Air quality and vehicular emissions

Evaluating vehicular emission contributions to and distribution of ambient particulate matter pollution with low-cost sensors in Richmond, Virginia

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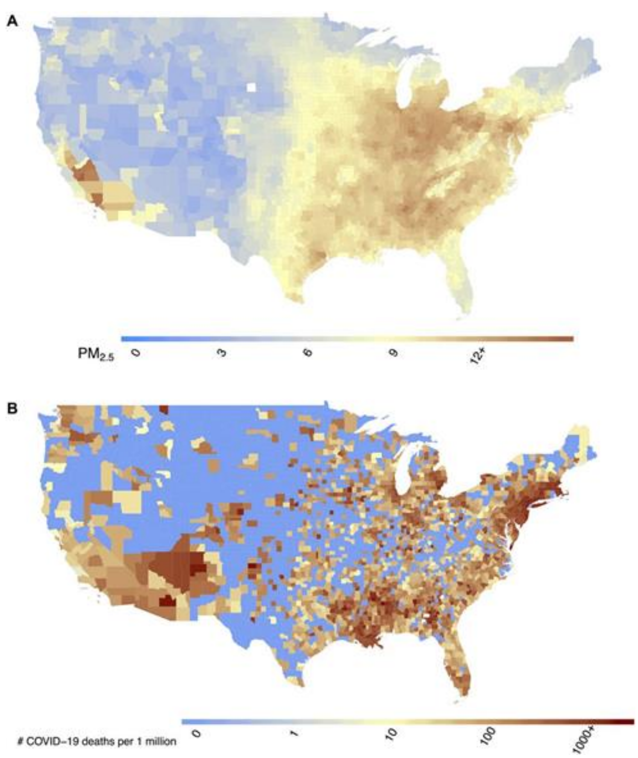
Abstract:

Hazardous air quality prematurely kills millions of people a year and exacerbates underlying health issues for millions more. Unsafe levels of particulate matter are typically associated with newly industrialized and developing countries, however, this is a misconception, especially when considering ambient air pollutants in densely packed urban areas. According to the Airbeam and Purple Air data collected on 07/15/2021, Richmond, Virginia has good air quality with the vast majority of values falling below the United States Environmental Protection Agency annual PM2.5 standard of 12 micrograms per cubic meter (μg/m3). Vehicular emissions may not account for a large percentage of PM2.5 levels in Richmond but considering other emission types and their effects on human health, preventive investment and action is necessary. The Virginian government, through the Richmond 300 project, is planning on expanding and improving on-street networks and amenities serving bicycles through further development of bike-sharing programs.

Introduction:

The acute and chronic health effects of short and long-term exposure to air pollution kills an estimated seven million people worldwide every year (WHO 2022). Air pollution has been linked with death from lung cancer and cardiopulmonary disease and contributes to excess mortality in certain U.S. cities (Dockery, D.W. et Al. 1993). Air pollutants can perturb in vitro anti-microbial and regulatory immune responses weakening the immune system and allowing for greater exacerbation of other health issues (Glencross et Al.2020). High levels of certain pollutants cause smog and acid rain which have corrosive effects on the surrounding eco-systems, causing harm to flora and fauna alike. Air pollution has also been linked with decreased life satisfaction, increased anxiety, mental disorders, self-harm, and suicide and can impair cognitive functioning and decision making (Lu et Al. 2020).

The COVID-19 global pandemic increased the relevancy and urgency of researching the relationship between poor air quality and injurious health as caused by or exacerbated by the coronavirus disease. A positive correlation between areas that had higher historical PM2.5 exposures and higher county-level COVID-19 mortality rates was established after specific area-level confounders were accounted for. However, the study used ecological regression analyses which are unable to adjust for individual-level risk factors such as age, race, and smoking status. Thus, the conclusions were based purely on ecological associations and not individual associations which can lead to ecological fallacies (Wu, X., et. Al 2020).



Map A: County-level 17-year long-term average of PM2.5 concentrations (2000–2016) in the United States (μg/m3)

Map B: County-level number of COVID-19 deaths per 1 million population in the United States up to and including 18 June 2020.

(Wu, X., et. al 2020)

An integrated exposure risk (IER) model was created to specifically look at the health impacts related to PM2.5 and incorporates data from 161 cities across nine regions in China. It found that premature mortality in densely populated cities was high (652,000) due to dangerous levels of PM2.5 which accounted for around 6.92% of total deaths in China in 2015 (Maji, K.J 2018).

