.24
Transport Network 200.0	6742.05***	0.0476	771.08	0.42
Weighted Population1000	0.07***	4925.9668	771.08	0.44
Road Density100.0	523.90***	0.28	771.08	0.19
Parking	69.04**	-	-	-
R^2 : 52.87% Adjusted R^2 : 51.93%				

*** significant at 99%
** significant at 95%
a Normalized βs are interpreted as the number of 95th and 5th percentile difference increases of the dependent variable for each increase in difference of 95th and 5th percentile of the independent variable

Chapter 4: Limitations

One of the limitations of this study is that I did not have sufficient equipment to maintain a permanent site for background concentration measurement. Having a background site would provide the ambient concentration of pollutants which could be effectively used to identify the elevated pollutant concentration due to proximity of pollutant sources. Another limitation includes higher data collection samples during afternoon compared to the morning peak hours. Furthermore, the only morning sample for Capital Crescent Trail had the lowest background concentration (1.2 $\mu g/m^3$). I applied the multiplicative background adjustment to the $PM_{2.5}$ concentration to adjust for average annual background $PM_{2.5}$ concentration using EPA data. Also, I could not cross-validate the equipment to ensure the accuracy and consistency of the equipment used for air quality monitoring in this study. Dixit K.K previously developed a correction factor of 0.442 for the same Sidepack (serial number 633) that I used for this study. The correction factor was developed based on another Sidepack corrected with Ultrasonic Personal Air Sampler (UPAS) [27]. Kuldeep K.K developed the correction factor of CPC 3007 and CPC 3783 (used for measuring particle number concentration) which was 1.072 with a R-squared value of 0.98 [27]. The micro-aethalometer used for this study is sensitive to mechanical shock. Hence, it is important to remove the spurious spikes resulting from shocks [2]. However, I could not remove the spikes and used the estimated black carbon concentrations recorded by the equipment. I calculated the 60 second average of the black carbon estimated concentrations and further conducted the 100 m spatial aggregation that smoothened the spurious spikes. Finally, I could not collect the meteorological parameters for the regression model. Using meteorological parameters is effective in terms of improving model performance [19].

Chapter 5: Conclusion

This thesis provides a detailed overview of the air quality in multi-use trails and identifies factors that could increase the air pollutant concentrations in multi-use trails. The average concentration of $PM_{2.5}$, particle number, and black carbon was 15.62 µg/m^3, 9857 pt/cc, and 595.36 ng/m^3 respectively in all the trail routes used for this study. The concentration of pollutants varied by data collection time and day of week. I found the pollutant concentrations were higher in the morning than in the afternoon and higher concentrations during weekdays than weekends that followed the regular pattern [17]. The difference in pollutant concentration in the morning and afternoon is due to dilution as found in previous studies [2]. I found the lowest concentrations of pollutants at Capital Crescent Trail which runs parallel to a principal arterial but completely separated from the road and also had an elevation difference. However, segments at close proximity to freeways had higher concentrations of $PM_{2.5}$ and black carbon than other segments of this trail route. On the other hand, I found the highest concentrations of pollutants on Custis and W&OD trail route running parallel to the interstate highway with noise walls at some segments. However, the noise walls were ineffective to reduce pollutant concentrations. I observed elevated $PM_{2.5}$ and particle number concentrations at trail segments adjacent to construction site. Similarly, particle number and black carbon concentrations were higher near the airport. Furthermore, the air pollutant concentration in different trail setting based on the proximity of roadway was different which clearly demonstrates the impact of proximity of roadways on the air quality of multi-use trails that may cause detrimental health effects on the health of trail users.

The pollutant concentration decreased significantly when the distance from nearby freeway or interstate and collector increased from 0 to 50 meters to 50 to 100 meters and it was lowest at 300 to 400 meters. Thus, avoiding the placement of multi-use trails within 50 meters of freeway or interstate and collector would reduce the air quality in multi-use trails and reduce the exposure to air pollution. The increase in distance from the park had minimal impact on the air quality due to the proximity of roadways. I found that the pollutant concentration in multi-use trails increased significantly when the AADT of nearby road was more than 3200.

The adjusted r-squared value for $PM_{2.5}$, particle number, and black carbon concentrations were 64.73%, 59.37%, and 51.93% respectively. The AADT of nearest road of a trail route segment was significant for all three models developed in this study. However, the magnitude of nearest road AADT was highest for black carbon concentrations and lowest for particle number concentrations. Transportation vehicles within 50m of trail segment, cooking place adjacent to trail, construction site was positively associated with the $PM_{2.5}$ concentration in trails. Similarly, airport, construction site, transportation vehicles within 100m of trail segment had a positive relation with the particle number concentrations at trails. For the black carbon model, I found parking space adjacent to trails, road density within 100m, transport network within 200m was positively associated with the black carbon concentration.

In conclusion, this thesis suggests that roadway proximity and traffic volume can increase the pollutant concentration in multi-use trails. While cities are moving towards providing facilities to encourage active travel, it is important to consider the location of these facilities as bicyclists and pedestrians are more exposed to air pollution. Hence, planning the trail network to avoid high traffic roadways can improve the air quality in trails which will further add to the benefits of active travel in health perspective.

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