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Abstract

Title of Document: Using Spiderwebs to Detect Spatial Differences in Metal Air Pollution

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Long term studies of air pollution have been limited to stationary monitoring conducted by government bodies or large research institutions. These official monitoring sites can only measure a limited area, and the data they collect is then spatially generalized. This leads to large gaps in knowledge, as air pollution can vary significantly over small areas. This spatial gap has led to air pollution becoming a major area of study for public science efforts. The development of small, low-cost air monitors has enabled individuals and communities to examine their own exposure at a fine scale and become better informed on their own health risks. However, no low-cost sensors yet exist for the measurement o heavy metals, so despite their known negative impact on health, heavy metals have rarely been a focus of study for informal monitoring. There is a need for low-cost air quality monitoring that can detect differences at fine-scale and over long periods of time. Spiderwebs have been used in several studies to test air quality, but never in a public science setting and not yet at the fine spatial scale this study proposes. Furthermore, their results have only been verified by brief co-monitoring, rather than long-term air pollution monitoring and modeling. This study collected spiderwebs to detect heavy metal air pollution in two neighborhoods of Southwest Baltimore, an area with a history of air pollution and known heavy metal releasing facilities, along with one of the highest levels of respiratory illnesses in the city

and state. Webs were also collected near the two chemical speciation monitors operated by Maryland Department of the Environment. These webs were then analyzed for metal concentration using an ICP-MS. Spiderwebs collected in Southwest Baltimore were able to detect fine scale spatial differences in metal pollution, but the relationship between these values and known sources of air pollution are still unclear.

Using Spiderwebs to Detect Spatial Differences in Metal Air Pollution

Nava Rastegar, 2021

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Introduction

Human Health and Air Pollution

Air pollution can have extremely negative effects on human health. According to the World Health Organization (WHO), air pollution contributes to seven million premature deaths annually[22]. Particulate matter (PM) refers to solid, respirable particles suspended in the air and is one of the most well-studied forms of air pollution. Health effects largely depend upon the size of the particles and their chemical makeup. Larger PM (around 10 μm) can cause skin and respiratory irritation, while smaller particles (around 2.5 μm or less) can lodge in the alveoli of the lungs and contribute to cancer, depending on their chemical makeup. Coarse particles, $PM_{2.5}$-PM_{10}, usually travel in the range of tens of kilometers, absent extreme weather events. $PM_{2.5}$ and below can travel hundreds of kilometers before they are deposited. The heavy metal content of PM varies widely by source[46]. Combustion by industry and operation of motor vehicles are major anthropogenic sources of metal carrying PM. Many of the trace elements in these particles come from vehicle traffic in urban areas, with freeway driving generally associated with the smaller particles and ‘stop-and-go’ street driving associated with larger ones. Other sources of particles in the air include domestic heating, oil and coal combustion, refuse incineration, construction dust, mining, agriculture, and the resuspension of soil particles into the air[11,13]. A review by Rohr and Wyzga examining the relationship between PM components and health outcomes found that most studies indicated that the composition of PM had a

more significant relationship with negative health outcomes than the mass of PM alone. This implies that the reduction of PM alone may not be enough to decrease negative health outcomes if the components of PM are ignored. Unfortunately, speciation data is limited in most areas, and many studies are forced to rely upon PM concentration alone in their evaluation of health outcomes. Most studies do not consider concentration of PM components, and those that do usually limit their analyses to forms of carbon and perhaps one or two metals[54]. Exposure to heavy metals transported through the air can contribute to or worsen health issues such as asthma, neurological damage, emphysema, and cancer[36]. Metals cannot be broken down within the body into less harmful molecules as some more complex chemicals of concern can. Instead, the major mechanisms available for disposing of metals are through the digestive system, where they are disposed of along with other wastes[23].

Many different metals influence human health, but I will focus on the five heavy metals which were tested in part two of this study: iron, aluminum, chromium, lead, and nickel. Iron, nickel, and aluminum were among the top five most common metals in a six-year study of Baltimore's particulate pollution[47]. Lead and chromium were far less common but were chosen as they are of particular concern for public health. A brief overview of the health risks and common sources for each of these metals is given below.

Iron is an essential element for human processes. However, when inhaled as particulate matter, iron can cause irritation and contribute to multiple disorders in the cardiovascular system, many of which are life threatening[61,73]. Pollution

exposure is particularly dangerous for children, pregnant people, and those with pre-existing respiratory ailments. For example, pregnant people's exposure to high levels of iron in the air has been linked to reduced cognitive ability in their newborns[48].

Aluminum, like many heavy metals, can exacerbate a variety of respiratory ailments, such as asthma[2]. Prolonged exposure to aluminum dust can cause aluminosis, or aluminum-induced lung fibrosis. However, this disease is generally limited to those who have occupational exposure to aluminum dust[40].

Lead pollution in the air is relatively low when compared to the metals discussed above, but it is particularly concerning, partially due to the high concentration that can accumulate in the body upon exposure and partially due to its well documented effects on children. Lead 'mimics' other essential elements, such as calcium and zinc, which allows lead to easily accumulate in the body's systems. Once lead has accumulated in the body, it is very hard to get rid of. Lead can take decades to dissipate, as the organs it is stored in have a very slow turnover rate. Like many other toxins, lead can accumulate in the kidneys and liver. High accumulation can result in kidney and liver failure[23]. Exposing children to even small amounts of lead has been linked to learning disabilities[5].

Chromium is a special case in terms of health effects. While Chromium III is essential for the activation of insulin in humans, Chromium VI ions are a known carcinogen[23]. Chromium VI is particularly dangerous when inhaled. Long term

exposure to air-borne Chromium VI can lead to lung cancer, pneumonia, and ulcers and perforations of the respiratory system. It may also harm other organs such as those in the gastrointestinal and reproductive systems[19]. Chromium III is approximately twice as common in the atmosphere, as Chromium VI is primarily introduced through industrial processes (largely manufacturing) while the more stable ion of Chromium III is produced through both industrial and natural processes[4].

The final air pollutant we tested for was nickel. Although most people get the majority of their nickel exposure in their food and water, there is little evidence of danger from this route of exposure. Nickel is most harmful when inhaled. There is evidence that nickel exposure increases the risk of respiratory cancers. It can also increase scarring in the lungs, which raises the risk of many different respiratory ailments[19].

The health effects of air pollution have received particular focus in my area of study, Baltimore City, MD. According to a study by the Environmental Integrity Project, 2010 asthma hospitalizations occurred in Baltimore at nearly three times the national average rate, and more than two times the average rate of asthma hospitalizations in Maryland. Four of the five zip codes with the highest rate of asthma hospitalization also contained areas where air pollution was much higher than the state average. Decreasing asthma hospitalizations have been correlated with reductions in air pollution in Baltimore city, driven by stricter air pollution laws. Many of the metals described above are linked to asthma hospitalizations. Furthermore, asthma hospitalizations are positively correlated with measures of

poverty. Poverty limits access to quality housing and medication that can help control asthma symptoms. Baltimore's poverty rate is twice that of the country and nearly three times the average of the state[39]. All these factors indicate that the level and distribution of air pollution is of particular concern for Baltimore city residents.

Range and Scale

Metal contaminants almost never occur in their pure elemental form in the air, instead they are attached to larger particles composed of multiple elements and molecules. The transport and fate of these metals is heavily influenced by the size and form of the particles. Once released into the air, particles containing metals will usually deposit within a few days. The transport range varies depending on the weight of the particles and the weather. Lighter particles usually travel farther, and precipitation can force early deposition onto the soil. For example, WHO estimates that with an average wind speed of 5 m/s, a 1 um particle of cadmium could be transported ~1300 km within three days[70].

Many studies have illustrated the high spatial variability of pollution. For example, from 2008-2012, a team of researchers in New York City monitored a range of pollutants across the city using more than 100 stationary monitors. This study found that metal concentrations in $PM_{2.5}$ could vary significantly within the relatively small area of a single city, related to the presence, size and type of sources such as roadways or industrial areas[35]. Studies of the influence of roadways on pollution have found that the measured concentration of particulate

matter becomes indistinguishable from the background level as little as 100 ft from the edge of the road, and the effect of a particular roadway is rarely detectable at more than 400 m from traffic[28]. Similar intensive studies have shown the variation of air pollutants over a small range[12,64]. PM_{10} is known to vary even more in small areas, as its higher weight causes it to deposit much faster than $PM_{2.5}$. For example, a study of pollution in Beijing found some spatial variation of $PM_{2.5}$ between three sampling sites: one located in an industrial area, one residential, and one near two major roads. However, there was a much higher variation in PM_{10} between sites[62]. This and other studies suggest that while there is significant mixing in $PM_{2.5}$, leading to more uniform concentrations at the small spatial scale of a city, PM_{10} concentrations are more heavily influenced by local releases. This suggests that while there is significant variation in $PM_{2.5}$ concentrations within the relatively small scale of a city, there may be even more significant variations in PM_{10} concentrations over small areas that have been ignored.

$PM_{2.5}$ is generally believed to be far more dangerous for human health than PM_{10}, due to the ease of inhaling smaller particles. However, some researchers have theorized that the high spatial variability of PM_{10} concentrations may lead to a significant research gap on the health effects of PM_{10} exposure. Most studies of the association between air pollution exposure and health risks are based on pollution measurements from a few centrally located monitors, which fail to capture the extreme variability of PM_{10}[33]. By its nature, air pollution varies within relatively small areas. Most particles in the range of $PM_{2.5}$-PM_{10} are

deposited within minutes to hours of their release, and rarely travel more than 100 kilometers from their source, although extreme weather events can cause these larger particles to travel many hundreds of kilometers before landing on the ground. Smaller particles can stay in the air for weeks or even months and be transported 100s of kilometers. The most common monitoring techniques fail to capture this variability, as monitoring networks are sparsely distributed[31,46].

The State of Air Pollution Monitoring

The air quality monitoring network of the United States was created as a requirement of the Clean Air Act, which intends to protect public health and welfare from the negative effects of air pollution. Currently, states are required to monitor $PM_{2.5}$ and PM_{10}, ozone, lead, carbon monoxide, nitrogen dioxide, and sulfur dioxide. These are also called “criteria pollutants”[42]. As shown in Figure 1, $PM_{2.5}$ monitors are required by the Environmental Protection Agency (EPA) for all metropolitan statistical areas (MSAs) whose $PM_{2.5}$ measurements are greater than 85% of the National Ambient Air Quality Standards (NAAQS) maximum limitation of 15 mg/m^3 or the annual arithmetic mean of $PM_{2.5}$. One monitor is required for qualifying MSAs of fewer than 500,000 people, two for MSAs of 500,000-1,000,000 people, and three for those with more than 1,000,000 people. $PM_{2.5}$ measurement is required for each MSA with more than 500,000 people no matter previous measurements[16].