Unsafe air quality has negative health effects on billions of people around the world, especially people who live in close proximity to busy roads (US EPA, O 2015). Exposure to high levels of air pollution can cause a range of cardiovascular issues and premature death such as heart attacks and strokes (EPA 2012). A study conducted in China on the effects of particulate matter on childhood pneumonia found that for every 10 μg/m3 increase in PM1, PM2.5, and PM10 concentrations over a consecutive three-day period (lag 0–2), the risk of pneumonia hospitalizations increased by 10.28% (95%CI: 5.88%–14.87%), 1.21% (95%CI: 0.34%–2.09%), and 1.10% (95%CI: 0.44%–1.76%), respectively. This indicates a greater short-term impact on childhood pneumonia from PM1 in comparison to the larger particulate matter classifications (Wang et. Al 2021), (Tian et.Al 2019).

Particulate matter is a mixture of suspended solid particles and liquid droplets that are classified according to each particle's diameter length; PM10 has a diameter of 10 micrometers or less (10 µm), PM2.5 $\leq$ 2.5 µm, and PM1$\leq$ 1.0 µm. Particulate matter toxicity and other human health impacts are determined based on the particulate matter size. There is growing evidence that particulate matter size is inversely correlated with the severity of the health impact; it is hypothesized that a decrease in size will increase acidity and its ability to penetrate the lower lung airways (Kim et Al 2015).

There are important differences between particulate matter interpretations: PM2.5 levels as measured by micrograms per cubic meter (µg/m3, 1.0 × 10-9 kg / m3) are considered "Good" by the United States Environmental Protection Agency if the concentration remains below the annual PM2.5 standard of 12 micrograms per cubic meter (µg/m3) and a 24-hour limit of 35 (µg/m3) (EPA 2015). The World Health Organization (WHO), on the other hand, has set its annual limit to 10 µg/m3 and a 24-hour limit of 25 µg/m3 which means that almost the entire global population (99%) breathes air that exceeds WHO guideline limits. Additionally, the U.S EPA processes the raw PM2.5 data to form the Air quality Index using this U.S EPA formula:

$$I_p = \frac{I_{Hi} - I_{Lo}}{BP_{HI} - BP_{Lo}}(C_p - BP_{Lo}) + I_{Lo}.$$

(AQI Technical Assistance Document)

Where Ip = the index for pollutant p

Cp = the truncated concentration of pollutant p

BPHi = the concentration breakpoint that is greater than or equal to Cp

BPLo = the concentration breakpoint that is less than or equal to Cp

IHi = the AQI value corresponding to BPHi

ILo = the AQI value corresponding to BPLo

Table 1: Shows the µg/m3 breakpoint values and the AQI equivalent.

(EPA 2015)

PM2.5 µg/m3	AQI (US)	Remark
0-12	0-50	Good
12-35	51-100	Moderate
35-55	101-150	Unhealthy for sensitive individuals
55-150	151-200	Unhealthy
150-250	201-300	Very Unhealhty
>250	>300	Hazardous

Vehicular Emissions

Vehicular emissions significantly contribute to air pollution in urban areas. Mobile sources of air pollution emit particle pollution (e.g. PM2.5 and PM10), nitrogen oxides, sulfur dioxide, and hydrocarbons. A study in China found that vehicular emissions account for 20–67% of carbon monoxide and 12–36% of the total nitrogen oxides in China and 12–39% of the volatile organic compounds (VOC) emissions in China (Lang Et al. 2012), (Zhang et al., 2009). Vehicular transport-related emissions are the primary source of ambient PM10 in cities and tail emissions from road transport account for up to 30% of PM2.5 concentrations in urban areas (Krzyzanowski et Al. 2005).

Birth cohort studies point to the relationship between increased longitudinal childhood exposure to traffic-related air pollution (PM2.5 and black carbon) and increased risk of asthma and asthma-related symptoms in childhood. Early childhood exposure to traffic-related air pollution is also associated with the development of asthma up to the age of twelve. There is some evidence that traffic-related air pollution is also associated with allergic diseases like eczema and hay fever (Bowatte, et Al. 2015). Additionally, studies have found an association between traffic-related air pollution and rhinitis symptoms in the first eight years of life (Gehring et Al. 2010). Exposure to traffic-related outdoor air pollution may lead to respiratory illness in children and even miscarriage and stillbirth after adjusting for indoor air pollution. However, indoor air pollution can exacerbate the effects of outdoor air pollution (Kashima et Al 2010).