TABLE D-5 OF APPENDIX D TO PART 58—$PM_{2.5}$ MINIMUM MONITORING REQUIREMENTS

MSA population[1 2]	Most recent 3-year design value ≥85% of any $PM_{2.5}$ NAAQS[3]	Most recent 3-year design value <85% of any $PM_{2.5}$ NAAQS[3 4]
>1,000,000	3	2
500,000-1,000,000	2	1
50,000-<500,000[5]	1	0

Figure 1: Requirements for $PM_{2.5}$ monitors by MSA population.[16]

The state of Maryland operates only two sites with sensors that are regularly used to estimate metals in air. Monitors in Essex and HU Beltsville collect $PM_{2.5}$ in filters every three days, which are then analyzed to find the mass of over 50 different ion, metal, and carbon species[42]. The EPA only requires one metal speciation site for most states, depending on their pollution history. Maryland has exceeded its legal responsibilities in this regard, as it has two metal speciation sites and no requirement by the EPA to monitor more than one site[16]. Along with this, there are special requirements for lead monitoring. Until recently, Maryland operated a devoted lead monitor in HU-Beltsville, but this monitor was decommissioned due to consistently low measurements (below 0.1 $\mu g/m^3$)[42]. The EPA mandates the use of air quality monitoring systems that use Federal Reference Methods (FRM) or equivalent (FEM). FRM and FEM systems cost tens of thousands of dollars in equipment and infrastructure and require multiple skilled workers to function[15]. At the moment, it is not possible to achieve fine-scale monitoring with FRM or FEM systems. Furthermore, there is evidence that local regulators are less likely to establish monitoring stations in more polluted areas. Along with avoiding polluted areas, regulators may avoid areas

with lower incomes or a relatively high BIPOC population[31]. This suggests that the communities most impacted by pollution may also be less likely to have access to monitoring data and the political power that data can provide.

As air quality has a significant effect on human health, there is great interest in obtaining detailed spatial information on air pollution for epidemiological research. Detailed spatial data allows health researchers to be more confident in their knowledge on the relationship between different types of pollution and different health effects[33]. To estimate air quality across wide areas based on this limited data, researchers have used methods from spatial statistics to predict pollutant concentration in unmonitored locations. Spatial interpolation methods such as kriging or inverse distance weighting average the measurements of the surrounding monitoring stations, giving a different weight to each station based on their distance from the point predicted. Land use regressions (LUR) are another method of predicting pollution in the absence of fine data. Instead of simply relying on monitoring station data as in the methods previously explained, LUR incorporates spatial variables such as traffic, elevation, and population density. The relationship between these environmental variables and pollution concentrations is described in an equation created from multiple regressions. LUR requires more data sources but usually yields more accurate predictions[72]. However, there is no substitute for a dense network of monitors to ground-truth model estimates. LUR requires a large amount of outside data, software, and specialized technical knowledge. Even the best LUR can only be used reliably for the area in which they were created[55].

Due to the spatial variability of air quality and the inability of the existing federal network to capture this variability, researchers and other concerned individuals are creating data with more spatial or temporal variability than fixed monitors can provide. Some researchers and organizations have attempted to fill this gap in data by consistently moving their available sensors, or by attaching small mobile sensors to individuals or vehicles and measuring air quality over an area of travel. While these studies gain a larger spatial range of data, they lose the ability to measure changes in pollution over time.

Low-cost (defined by the EPA as those costing >$2500[69]) sensors still require testing and calibration in their monitoring environment to ensure reliability. Sensors may need regular testing and recalibration to ensure their measurements do not 'drift'. Furthermore, many low-cost sensors have proved delicate and may break or malfunction frequently under the outdoor conditions they are regularly used for, and replacement or repairs may be financially unfeasible[45]. These factors have limited the use and trustworthiness of low-cost monitors. The specifications of these sensors may be difficult to find and interpret by lay people, and the cost of even 'low-cost' instruments and the infrastructure they require (such as external power or Wi-Fi) is still high enough that without convenient data-sharing abilities the number of monitors, and therefore the scale and quality of data, available to any one group may be highly limited[15]. DeSouza and Kinney's study on the distribution of one popular low-cost monitor (PurpleAir) suggests that these low-cost monitors are concentrated in areas that are whiter, wealthier, and less polluted than the US at large[21]. Finally, despite the

development of so many new technologies, there are still no low-cost sensors capable of detecting or analyzing heavy metal air pollution[17].

Public Science for Air Monitoring

Scientific research carried out by people other than professional scientists is often referred to as citizen science or public science, which is the term that will be used throughout this review. Public science refers to the collection and/or analysis of data by unpaid amateurs to meet scientific research goals[68]. It is a particular form of public participation in scientific projects that places an emphasis on hands-on involvement and harnesses the power of the crowd to collect large amounts of information. Some projects also include lay people in setting research goals and developing methods[52]. The strict boundary between professional and amateur scientists is relatively new. For centuries, valuable information has been collected and analyzed by people who would not have considered themselves scientists[44].

Public science promises many results for the non-scientists it involves. First, it can provide scientific education, if designed with education in mind. This is particularly beneficial in projects involving youth of school age. Unfortunately, many projects limit involvement to data collection[18]. Studies suggest that involvement must go beyond simple collection to yield educational benefits. Inclusion in methodology selection, data quality assurance, and dissemination of results may be particularly important in promoting scientific education[6]. Within the environmental sciences particularly, public science has been portrayed as a way

of increasing people's investment in their surroundings and spur environmental advocacy and behavior change[43]. Knowledge obtained from public-led projects has been used as a tool for activism and community empowerment[10]. The results from some projects have successfully been used to push for formal evaluations and environmental protections[14]. Finally, public science is believed to contribute to the goal of making science itself more democratic, by allowing the public to direct scientific research towards questions of relevance to them. This is of particular concern for community-led research, where goals and results are co-created by the relevant communities and academic researchers to answer questions of importance to the community[41].

Public science has attracted such attention both for its ability to bring in huge amounts of data and it's potential to remove the aura of mysticism that professionalization has created. 'Crowdsourcing' data collection and classification is considered an area of great potential in fields like ecology, where determining a reliable species distribution or count is nearly impossible to achieve with the limited time and money of professional ecologists. For the public scientists themselves, participation in scientific research can increase their knowledge of the world around them, create a sense of agency when faced with previously distant technical problems, and help individuals acquire or develop related skills. It can also allow them to answer questions that may not be prioritized by professional researchers.

Air quality monitoring has been a particular area of focus for many public science projects. Communities with high levels of respiratory illnesses may want

to investigate their surroundings. Communities in neighborhoods with high levels of pollution may want to collect their own data on pollution to challenge the narratives and decisions of government and industry. Literature on environmental injustice has shown that polluting industries use their political and economic power (i.e., lobbying and job creation) to gain and retain permits in locations that are disproportionately near low-income and/or BIPOC communities[50]. Organizing around instances of environmental injustice often begins with community led monitoring projects, to establish proof of high contamination in a form that can hopefully force acknowledgement and change from polluters and their supporters[14]. For example, advocates in Flint, Michigan used a community monitoring project to establish that residents were being exposed to highly elevated lead in their water, in a now-infamous case of environmental injustice[28]. Individuals with health concerns or simply scientific curiosity may also want to investigate the pollutants in their environments[17].

Whatever their motivation, community groups and individuals have used a range of technologies and methodologies to measure their personal exposure to dangerous pollutants more accurately than the sparse monitors maintained by government and research institutions allow. Their methods have included the use of emerging mobile air quality sensors and the creation of pollution estimation models[17,72]. The information collected has been used to inform individual and community behavior in order to reduce exposure, but also used to advocate for the enforcement or increase of regulations against pollutants[14,17].

Bioindicators for Air Quality Monitoring

Bioindicators are one technique used to fill the spatial gap in knowledge and reduce the high costs and infrastructure requirements of traditional monitoring equipment. Bioindicators are natural features, generally plants, that can be observed or tested to determine levels of pollution. Some of the most common and well-established types of bioindicators are mosses and lichens, which are used to monitor a range of air pollutants, particularly in Europe. For example, the Open-Air Laboratory (OPAL) air survey asks public scientists to identify species of lichen to determine nitrogenous pollution. The OPAL project relied on the fact that different species of lichens are known to have different tolerances of nitrogenous pollution and used the presence or absence of these species as a proxy for pollution levels. The OPAL project asked public scientists to identify only nine lichens in three different categories of pollution tolerance, a deeply simplified categorization system. Other systems have used dozens of species with far more divisions[65]. Lichens are also known to react negatively to sulfuric oxide, and these methods of determining relative pollution through lichen observation have been studied since the 1960s[32]. Other plants have been used as well. For example, observation of the lesions on tree leaves has been used to monitor ozone pollution. These studies used plants as ‘floristic’ rather than ‘analytic’ bioindicators, relying on observation of their physical features or range, rather than accumulation and chemical analysis of the pollutants within their tissues. These studies have been able to provide both qualitative and quantitative estimates of pollution. Analytical studies have analyzed the tissues of

mosses and lichens for the monitoring of gaseous and particulate matter pollutants, from heavy metals to radioactive fallout to polychlorinated biphenyls. Many studies have analyzed species of mosses and lichens to determine heavy metal pollution[26].

However, these techniques are underutilized in the US and in community monitoring programs[9]. A possible reason for this limited use of mosses is the difficulty of distinguishing between species to find appropriate biomonitors. These techniques require the identification of multiple different species of trees or lichens, species that may not be present in every environment for reasons unrelated to pollution. Spiderwebs, however, are common in all sorts of ecosystems: they are easily found in both dry and humid climates, urban and rural areas, and fall into a few broadly defined designs that are easily distinguished with little training[58]. Furthermore, as mosses are living organisms they are able to cycle out elements that they take up from particle deposition. The relationship between the cycle of uptake and release and concentration of metals in mosses is little understood. Spiderwebs solely collect particles that land on their surface and are unable to dispose of contaminants as living things can[9].

While the potential for spiderweb air monitoring to fulfill an important need in pollution research is clear, it is still a relatively new method with limitations. Only specific types of webs are suitable as biomonitors. Most studies have used the web of Agelenidae spiders. Agelenidae, also known as funnel weaver or grass spiders, are a family of spiders commonly found on all continents except Antarctica[3].They build tightly layered, non-sticky webs with a distinctive ‘funnel’ in

the center. This web structure easily collects any materials that settle upon them. Unlike many other families of spiders, Agelenidae do not destroy and eat their webs after they are damaged, and so their webs remain out for longer than most spiderwebs[58]. Furthermore, almost all the species of Agelenidae are harmless to humans, and none in the United States are of medical importance, meaning none of them have bites venomous enough to a non-allergic adult to require medical attention. *Eratigena agrestis*, or the hobo spider, is found in the Pacific Northwest and has occasionally been linked to hospitalizations, but many scientists believe that these bites were misattributed, and that the hobo spider is not sufficiently venomous to cause such harm[30]. For these reasons, Agelenidae webs are particularly suited as heavy metal biomonitors and, in many parts of the world, can be safely collected by those untrained in spider identification.