Background

Research into the distribution of point source emissions has been conducted in the Richmond area. Findings suggest uneven distribution of air pollution and temperature in Richmond, Virginia, indicating certain demographics of the Richmond population encounter unsafe levels of air pollution or temperature extremes annually. There is an uneven distribution of temperature in Richmond, Virginia with vulnerable neighborhoods in the East end and highly developed parts of the city experiencing significantly higher temperatures than suburban neighborhoods in the west which have greater green space areas (Eanes et Al 2020). Air pollution traps excess longwave radiation leaving the earth's atmosphere, effectively creating a positive feedback loop of increasing temperature and perhaps PM2.5 levels, however, more in-depth studies need to be conducted until any accurate relationship between PM2.5 and temperature can be described. Individuals who live in areas with poor air quality are at higher risk of getting cancer and exacerbating cancer, allergies, asthma, and other respiratory illnesses, particularly concerning impacts on childhood development. Communities in the west end have significantly better air quality and fewer socio-economic and health-related stressors than communities in the east end of Richmond which has resulted in individuals living in west end neighborhoods having life expectancies of up to twenty years higher than communities in the east end (Eanes et Al 2020).

Based on previous air quality studies both in Richmond and in other urban areas, this research attempted to uncover the distribution of PM2.5 levels in Richmond, Va. If an accurate spatial pattern existed, it could be overlapped with a vulnerability index to determine whether a correlation exists. Additionally, this research was designed to further investigate whether there was a correlation between vehicular emissions and PM2.5 levels in Richmond. Finally, this paper was aimed at expanding our understanding of emission quantities based on vehicle type and to help paint a clearer picture when considering what subsect of vehicular emissions further research should be focused on when considering the contribution to pollution.

2. Methods

2.1 Site Description

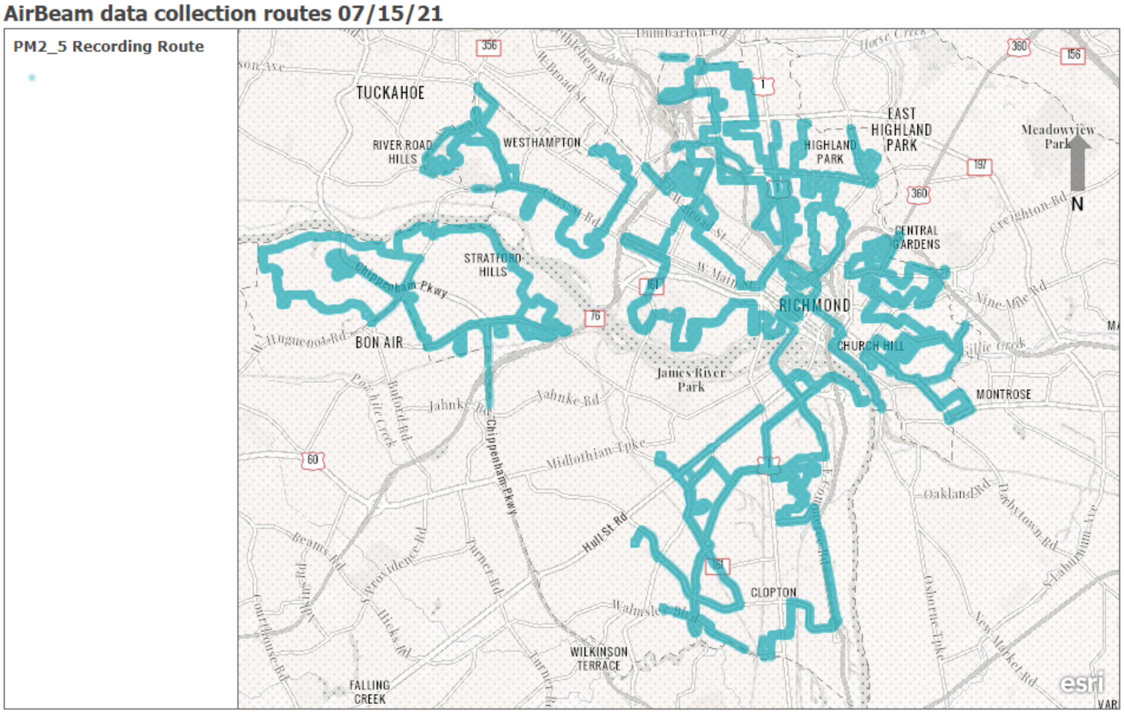
Over 230,000 residents call Richmond home, making it one of the largest cities in Virginia. Due to Richmond's area and population size, public transportation is limited to certain bus routes, with the city lacking any metro or tram system. Bike lanes are rare and there is only a minuscule ad hoc walking and cycling commuting culture present in the city, therefore most of the commuting and ordinary travel is via road vehicles. Richmond's population density is around 3,906.40/sq mi (mi^2) which is relatively low for a city.

Particulate matter issues are especially relevant in Richmond, Virginia as it is ranked the second most challenging city in the U.S for asthma sufferers to live in considering prevalence, hospitalization and death rates (VDH 2018). In 2016, an estimated 874,713 people were diagnosed with asthma at some point in their lifetime, out of an estimated population of 8,411,808 or, in other words, one out of ten adult residents in the Commonwealth of Virginia have been diagnosed with Asthma in their lifetime (VDH 2018).

2.2 Data Collection

On July 15th, 2021 a group of citizen volunteers collected air quality data in Richmond city using HabitatMap AirBeam devices and cycled along various pre-ordained routes in three sessions: morning, afternoon, and evening. Unfortunately, data from several of the routes had to be discarded or were not collected at all by citizen volunteers. AirBeam sensors are highly portable low-cost devices and therefore can take measurements over distance and can be paired with a mobile app.

AirBeam data collection routes 07/15/21



Map 1: Shows the air quality data collection bike routes taken on 07/15/2021 by a group of citizen scientist volunteers.

Both Airbeam and Purple Air monitors track other particulate matter sizes, such as PM10 and PM1, however, this research paper primarily focuses on PM2.5 alone. Purple Air monitors are still classified as low-cost but are more expensive than AirBeam sensors, however, they are for stationary use only and can run throughout the year. Only fourteen out of sixteen Purple Air sites can be seen in Map 2. Some of the AirBeam data lay outside the 1 km buffer zones created to average AirBeam PM2.5 data around Purple Air monitors for cross-device PM2.5 concentration analysis. Therefore, the relevant Purple Air sites were located more toward the center of Richmond where the AirBeam collection occurred.

Map 2: Shows the locations of fourteen (of sixteen) fully functioning Purple Air monitors on 07/15/2021.

A corrective equation, from a 2020 Environmental Protection Agency report, was applied to the Airbeam and PurpleAir PM2.5 values to account for humidity and temperature at the time of collection since these devices can be influenced by small environmental changes (Malings et Al. 2020), (Barkjohn 2020). PM 2.5 values may also be skewed depending on specific conditions which lead to data inaccuracies, such as a brief gust of wind suspending dust near the monitor. Corrective equation:

T & RH: $PM2.5 = 0.39*PA + 0.0024*T - 0.050*RH + 5.19$, $R^2=0.72$

Units:

PM2.5= μg m-3

T= Temp. in Fahrenheit

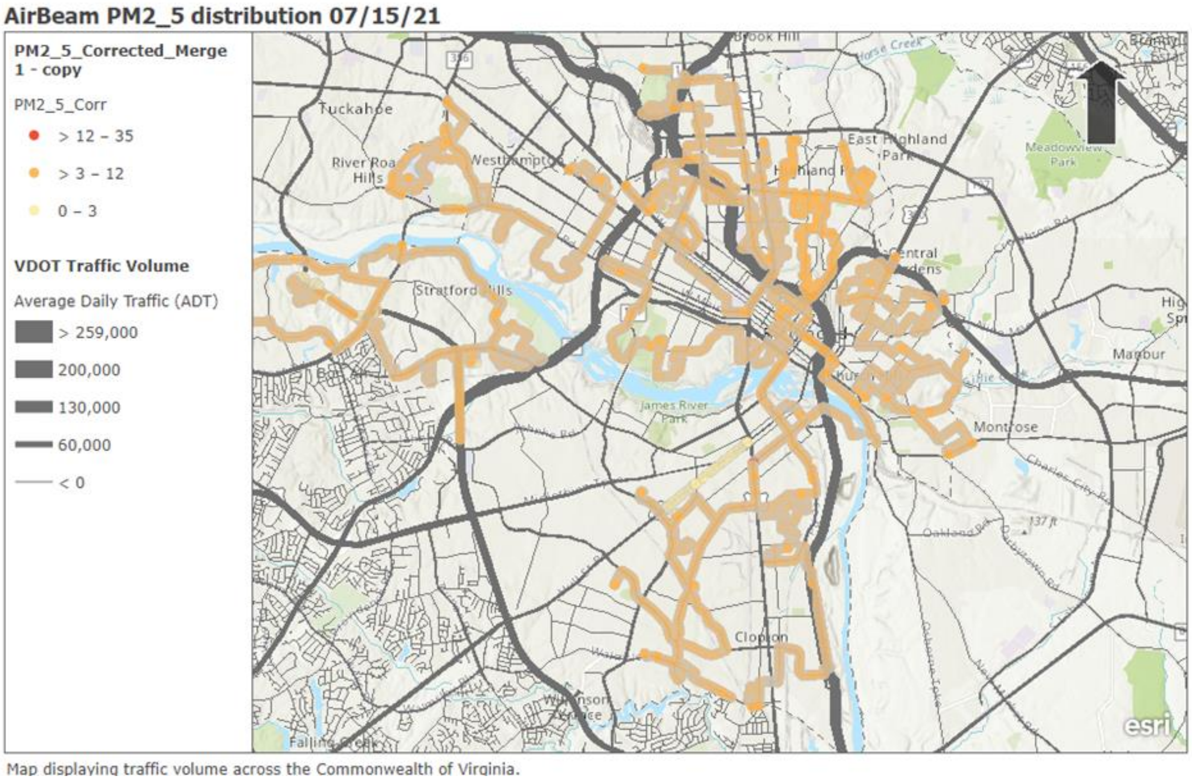
RH=% (Relative Humidity)