Previous Studies

Though this is a very new method, the few studies published at the time of these experiments yield some interesting findings. Most web studies have focused on the analysis of elemental pollutants (single elements such as arsenic or zinc in their solid forms), particularly heavy metals. The ability of spiderwebs to accumulate polycyclic aromatic hydrocarbons, a type of gaseous organic pollutant, is also being investigated[59]. Xiao-li et al. compared the accumulative characteristics of two different types of web structure in Wuhan, China. The researchers compared the webs of *Achaearanea tepidariorum* and *Araneus ventricosus*. *A. tepidariorum* creates tangle webs, which extend both horizontally and vertically and are often tightly woven, if unstructured. Furthermore, the webs

are not frequently remade. *A. ventricosus* creates horizontal orb webs, which are far more loosely woven. These webs are damaged regularly and must be repaired and are also consumed and remade every 7-10 days. They found that *A. tepidariorum's* webs were more effective at collecting metals than *A. ventricosus*, and consistently collected more heavy metal particles by weight[71]. The webs of the funnel weaver are similarly long-lasting and even more tightly woven than the webs of *A. tepidariorum*, and multiple studies have found them effective at accumulating airborne particulate matter[51,56,57].

A 2018 study in Poland tested the magnetic susceptibility of webs from spiders of the Agelenidae, Pholcidae, and Linyphiidae families in both indoor and outdoor environments. The Linyphiidae family of spiders are commonly known as sheet web spiders. They build small, tightly woven, and non-sticky horizontal webs like those of the funnel weaving Agelenidae family, although they lack the eponymous funnel. Pholcidae create irregularly structured, non-sticky tangle webs. Magnetic susceptibility was used as a proxy for the total amount of metals accumulated in the web. This study found that the webs of the Agelenidae family had higher mean and median magnetic susceptibility values than those of the other two families[51]. An early study in Australia found that the webs of the common Stiphidion, or South Pacific sheet weaver family, and the uncommon Desidae spiders were effective at catching lead and zinc-containing dust in Australian caves. They also found that when the collected webs were washed, the measured lead and zinc levels were significantly ($p < .05$) lower than the unwashed web, suggesting that most of the metal content determined during

Atomic Absorption Spectrometry (AAS) was present in the collected dust rather than the web themselves[34]. Later studies showed similar results when comparing the washed and unwashed webs of spiders that do not consume their own webs (such as Agelenidae)[57]. This finding regarding the level of metals within webs was echoed in a 2019 study of orb weaving spiders. This study found that even when the spiders' prey was spiked with metals, the metal concentration in webs dropped significantly when washed, indicating that the majority of contamination came from the remains of insects within the webs[60]. A study in Lahore, Pakistan used webs of the Pholcidae family to measure pollution in four study sites. They found that the metal content of the webs was correlated with the differing levels of traffic in each study site[63].

A study of six sites of varying pollution levels (two residential, two low traffic, and two high-traffic roadsides) in Wroclaw, Poland found differences between the concentrations of 16 different elemental pollutants, including heavy metals, in the webs of Agelenidae spiders. The measurements of most pollutants were higher in the high-traffic sites and lower at the low-traffic sites. However, some of the elements were found in concentrations that did not match those expected when looking at the traffic. Lack of historical data on pollution in these areas made these unexpected differences hard to explain. This article also suggested that most particles collected in spiderwebs could be assumed to be PM_{10} as smaller particles are generally deposited by precipitation, and the collected webs were protected from rain[57]. However, it is possible that because of this, less protected webs may be collecting a higher proportion of smaller

particles. An earlier study in Poland found that levels of zinc, lead, and platinum in the webs of two Agelenidae species was correlated with traditional measurements of those elements. However, this study only looked at measurements from two sites[56]. A later study in Poland indicated a strong positive correlation between the concentration of zinc and lead in collected Agelenidae webs and the concentration in speciated $PM_{2.5}$ and PM_{1} collected using impactors, a traditional method of particulate matter collection[58].

These previous studies have shown the effectiveness of these methods, but all of them have been conducted by professional scientists in highly controlled settings. Although the analysis of metal content in spiderwebs requires high levels of technical skill and equipment, the collection of spiderwebs is relatively easy. Volunteers can be trained to identify the distinct funnel web of the Agelenidae family and collect webs using any clean rod or gloves. These techniques will be elaborated upon in Methods. The simplicity of spiderweb collection means that these methods may be easily and reliably executed by non-scientists. This could allow individuals and community groups to learn about their local air quality and exposure cheaply and independently.

Research Gaps

Previous studies using spiderwebs have compared pollutants at only a few different sites, with little relationship between the sites, and relied on the correlation of spiderwebs with brief measurements using more traditional PM monitoring devices as a form of verification. As will be explained further in the

methods section, this study instead employs a unique grid design. Data collected from webs was compared with a detailed map of the study area to correlate differences in human and industrial activity with the concentration of heavy metals by square. I also compared web concentrations with the measurements from MDE's metal speciation monitors, a far more direct comparison than PM monitors. No studies have yet been conducted in North America, with North American Agelenidae species.

All the studies discussed have left data collection to professional researchers. Most of the costs in data collection are in the processing and analysis stage, but the collection of spiderwebs is very cheap, as opposed to traditional monitors where both PM collection and filter processing can be very expensive. This study allows participants to collect the webs of all Agelenidae species, rather than limiting collection to a handful of species as some previous studies have. If this expanded species pool is proven reliable, the job of public scientists would be simplified. Previous research attempted to identify pollution from mobile sources (namely vehicles on major highways) rather than including pollution from point sources like the industrial facilities present in Brooklyn/Curtis Bay[56,57,58,63]. Although spiderweb monitoring is currently unable to obtain the same level of accuracy as traditional methods of PM collection for metal speciation, the low price and ease of collection could make it a useful tool for public scientists to explore metal distribution and discover potential hotspots. Although no one measurement of metals in a spiderweb may be very accurate, studies have indicated that averages from multiple webs can obtain results

significantly correlated with those from traditional methods[56,58]. Furthermore, webs could help detect hotspots in areas that are not monitored by existing networks which may then spur more precise monitoring. This study aims to learn whether the webs of American Agelenidae spiders can detect hotspots of heavy metal pollution when collected and identified by public scientists.

Methods

Location Choice

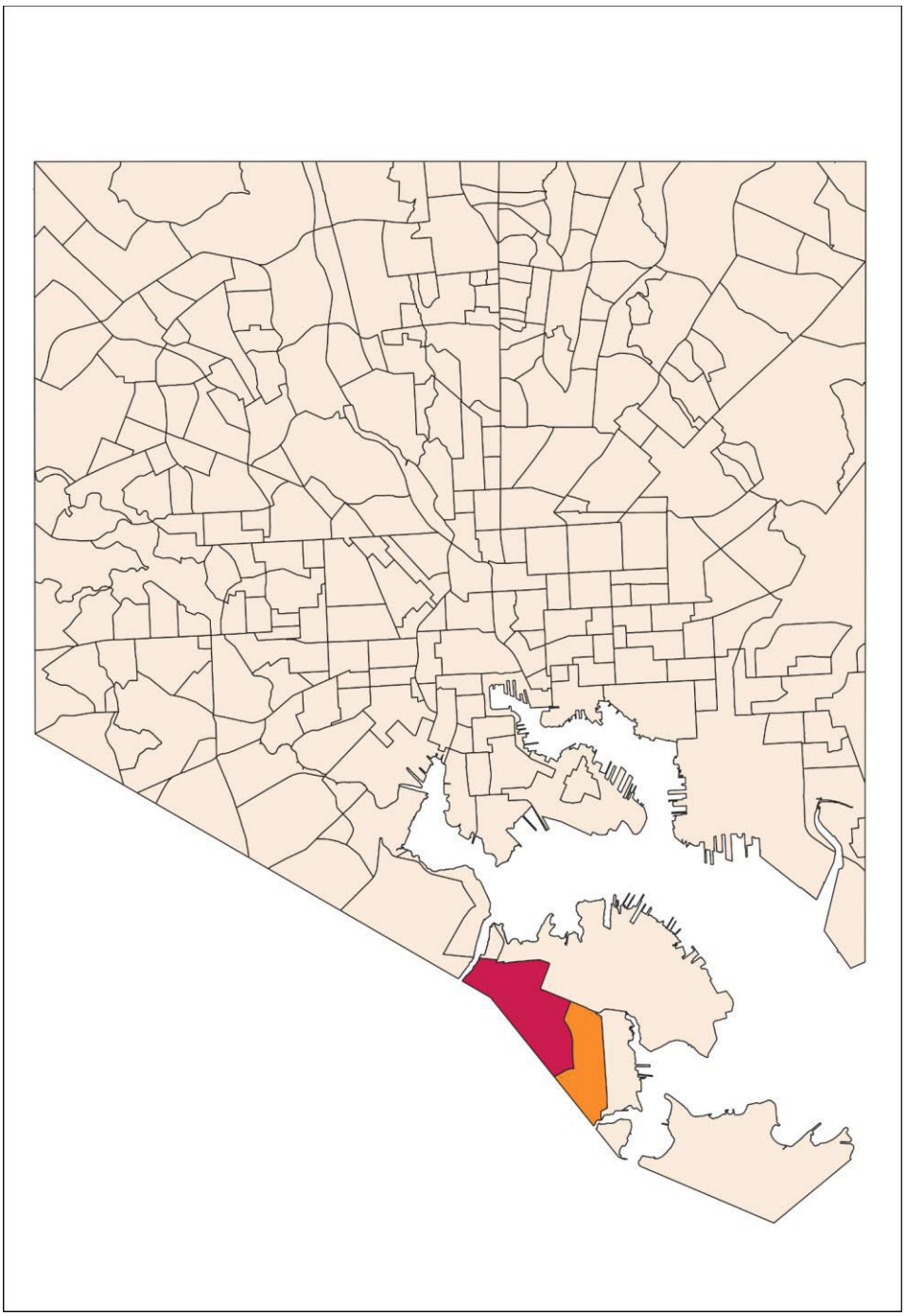


Figure 2: A map of Baltimore City, showing the neighborhoods of Brooklyn (orange) and Curtis Bay (red).