A 1km radius buffer analysis around each of the Purple Air monitor sites rendered AirBeam PM2.5 averages by using the "summarize within" function and running a statistical analysis of the highlight values. However, only fourteen out of the sixteen fully functioning Purple Air monitors had AirBeam PM2.5 within a one-kilometer radius.

The Commonwealth of Virginia Department of Transportation (VDOT) collects traffic count data from sensors in or along streets and highways. The 'Annual Average Daily Traffic data' or AADT (ADT on Map 1) is an estimate of the typical traffic count on a road segment divided by 365 days. The incorporation of the prediction model data gauges the thickness of the roads on the map with natural break intervals (< 0, 60,000, 130,000, 200,000, > 259,000). The traffic volume data incorporated in this study was from the 2019 VDOT report. The decision to omit the 2020 record in favor of the 2019 traffic volume data was done to best avoid any anomalies due to the immense impact the Covid-19 pandemic had on transportation.

Results:

Geospatial analysis of the AirBeam PM2.5 readings taken on 07/15/2021 indicates that PM2.5 levels did not significantly differ across Richmond city and only 0.1% of all the PM2.5 crossed the AQI threshold of 12 μg/m3 (moderate) set by the EPA. As seen on Map 1, the distribution of PM2.5 did not differ significantly across the AirBeam routes, and the vast majority of readings fell within the 3 μg/m3 -12 μg/m3 range. The PM2.5 distribution based on AirBeam results shows no increased concentration near major roads (greater than 200,000), therefore it would be inaccurate to attempt to conclude on a defined spatial relationship without more PM2.5 readings that span the same area as the roads.



Map 3: Shows the spatial distribution of the Airbeam values collected on 07/15/2021, underlapped by VDOT traffic volume data.

However, Purple Air PM2.5 readings for the same day are significantly different from the AirBeam counterparts. As seen in Table 2 in the discussion section, most of the Purple Air values indicate PM2.5 levels double that recorded by AirBeam sensors. Furthermore, the AirBeam and Purple Air averages did not correlate based on their geographic location within Richmond, (R-squared=0.03). The large value gap between the AirBeam sensors and the Purple Air monitors and the apparent lack of site-specific correlation points to environmental or technology-related influences skewing the accuracy of AirBeam data collection. There were sixteen functioning monitors on which we were able to extract data on 07/15/2021, however, only fourteen are represented in the data table and map with AirBeam PM2.5 readings due to the proximity buffer.

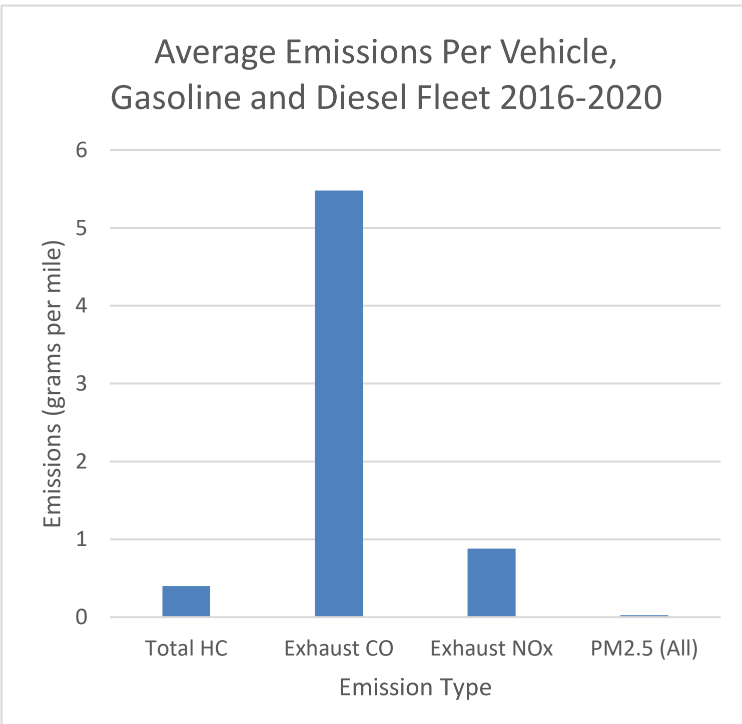
Discussion and Conclusion:

The results from the analysis of PM2.5 levels in Richmond indicate good air quality in Richmond, however, environmental conditions and technological malfunctions can easily lead to record inaccuracies. Although PM2.5 levels were considered safe during the day of data collection, these data are instantaneous whereas breakpoints are daily averages, such as the EPA standard of 12 µg/m3. The PurpleAir monitors report much higher PM2.5 levels for the same day, fluctuating just below the 12 µg/m3 breakpoint. The sites monitored by Purple Air devices still lie in the "Good" zone for both the EPA AQI and the EPA µg/m3 measurement tools. Again, this data represents one day and is not a good representation of PM2.5 levels around Richmond through out the year. Table 2 was constructed by extracting PM 2.5 averages from the values that lay within one-kilometer radius proximity to fourteen Purple Air monitors.

Site Name	PurpleAir 07/15/2020	AirBeam 2.5 07/15/2020
vcu6	9.984922	4.27678197
UR_06_SMV_d8bc	11.049064	5.40401052
UR_02_Vasen_dec	10.601368	5.32568885
UR_04_Campus_dc8	8.8328	5.44420515
IMLS_SMV_ClaySt_JJ	10.948716	5.40041797
IMLS_SMV_Diamon	11.530328	5.43905996
UR_09_VUUnorth_d31c	9.940428	5.63089115
UR_03_SixPts_e34	10.171872	5.16927162
SMV_BryanPark	11.206902	5.21014093
VCU2-MSiC	9.59492	4.82582151
East Henrico	10.465698	4.79063034
UR_08_ChurchHill_92c5	10.471308	5.04510003
IMLS_SMV_CatherineSt_MR	10.908846	5.44422861
33_UR_07_NRCFulton_d6ff	10.890302	4.79545045

Table 2: Shows average Purple Air and AirBeam records from fourteen sites in Richmond, VA on 07/15/2020

The Purple Air monitors attain data more accurately and reliably, as compared to the AirBeam sensors, and are used by the Science Museum of Virginia in the RVAir initiative. However, Purple Air monitors are not as low cost as AirBeam sensors and lack the mobility needed to accumulate data across the city. Currently fully functioning Purple Air monitors are sparsely spread out throughout the city of Richmond and can only produce accurate readings for a limited area. PurpleAir (PA) stationary sensors served as an alternative monitoring instrument that has proven to be fairly reliable and accurate. These sensors establish a rough understanding of air quality spatial variability from site to site and temporal trends, recording measurements at two-minute intervals and collecting data for PM2.5 and temperature at each site. Thus, to create a citizen science project that can accurately analyze the particulate matter and other pollutant spatial trends in Richmond there needs to be an increase in Purple Air installations all around the city or an alternative sensor/monitor.



Graph 1: Shows the average emissions (grams per mile) per vehicle for both gasoline and diesel fleets from 2016-2020 in the U.S.