Brooklyn and Curtis Bay

The primary location of this study, the Baltimore neighborhoods of Brooklyn and Curtis Bay (see Figure 2), was chosen as it is an area known to have high levels of air pollution and a history of environmental advocacy around the issue. Figure 3 shows heavy metal releasing facilities on the 2019 Toxic Release Inventory (TRI) list near the study area. Four of these are within two miles of the study site. These facilities include a shipping terminal, a concrete plant, a plastic plant, and a chemical production facility.

The Wheelabrator Trash incinerator, the city's single largest polluter, is only a few miles away[20]. Curtis Bay/Brooklyn has a history of advocacy around environmental injustice, particularly related to the disproportionate air pollution advocates allege the residents of these neighborhoods experience. Perhaps most famously, neighborhood advocates succeeded in preventing the placement of a new trash incinerator in their neighborhood in 2016[27].

Maryland is the state with the highest median income in the country[67], but Baltimore is the poorest city and county in the state, with a median income well below both the state and national average, and a poverty rate twice that of the rest of the country[66]. A 2014 study estimated that there are 191 pounds of released toxins per Baltimore city resident, as compared to 47 pounds for the average county resident[8]. The Curtis Bay/Brooklyn area is an area with many industrial sites that used to have even more heavy industry. The neighborhood has a poverty rate more than 10% above the city's average, and although Curtis Bay/Brooklyn overall has a higher percentage of white residents than the city

average, the proportion of Black and Latino residents has grown steadily over the last few years[1,7]. It has often been called the most polluted neighborhood in Baltimore[27]. A study conducted by the Baltimore City Health Department found that between 2005-2009, the rates of mortality from lung cancer, lower respiratory infections, and heart disease were some of the highest in Baltimore City. As of 2017, the neighborhood had the third-highest rate of death from chronic respiratory infection among 54 Baltimore neighborhoods[7]. Curtis Bay/Brooklyn could be called an environmental justice community: a community whose marginalization has led to disproportionately high exposure and vulnerability to pollution.

These concerns have contributed to a history of community-led air-pollution monitoring and advocacy[37]. This advocacy has included the creation of community monitoring projects to measure local pollution. The Environmental Integrity Project operated stationary $PM_{2.5}$ sensors at three sites in the Curtis Bay/Brooklyn neighborhood between 2013 and 2015. These sensors recorded consistently higher $PM_{2.5}$ concentrations than the two nearest monitors maintained by MDE[38]. Using the Neighborhoods shapefile available on Open Baltimore, I created a grid of 1000 x 1000-foot squares across the Curtis Bay/Brooklyn neighborhood. After removing the squares for which more than half of their area lay within a body of water, 39 squares remained. 14 were in the Curtis Bay neighborhood and 25 in the Brooklyn neighborhood.

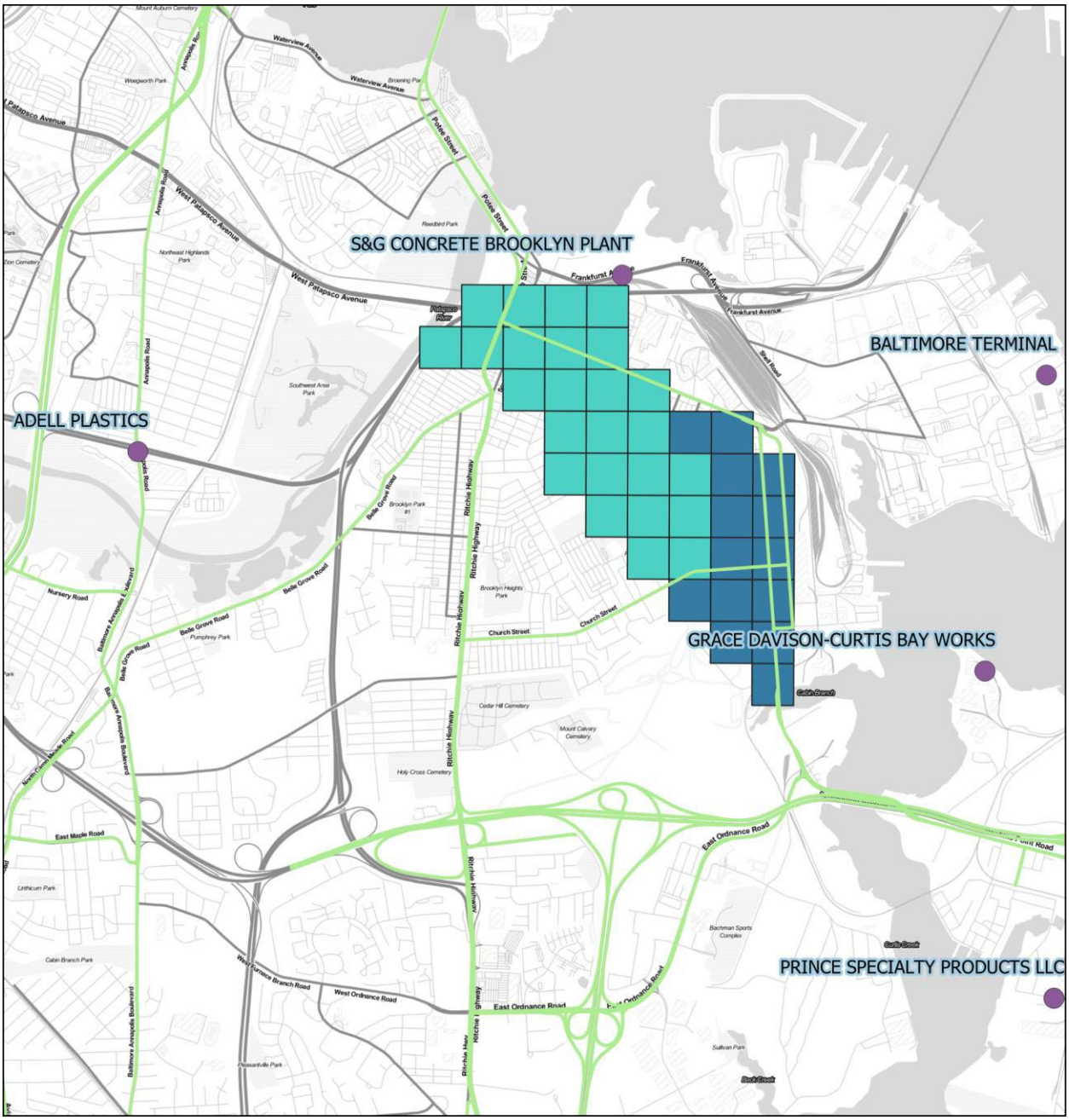


Figure 3: Study squares in Brooklyn (teal) and Curtis Bay (dark blue). Highways are highlighted in green, and 2019 TRI indicated in purple.

MDE Air Monitoring Sites

In the Fall of 2020, webs were collected from the surroundings of two of MDE's air monitoring stations. These two sites, which can be seen in closeup in Part E of the appendix, are the only stations operated by MDE which regularly collect particulate matter and chemically speciate it. One site is in the Howard University Beltsville Campus (HU Beltsville), a research park within a large, wooded area to the southwest of Baltimore City. According to MDE, the HU Beltsville monitor's purpose is to establish a "background level" of pollution. The other monitor is in the parking lot of Essex Senior Center, within a mixed business and residential suburban area to the East of Baltimore City. Although only the HU Beltsville monitor is part of the federal Chemical Speciation Network and the Essex monitor is not, both monitors use the same method in collection and analyzing samples. Once every three days, three or four filters are simultaneously run in an FRM manual gravimetric monitor for a period of 24 hours. These filters are then sent out for chemical analysis to an EPA contact laboratory[42]. The results are then posted online, although it can take up to 6 months for results to be finalized.

Collection Process

In September of 2019, a volunteer and I collected 10 webs from each of the 11 Curtis Bay squares during the first round of collection. An attempt was made to limit collection to webs with at least some cover (such as tree canopy) that would reduce the risk of web damage or destruction during weather events, though this was not possible in all squares. Originally, there were 14 squares

within the Curtis Bay area, but three of the squares were almost entirely contained within a privately owned, gated plot, so we were unable to collect from these three squares. We then returned approximately three weeks later to the described locations to collect five webs from each square during the second round. This two-step collection process was designed to create a time-series with a standard length of time in which webs were exposed to ambient particulate matter. Agelenidae webs were identified, collected, and their locations spatially described by volunteers to assure that we would return to the same site for the second round of collection. We also took notes on the weather conditions for destruction and collection days.

Three weeks later, the newly created webs were collected using clean glass vials and glass rods cleaned with acetone in between each collection. Webs were then frozen after collection to kill any organisms that were inadvertently carried in the web. If all the previous webs at each location had been destroyed and their locations recorded accurately, we could be certain that the webs collected were built by spiders less than three weeks prior. Many spiders are known to return to the same familiar site to remake their webs after they are damaged or destroyed and do so very quickly[57].

The first-round webs, whose age range is unknown, were compared to the webs of known age and used for initial exploratory analysis of the common metals in the area. The results of this analysis will be discussed in the results section. In October of 2019, we performed the same two-part collection process within 23 squares in the Brooklyn neighborhood over a period of approximately

three weeks. 10 people divided into five teams to collect webs in these squares. These teams consisted of college students, scientists, and lay-people who were briefly trained in funnel web identification and collection. Volunteers collected more than 300 Agelenidae webs over three collection days.

A similar method was used when collecting webs to be compared to results from the two metal speciating air monitoring systems operated by MDE. This collection took place in October 2020. Webs were identified and cleared from sites within 150 m of both air monitors, and new webs in the same identified locations were then collected two weeks later using the spiderweb collection methods described previously. At the HU Beltsville site, 13 freshly made webs were collected from a small, abandoned graveyard across from the monitoring station. In Essex, 19 freshly made webs were collected from a sign outside of the senior center and bushes outside of a Bay Vanguard Bank.

Processing

After defrosting, webs were cleaned by hand of organic debris using thoroughly cleaned plastic tweezers. Debris within webs includes insect corpses, fur, and vegetation. Organisms within the webs may be exposed to air pollution sources far from these webs or take up metals through other pollution sinks such as water or soil. Webs must be cleaned of this debris to reduce the risk of any metals in these organisms contributing to the metal speciation results[56,57,58]. Webs were then dried at 70°C for a period of at least 48 hours and weighed to the nearest hundredth of a milligram.