(U.S. Environmental Protection Agency, Office of Transportation and Air Quality)

Graph 1 allows us to conclude that PM 2.5 quantities do not contribute heavily to the vehicular emission profile compared to other emission types like carbon monoxide and nitrogen oxides. PM2.5 (All) includes Exhaust PM2.5, Brakewear PM2.5, and Tirewear PM2.5 which combined account for 0,025 grams per mile according to data collected by the U.S. Environmental Protection Agency, Office of Transportation and Air Quality. Carbon Monoxide Exhaust is significantly the most emitted pollutant per vehicle (5.481 grams per mile), followed by Nitrogen Oxide Exhaust (0.88 grams per mile), and then Total Hydrocarbon emissions (0.4), with total

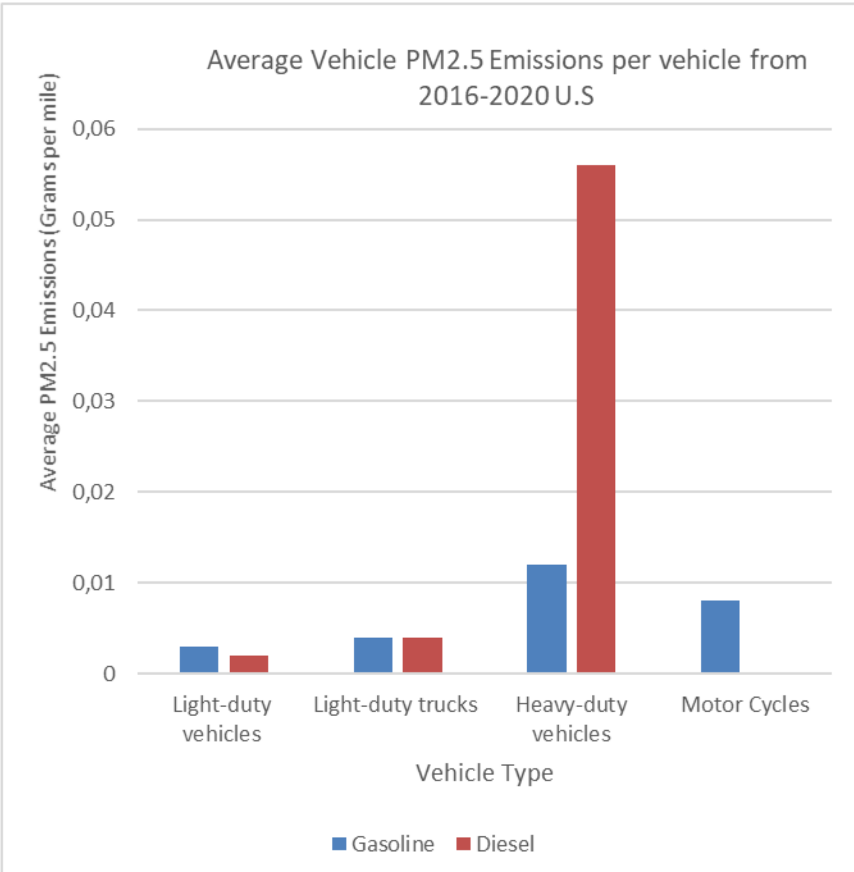
PM2.5 only accounting for 0.37% of emissions (grams per mile) among the four pollutant types measured by the EPA.

Data from the Virginia Department of Transportation represented in Graph 1, PM 2.5 quantities do not contribute heavily to vehicular emission profile compared to other emission types like carbon monoxide and nitrogen oxides. Future research on air quality and vehicular emissions in Richmond, requires a larger data pool, especially while interpreting vehicular emissions and air quality throughout the city. Investing more time and money into gathering extensive air quality data over a longer period in which accurate averages can be derived and a greater scope of emission types can be analyzed; through the use of more refined equipment and more robust sampling of pollutants such as CO, CO2, NO2, O3, and SO2.

Unsafe levels of air pollution in Paris and London sparked a longitudinal study beginning in 2005. NO2 concentrations from roadside traffic increased from 2005-to 09 in both cities before an overall decrease in PM2.5 and NO2 from 2010–to 16 in Paris and London which is accredited to the introduction of Euro V heavy vehicles (Font, et Al 2019). Another study in London found that a substantial proportion of the children lived with high levels of NO2 exposure that do not meet EU targets, with most schools and residences residing within 500 meters of busy roads. The study found inverse correlations between lung function and exposure to urban air, particularly to NOx and NO2, which point to high concentrations of diesel emissions in London. However, although the study found small improvements in air quality in highly polluted urban areas there was no evidence of a reduction in the proportion of children with small lungs between 2009-10 and 2013-14(Mudway, I.S. et Al 2019).