When analyzing the webs collected in the Brooklyn area, the first-round webs (those with no known age) were divided into two groups. One set of webs was processed based on the methods described in multiple papers by Justyna Rybak and colleagues which tested webs for metals[56,57,58]. The other set was processed using methods described by the EPA, originally intended for the analysis of metals in soil[25]. I will refer to these procedures as the “Rybak Methods" and “EPA Methods" respectively. An attempt was made to divide the webs collected from each square equally between the groups, but unfortunately, some early errors in database management and contamination of samples meant that was not always possible. In each of the 23 squares for which we processed first-round webs, an average of 4.17 webs, and a median of 4 webs was processed using the Rybak method. The EPA method was used with a mean of 4.45 webs, with a median of 4.5 per square.

The Rybak method is as follows: Each cleaned and dried web is dissolved in 2 ml of fresh Aqua Regia (3 HCL: 1 HNO_3) solution slowly raised to 120°C in a dry bath over 4 hours. 1 ml of each sample was then combined with the other samples from the same square and method. ‘Blank’ aqua regia solution was added to each vial to bring it up to the 6 mL minimum necessary to be processed in an Inductively Coupled Plasma Mass Spectrometer (ICP-MS) at the UMBC Molecular and Chemical Analysis Center (MCAC). The EPA method combined 0.5 mL of water with 1 mL of HNO_3 to digest the spiderwebs, which were placed in a dry bath at 90°C for two hours. After two hours, 0.2 mL of water and 0.3 mL of H2O2 were added, and the mixture was heated for two more hours. After

cooling, this mixture was divided into two vials, and 0.5 ml of HCL was added to each vial, which then were heated at 90°C for 15 minutes. 2 ml of each sample was combined with other samples from the same square and method. First round webs were sent to the MCAC to be analyzed for the 6 most common metals found in a 6-year study of particulate pollution in the Baltimore area: nickel, zinc, chromium, iron, aluminum, and copper[47]. They were also analyzed for lead, which is far less common but of particular concern for human health. A 'blank' sample of the processing solution which did not contain any web was submitted to the MCAC as a control, which allowed them to determine the baseline level of metals in the uncontaminated solution and create a correlation curve with which they could calculate the ppb of metals from the webs alone. Through this analysis, I hoped to determine which five metals were most common in the study area, and to determine which processing method was best able to detect the metals of interest.

This analysis unfortunately did not yield a clear indication of which method was best for determining metal concentrations (see appendix Part A). As there was no strong indication, we decided to move forward with the EPA based method, due to the clear instructions available, the established use of these methods, and observation which suggested that there was less risk of contamination or damage to equipment with these methods. All seven metals were detectable in high concentrations in an initial analysis of webs of unknown age. In the second round, we chose to test for the three most common metals in webs along with two metals of particular concern for human health: chromium

and lead. This is important because there was concern that some metals might not be detectable in the younger second round webs, so for this initial study I chose common pollutants that we were more likely to detect, even in very ‘new’ webs.

Second-round webs were processed using the EPA methods previously described. However, all webs were analyzed for metals individually, rather than by square as in the first round, to give an idea of the spread of data within each square. When processing second-round webs, there was a mean of 4.09 webs per square and a median of 5. The same method was used in processing and analyzing webs collected at MDE monitor sites.

Web Data

Data Preparation

To compare values of metals between webs of different weights, the ppb values given by the MCAC were converted to the percent of metal content in each web. I used the below formula to convert the ppb values to percentages.

(Metal ppb/((Spiderweb (mg)/solution (ml))* 1,000,000))*100

In addition, all round two percent values were divided by number of days between web clearing and collection to account for the slightly different collection times due to the large size of the area covered. Four of the five metals tested (lead, iron, chromium, and nickel) in the second-round webs had values which were below the level of quantification (BLQ) of the ICP-MS. Most of the

chromium and nickel results were BLQ, so those metals were excluded from the round two analysis.

Statistical Analysis

To test whether there was a relationship between the weight of the webs (and presumably their age) and the concentration of metals detected, I ran a Spearman's correlation test for both round two and round one webs. Much of the data was heteroskedastic along with having a non-normal distribution. Therefore, to test whether volunteers were successfully identifying the new webs in round two, I ran a Mann-Whitney U test comparing the concentration of metals in round one and round two webs.

Using QGIS, results were spatially tied to variables of interest. Vials were linked to Maryland 2019 Average Annual Daily Traffic (AADT) to test if there was a correlation between sources of automobile exhaust and web metal values. I created a file of AADT summary statistics by square which contained the maximum, mean, and sum of 2019 AADT values of all roadway lines intersecting with each square. To test whether there was a correlation between known point sources of metal pollution and web metal values, vials were also linked to the four 2019 metal releasing TRI sites within two miles of the study squares. Using QGIS's 'distance to nearest hub' tool, I created a table with the distance in meters between each square and those four nearby TRI sites. To test whether there was a correlation between population density and web metal values, I linked each vial to population per square mile as obtained from 2019 census

block group data. I created a table of each study square linked to the census block it shared the most area with. I then used Spearman's correlation test to test the correlation between the percent of aluminum, lead, and iron in webs by day and population density, TRI distance, and AADT data. To test whether spiderwebs could be used to detect fine-scale differences in pollution, metal values from webs were compared between squares using a one-way ANOVA and a non-parametric Kruskal-Wallis test. Similarly, metal values from webs were compared between neighborhoods and between monitor sites using Welch's two-sample t-test. The non-parametric Mann-Whitney U test was also performed.

MDE Monitor Data

Data Preparation

To contextualize the results from webs collected near monitors, I ran tests on the last ten years (2011-2020) of $PM_{2.5}$ and elemental speciation data available from the HU Beltsville and Essex monitors. As air pollution is known to have seasonal trends[47], I only downloaded data from Autumn (September to November) of each year, as we only collected webs in this season. All values from MDE monitors were downloaded from the EPA's Air Quality System Application Programming Index (AQS API). All tests involving speciated metal data were run using the raw reported values ($\mu g/m^3$), and then again using the percent of metal in the reported $PM_{2.5}$. These percentages were created to compare the monitor data more easily with web data, which was also only available as a proportion of the matrix it was contained within. The EPA began to

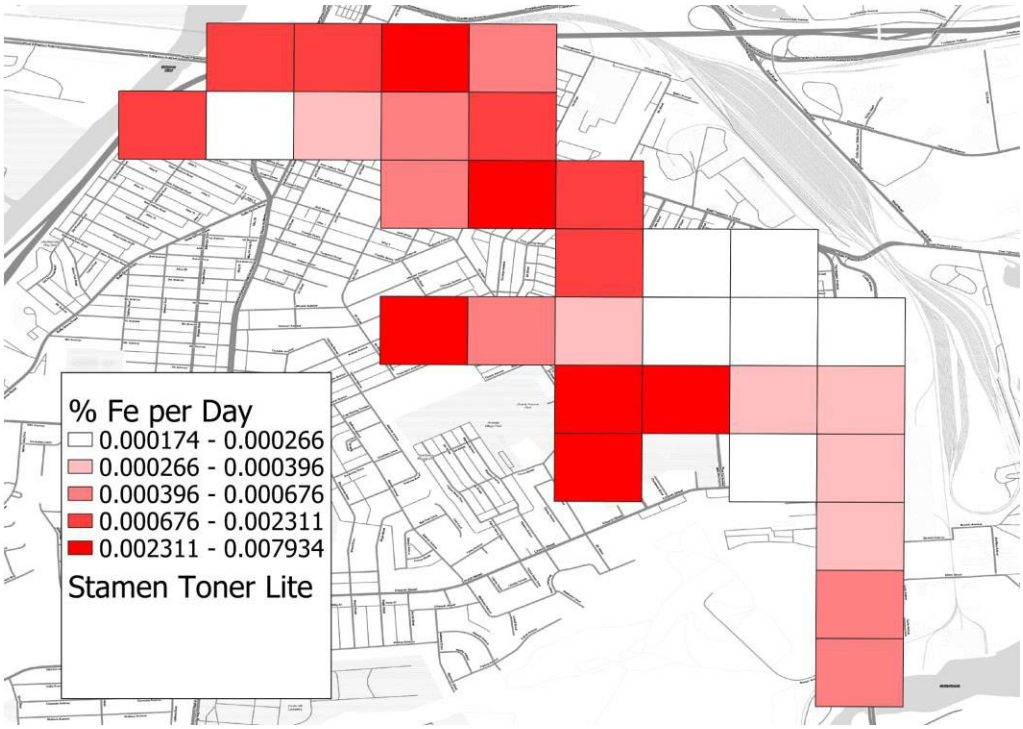
accept negative values of metal speciation data in 2016. However, the minimum value before 2016 was 0 $\mu g/m^3$. To compare across 10 years, and due to the impossibility of 'negative' air pollution, all negative values were replaced with 0s.

Statistical Analysis

To see whether differences in the monitor data lined up with differences in the web data by site, I ran t-tests and Mann-Whitney U tests comparing 2020 values of Al, Pb, Fe, and $PM_{2.5}$ between the two sites. I used t-tests and Mann-Whitney U tests to determine whether the year and month in which I surveyed were significantly different from the decade's seasonal average. I ran the same tests on the decade of $PM_{2.5}$ data available from the downtown Baltimore FRM monitor.

Results


% Pb per Day
0.000066 - 0.000151
0.000151 - 0.000257
0.000257 - 0.000296
0.000296 - 0.000699
0.000699 - 0.016449
Stamen Toner Lite


% Fe per Day
0.000174 - 0.000266
0.000266 - 0.000396
0.000396 - 0.000676
0.000676 - 0.002311
0.002311 - 0.007934
Stamen Toner Lite

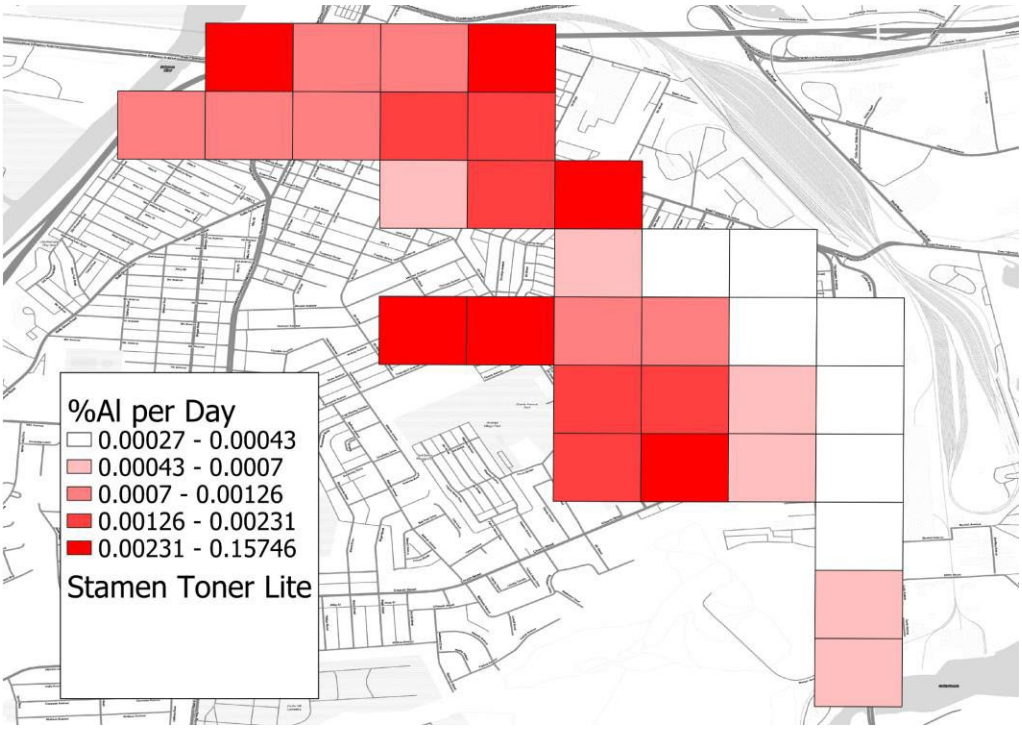


Figure 4: Baltimore round two results by square for lead, iron, and aluminum.