European Union (EU) Clean Air Directive is one of the strictest legislation passed in an attempt to reduce PM10 air pollution with specific attention to vehicle emissions. The policy restricts vehicles that are not qualified as “low PM10 emitting vehicles” from entering “Low Emission Zones”. The implementation of strict LEZ policies in Germany had a ripple effect on the community; commercial truck and bus companies felt slighted as they were no longer permitted to enter LEZs and had to re-configure previous routes. Local business owners also struggled with the introduction of LEZs, complaining of a reduction in sales. Above all, it potentially affects thousands if not hundreds of thousands of residents who may live in that zone that is now deemed an LEZ (Wolff, et Al 2010). According to the Airbeam and Purple Air PM2.5 results there is no pressing need to implement highly disruptive transportation policies (e.g. LEZs) in

Richmond. If in fact, further studies find unsafe concentrations of PM2.5 or other pollutants present in the vehicular emission profile, there will need to be accurate, current data spanning across Richmond city to effectively develop and implement low emission zones. Based on Graph 2, Heavy-duty vehicles, especially diesel engines, should be the type of vehicle considered "High emitting" and disallowed from entering LEZs.



Graph 2: Shows average vehicle PM2.5 emissions based on vehicle type and fuel type from 2016-2020 U.S.

(U.S. Environmental Protection Agency, Office of Transportation and Air Quality)

An alternative government initiative, such as bike-sharing, could kickstart Richmond's vehicular emission reduction campaign and culture. Increased cycling results in decreased car use and therefore a reduction in vehicular emissions especially if the infrastructure is set up to facilitate cycling daily commuters. Cycling in residential neighborhoods decreased particulate number concentrations by 17% relative to the ambient average level, and by 22% when cycling through green spaces or parks (von Schneidemesser et Al. 2019).

A case study in Seoul, Korea found that short vehicle trips, of three miles or less, are a primary cause of air pollution. Bicycles can be an environmentally and economically effective replacement for vehicles for these short trips. A p-median model was produced to configure an even distribution of bicycle stations across the city and the MCLP model places high concentrations of bike stations where the most demand is predicted to be (Park, et Al 2017). Realistic bicycle travel distances were established (equal to a 30-minute ride) to propose the replacement of cars with bicycles for short trips, especially for commuting communities. A similar model was hypothetically tested for the demographics of Stockholm County, Sweden. If all the car drivers living within a distance that is equal to a maximum of a 30 min bicycle ride to work would change from driving cars to commuting by bicycle the mean population exposure to NOx and black carbon would both be reduced by 7% in the most densely populated area of Stockholm. If this air pollution reduction occurred, the study calculated with a 95% confidence interval, using NO2 or black carbon as an indicator of health impacts, 395 and 185 years of life would be saved for the population (Johansson et Al 2017). However, although there are numerous benefits to cycling, there are also negative consequences of increasing cycling in heavily trafficked areas of the city concerning increased PM2.5 exposure for the cycling population. If an area consistently has unsafe levels of air pollution, then other policies need to be implemented before encouraging and developing bike lanes and bike-sharing programs in that area (Hu, H. et al 2021). The Virginian government is planning on expanding and improving on-street networks and amenities serving bicycles through further development of bike-sharing programs (Richmond 300, 2020). Not only will the environment and in turn, the general city population benefit from reduced car usage but also individuals who choose to walk or bike will greatly benefit physically and mentally from the exercise. If bike paths and bike-sharing programs are feasible then the next steps should be aimed at figuring out the best strategy for implementation.

Vehicular emissions may not account for a large percentage of PM2.5 levels but considering other emission types and their effects on human health, preventive investment and action is necessary. The Virginian government, through the Richmond 300 project, is planning on expanding and improving on-street networks and amenities serving bicycles through further development of bike-sharing programs. Hopefully, improvements in infrastructure and accessibility will lead to a cycling commuting culture that will vastly benefit Richmond city's future grapple with air pollution. Future research on air quality and vehicular emissions in Richmond, requires a larger data pool, especially while interpreting the relationship between vehicular emissions and air quality throughout the city. Investing more time and money into gathering extensive air quality data over a longer period in which accurate averages can be derived and a greater scope of emission types can be analyzed; through the use of refined equipment and more robust sampling of pollutants such as CO, CO2, NO2, O3, and SO2.

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Figure References:

Map A and B: Wu, X., Nethery, R.C., Sabath, M.B., Braun, D. and Dominici, F., 2020. Air pollution and COVID-19 mortality in the United States: Strengths and limitations of an ecological regression analysis. Science advances, 6(45), p.eabd4049

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Map 1: AirBeam citizen science

Map 2: PuprleAir (RVAir initiative)

Table 2: AirBeam citizen science and PuprleAir (RVAir initiative)

Graph 1: U.S. Environmental Protection Agency, Office of Transportation and Air Quality

Graph 2: U.S. Environmental Protection Agency, Office of Transportation