A Note on Reporting

Much of the data violated the assumptions needed for parametric tests. Along with having a non-normal distribution, the data was often heteroskedastic and contained unresolvable outliers. I ran both parametric and non-parametric tests, but I will be reporting only the results of the non-parametric test as there were no cases where the data did meet assumptions of normality and variance and there was a disagreement in significance ($p<.05$) between the two tests. All test results are included in the appendix for completeness. All testing was done in R, and the code is available here: https://github.com/nrasteg1/NavaRastegarThesisDocs.

Baltimore City Webs

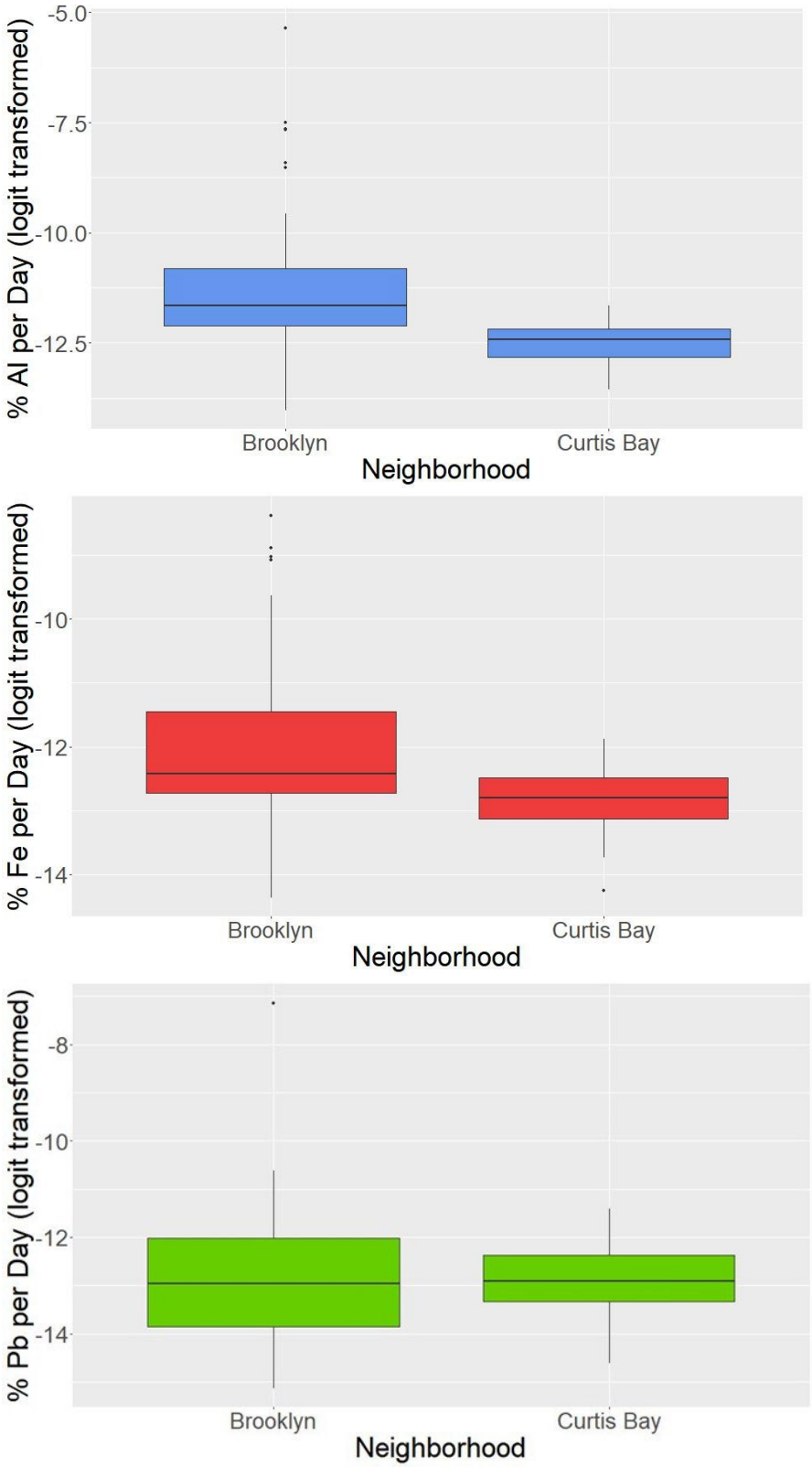


Figure 5: Boxplots of Baltimore round two results by Neighborhood for aluminum, iron, and lead.

To test whether the volunteers were successfully identifying new webs during the second-round collection, I ran a Mann-Whitney U test comparing the total mass of round one and round two webs. There was a significant difference (W=19389, p=8.888e-07) between round one (med= 8.355 mg) and round two (med=4.18 mg). I also ran a Mann-Whitney U test comparing the concentration of iron, lead, and aluminum between round one and round two webs. There was a significant difference in the concentration of iron (W=380, p= 2.90E-11) with round one (med= 1.165316%) greater than round two (med= 0.02309385%). There was also a significant difference (W=351, p= 1.34E-05) in concentration of aluminum with round one (med= 0.3369988%) greater than round two (med= 0.03271923%).

Parameter 1	Parameter 2	W	p	P1 Median	P2 Median
Al Round one	Al Round two	351	1.34E-05	0.338376%	0.000583%
Pb Round one	Pb Round two	158	0.3803	0.005791%	0.000245%
Fe Round one	Fe Round two	380	2.90E-11	1.165316%	0.000331%
Weights Round one	Weights Round two	19389	8.89E-07	8.355 mg	4.18 mg

Table 1: Chart of Baltimore Round Two vs. Round One web medians and Mann-Whitney results

To see if there was a relationship between the size of the web and the concentration of metal within it, I used a Spearman's correlation test comparing concentration of web in solution and concentration of metal in solution. There were significant, positive results for round one aluminum (rs(660)= 0.6273292, p=0.002226), iron (rs(600)= 0.6612084, p=0.001076), lead (rs(722)= 0.5923207, p=0.004355), copper (rs(594)=0.6645963, p=0.0009956), and zinc

(rs(778)=0.5607002, p=0.007536). There was no significant relationship between round one web concentration and chromium or nickel concentration. Round two also showed significant, positive relationships between the concentration of web in solution and aluminum (rs(103960)= 0.722523, p < 2.2e-16), iron (rs(107632)= 0.5403008, p= 7.817e-10), and lead (rs(59785)= 0.7641226, p < 2.2e-16). I found no significant positive relationship between metal concentrations and the days between round one and round two collection. Round one webs of unknown age were significantly heavier and had significantly higher concentrations of most metals than weeks-old round two webs. Higher concentrations of metals were also significantly correlated with higher weights of webs.

To test whether spiderwebs could detect spatial differences at a fine scale, I ran a Kruskal-Wallis test comparing the round two metal results by square (see Figure 4). There were significant differences in percent aluminum (H(31)= 68.253, p=0.0001289), lead (H(30)= 64.326), p=0.0002673), and iron (H(30)= 58.699, p= 0.001319) per day between squares. When I ran a post-hoc Dunn's test, 130 of 465 pairs of squares had significant differences in lead, 146 of 496 had significant differences in aluminum, and 134 of 465 had significant differences for iron (these results are not included in the Appendix for length but can be viewed on my GitHub). I also ran a Mann-Whitney U test comparing round two results between Brooklyn and Curtis Bay (see Figure 5). Significant differences were found for percent aluminum by day (W=3514, p=7.01E-11) and percent iron by day (W=2216, p=0.0001623). As seen in Part C of the appendix, the median value of aluminum in Brooklyn (med=0.0008729905%) was greater

than the median value of aluminum in Curtis Bay (med=0.000403471%). Likewise, the median value of iron in Brooklyn (med=0.00040F2018%) was higher than the median value in Curtis Bay (med= 0.000274842%). A Moran's I index found no significant spatial clustering for any of the round two metal values by square.

Parameter 1	Parameter 2	W	p	P1 Median	P2 Median
%Al/day Brooklyn	%Al/day Curtis Bay	3514	7.01E-11	8.73E-04	4.03E-04
%Fe/day Brooklyn	%Fe/day Curtis Bay	2216	0.000162	4.02E-04	2.75E-04
%Pb/day Brooklyn	%Pb/day Curtis Bay	1646	0.971	2.34E-04	2.48E-04

Table 2: Chart of Brooklyn vs. Curtis Bay web medians and Mann-Whitney results

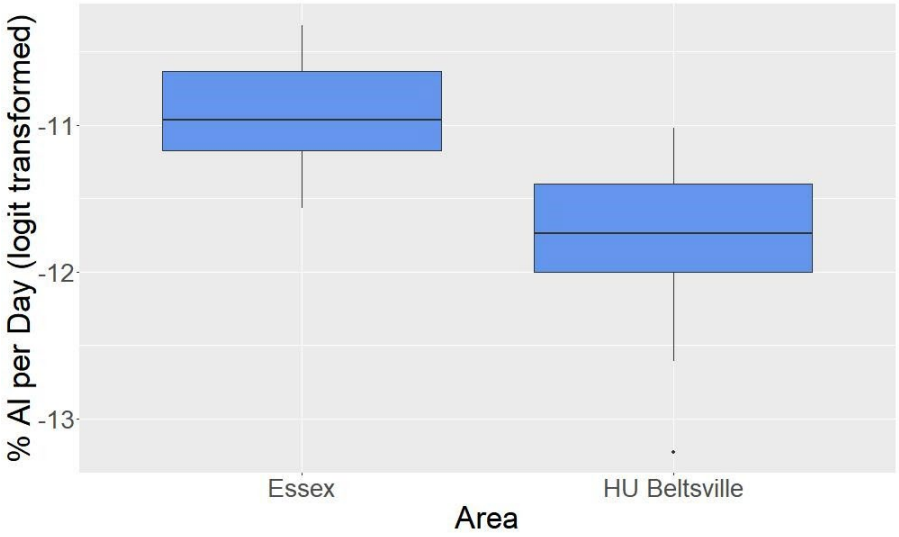
I used a Spearman's correlation test to see if there was a significant correlation between any of the metal concentrations and known sources of metal pollution- automobile traffic and the four nearest metal releasing TRI sites. There were significant positive correlations between percent iron by day and AADT sum ($r_s(186729)= 0.2024742$, $p=0.03228$), mean ($r_s(185218)= 0.2089293$, $p=0.02705$), and maximum ($r_s(181341)= 0.2254884$, $p=0.01683$). I found no other significant correlation between metals and AADT values. There were no significant negative correlations between distance to TRI sites and metal values, as might be expected if higher metal concentration in webs were related to lower distance from facilities, but there was a significant slightly positive correlation ($r_s(295787)=0.210518$, $p=0.0158$) between distance to TRI site Grace Davison Curtis Bay Works and percent aluminum per day. There was also a significant

slightly negative correlation (rs(280330)=-0.1973, p=0.037059) between percent iron per day and population density.

Parameter 1	Parameter 2	Cor	p
% Al/day	Distance to Grace Davison	0.210518	0.0158
% Fe/day	Density	-0.1973	0.037059
% Fe/day	Maximum AADT	0.225488	0.016828
% Fe/day	Mean of AADT	0.208929	0.027053
% Fe/day	Sum of AADT	0.202474	0.032276

Table 3: Chart of significant Spearman Correlations

Monitor Webs



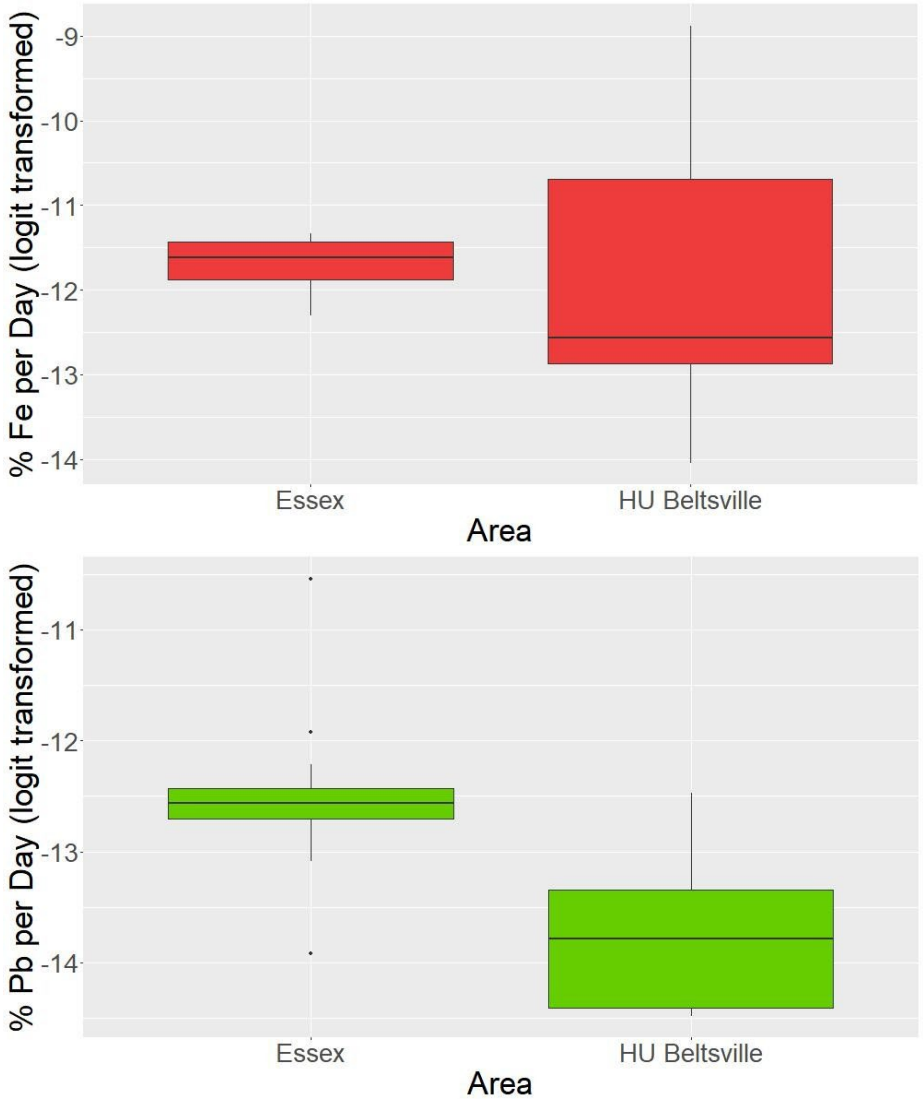


Figure 6: Boxplots of near-monitor web results by site for lead, iron, and aluminum.

To see if spiderwebs could detect pollution differences between a suburban and rural area (see Figure 6), I ran a Mann-Whitney U test comparing the metal values from webs collected near the HU Beltsville and Essex monitors. As seen in Part C of the Appendix, there were significant differences between percent aluminum per day (W= 231, p= 5.23E-06) and percent lead per day (W=121, p= 0.001126). The median value of lead in Essex webs (med=

0.001730257%) was higher than the median value of lead in HU Beltsville webs (med=0.000797753%). Similarly, the median value of aluminum in Essex webs (med=0.000349624%) was greater than the median value of lead in HU Beltsville webs (med=0.000105144%).

Parameter 1	Parameter 2	W	p	P1 Median	P2 Median
% Al/day Essex	% Al/day HU Beltsville	231	5.23E-06	0.001730257	0.00079775
% Pb/day Essex	% Pb/day HU Beltsville	121	0.001126	0.000349624	0.00010514
% Fe/day Essex	% Fe/day HU Beltsville	127	0.05647	0.000905654	0.00034783

Table 4: Chart of Essex vs. HU Beltsville web medians and Mann-Whitney results

MDE Monitors

To see if differences in metal concentrations between webs near the monitors were reflected in the values from MDE monitors, I ran a Mann-Whitney U test to see if there were significant differences between Fall 2020 metal and $PM_{2.5}$ values in HU Beltsville and Essex. There was a significant difference (W=103, p=0.001892) in percent iron in $PM_{2.5}$, which was smaller for Essex (med= 0.516129%) than HU Beltsville (med=1.361702%). When analysis was expanded to cover 2011-2020, percent iron values were still significantly higher (W=40480, p=8.16E-06) in HU Beltsville (med= 1%) than in Essex (med=.8%). Furthermore, there was a significant difference between both raw (W= 30820, p=0.0003148) and percent lead in $PM_{2.5}$ (W=28825, p=0.0108), which was larger for Beltsville (med=.002 μg/m^3, med= 0.02424242%) than Essex (med=0 μg/m^3, med= 0%). Percent iron values were significantly higher (W=40480, p=8.16E-06)

in HU Beltsville (med= 1%) than Essex in (med=.8%). There was a significant difference (W=52803, p=1.114e-06) between sites for a decade (2011-2020) of autumn values of $PM_{2.5}$. The median $PM_{2.5}$ for the decade in Essex (med= 6.8 $\mu g/m^3$) was larger than in HU Beltsville (med=5.6 $\mu g/m^3$).

Table 5: Chart of Essex vs. HU Beltsville monitor medians and Mann-Whitney results.

I also used a Mann-Whitney U test to compare Fall 2020 parameter values in both sites to the rest of the decade, values of which can be seen in Part D of the Appendix. The only significant difference (W=4468.5, p=0.04128) was in HU Beltsville, where $PM_{2.5}$ values were significantly lower in Fall 2020 (med=4.8 $\mu g/m^3$) than in Fall 2011-2020 (med=5.6 $\mu g/m^3$).

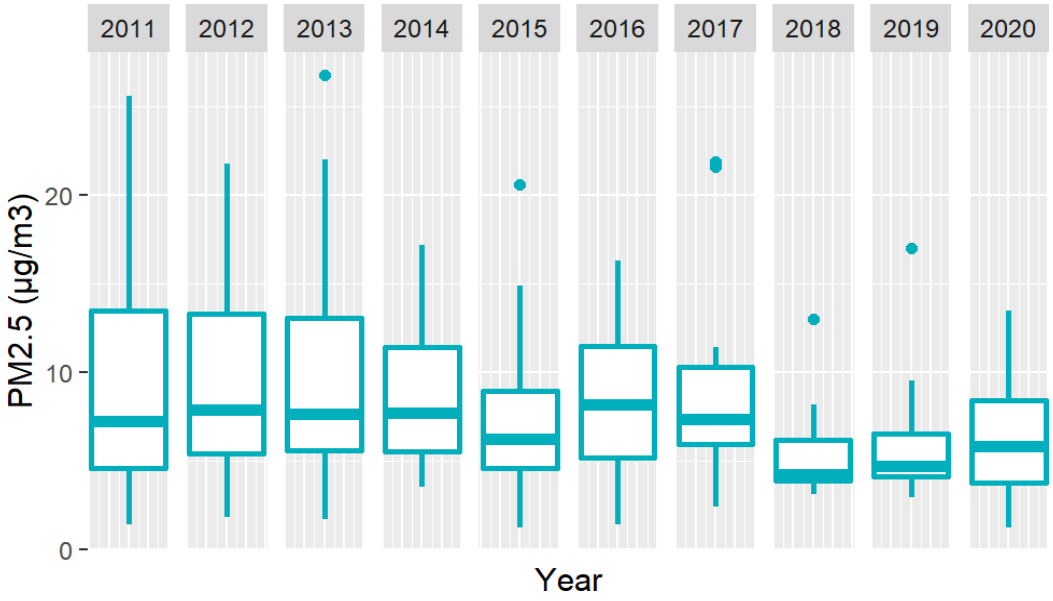


Figure 7: Boxplot of Essex $PM_{2.5}$ monitor results from 2011-2020.

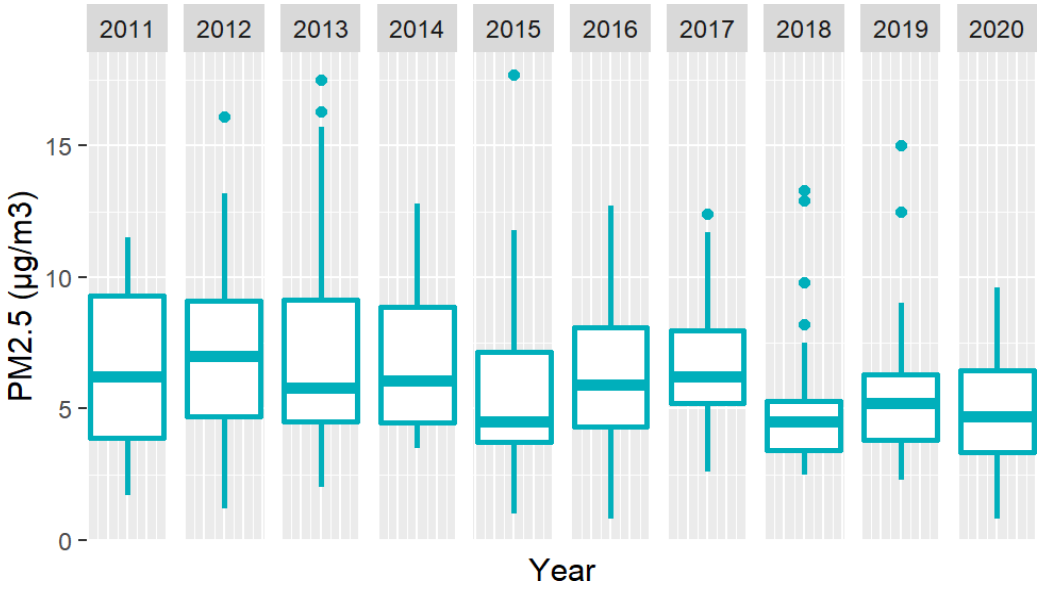


Figure 8: Boxplot of HU Beltsville $PM_{2.5}$ monitor results from 2011-2020.

Finally, I compared a decade of October with a decade of total autumn values to see if October pollutant values were significantly different from the rest of the season. October $PM_{2.5}$ values were significantly different from the season's

median in both HU Beltsville (W=17513, p=0.04422) and Essex (W=8541, p=0.02035). In HU Beltsville, October $PM_{2.5}$ values (med=4.85 μg/m^3) were significantly lower than the seasonal average (med=5.6 μg/m^3). In Essex, the same was true- October values (med=5.9 μg/m^3) were significantly lower than the seasonal average (med=6.8 μg/m^3). October and September values of $PM_{2.5}$ differed significantly in the downtown Baltimore monitor as well (W=27470, p=0.003346), with September (med=7.35 μg/m^3) higher than October (med=6.2 μg/m^3).

Parameter 1	Parameter 2	W	p-value	P1 median	P2 median
PM2.5 HU October	PM2.5 HU All months	17513	0.04422	4.85	5.6
PM2.5 ES October	PM2.5 ES All months	8541	0.02035	5.9	6.8
PM2.5 BM October	PM2.5 BM All months	63891	0.003197	6.2	6.9
PM2.5 BM October	PM2.5 BM September	27470	0.003346	6.2	7.35
PM2.5 HU 2020	PM2.5 HU all years	4468.5	0.04128	4.8	5.6

Table 6: Chart comparing monitor monthly medians and overall medians with significant Mann-Whitney Results.

Discussion

This study was designed to answer the following research questions: Can fine scale spatial differences in heavy metal pollution be detected by collecting and analyzing Agelenidae webs? Can the concentrations of metals in Agelenidae webs be correlated with known air pollution sources and influences, namely TRI sites, traffic, and population density? How do the differences in metal air pollution detected using webs compare to the differences in pollution detected by established FRM and FEM monitors?

There are a few assumptions that this study is built upon. The fact that there were significant differences between weights and all metal percentages in round one and round two webs implies that volunteers were successfully reidentifying the location of their webs and collecting younger webs. Furthermore, the significant relationship between weight of webs and the percent metals within for five of seven metals in round two webs and all three metals in round two webs indicates that webs collect more metals as they grow and age. These significant results suggest that the basic assumptions our later tests rely upon are valid.

Significant differences between squares were detectable for round two results of all three metals, indicating that spiderwebs can detect fine spatial differences in pollution. Significant differences between neighborhoods were also detectable for two of the three metals. However, I was not able to relate these differences to known pollution sources for any metal but iron. There is a weak positive relationship between iron rates and nearby traffic. This may be due both

to fuel combustion and non-exhaust emissions. Non-exhaust emissions from roadways include particles from brake wear, tire wear, road wear, and resuspended road dust. These particles have been estimated to compose up to 90% of the PM emissions from traffic, a proportion that is only rising as restrictions on exhaust pollution tighten. Iron is common in many of these non-exhaust emissions sources, while lead and aluminum are less common[48]. The reason for the positive correlation between distance to Grace Davison works and aluminum concentration in webs – implying that aluminum concentrations were higher in webs further from Grace Davison – is difficult to explain. The 2019 TRI reports vanadium and nickel releases from Grace Davison, but not aluminum. Reporting limits can be quite high. Companies are not required to report aluminum dust releases if they estimate those releases to be under 25,000 pounds a year[24]. All metal releasing TRI sites were included in analysis due to a belief that sites releasing one type of metal might be likely to release other metals, even if those releases were below the reporting limit for the TRI. However, it is quite possible that there were no significant releases of aluminum from Grace Davison, and that the positive correlation is due to a coincidental, unrelated variable. Inclusion in the EPA's TRI list is a flawed proxy for actual, exact measurements of all metal releases, and future research may want to investigate other data sources. Population density and iron were also slightly negatively correlated, implying that as population density increases the percentage of iron in webs decreases. This correlation is also counter intuitive-most studies have found that population density is positively correlated with

pollution levels[55,72]. This negative correlation could be due to a variety of factors. Iron is generally tied with industry and traffic emissions, which may have little relationship with where people live[35,49]. The most populated residential areas may not be the areas that people engage in activities that lead to iron pollution. My way of determining population density may also have been flawed- I assigned population density to each square based on the population density of the census block that each square shared the most area with. This may have obscured or misidentified the actual differences between population in each square. Future research should investigate these issues of scale and examine the relationship between pollution and job locations, rather than simply population density.

Further research is needed to draw out the differences between the neighborhoods- although both AADT values and density were on average higher in Brooklyn, these tests did not reveal any significant relationship between those factors and metal values except in the case of AADT and iron. Future research should investigate other pollution sources, and perhaps look at a finer spatial scale, with spiderwebs as point data rather than generalized by square. Expanding to a larger spatial area, such as across a city, might also allow researchers to find clustering across a larger spatial area.

Webs were also able to detect significant differences in metal pollution between a wooded area (HU Beltsville) and mixed-use suburban area (Essex). These differences are only partially supported by a decade of seasonal data from nearby monitors maintained by MDE. Raw and percent average and median values of lead are significantly higher in Essex than HU Beltsville, agreeing with

the higher values from nearby webs. Mean and median values of $PM_{2.5}$ are also higher in Essex than HU Beltsville. However, the HU Beltsville FRM monitor has recorded higher mean and median percent values of aluminum than the Essex monitor over the last decade, though these differences are not statistically significant. This disagrees with the significant differences in web values of aluminum, which were higher in Essex than HU Beltsville. This may be due to differing placement of the sensors and webs- while the collection of webs is limited by the height of the collector, the monitors are raised multiple meters from the ground. This may lead to webs collecting heavier particles than the monitors, as those heavier particles drop more quickly. One previous study suggested that PM_{10} may be a greater contributor of metal in spiderwebs than $PM_{2.5}$, but unfortunately PM_{10} values are only recorded at HU Beltsville and therefore cannot be compared between sites[57]. PM_{10} collected at this monitor is also not chemically speciated. The monitors are placed to detect neighborhood or background levels of pollution, while webs may be detecting differences at a far finer scale. Furthermore, October is a month that is significantly lower in $PM_{2.5}$ pollution than the rest of the Fall in both Essex and HU Beltsville, and HU Beltsville experienced significantly lower $PM_{2.5}$ pollution in the Fall of 2020 than in the rest of the decade. This may have been a particularly unique time to collect webs, and therefore difficult to compare with overall trends. Future researchers may want to collect the same site at multiple points throughout the year. This would give a better idea of how spiderweb results compare with overall trends in FRM monitor data.

An analysis of the last 10 years of $PM_{2.5}$ collected at the Baltimore city Oldtown monitor showed that September values of $PM_{2.5}$ were significantly larger than October values. However, Brooklyn webs collected in October showed significantly higher values of aluminum and iron than webs collected in Curtis Bay in September. This suggests that the difference in web results is not simply due to seasonal differences in $PM_{2.5}$. Without chemical speciation data from this site, it is difficult to rule out the possibility of temporal trends in $PM_{2.5}$ components influencing the web values. PM_{10} data may also be too limited to rule out PM_{10} temporal trends as a contributing factor. Although a t-test and Mann-Whitney U test performed on Fall PM_{10} data in Baltimore city indicated no significant difference between September and October values, Baltimore PM_{10} data has only been collected since 2017.

Future Research

Collecting spiderwebs to monitor air pollution is a relatively new method, and best practices are not yet established. While this study only distinguished between webs by structure type, more investigation would be necessary to determine whether the Agelenidae species creating the funnel web affects the accumulative ability of the webs, and to determine whether concentrations of metals in different specie's webs are comparable. Future research should investigate the ideal length of time to leave webs out, balancing the desire to obtain measurable values of the pollutants of interest while also limiting the risk of the web's destruction and loss as a data source. Generalizing results by square may have obscured important spatial differences in the pollutants collected by each web. Using the exact location of each web would allow a better understanding of the relationship between pollution sources and pollutant concentrations. Completing multiple collections over time would allow researchers to discover if temporal trends in spiderweb metals correlate with temporal trends from established monitoring systems. Webs should also be tested for different elements, as the efficacy of spiderwebs as pollutant collectors may vary by pollutant type. Researchers may also wish to compare results from webs to those from other bioindicators, such as mosses or leaves[53] to learn more about the strengths and weaknesses of the different bioindicators, and if they could be used in concert. As these techniques have great potential in public science, research into the attitudes, needs and experiences of potential users of this technique would be invaluable in fine tuning education and outreach.

Conclusions

Air pollution can vary widely over a relatively small spatial scale. The majority of long-term monitoring conducted by government bodies, while highly accurate, is also highly spatially generalized due to cost and technology limitations. As differing exposure to air pollution can have significant effects on human health, questions regarding the spatial variation of air pollution have driven many public science projects. There have been great technological advances in low-cost air monitoring. However, the expertise and cost barriers for using these instruments can still be restrictively high for much of the public, particularly the marginalized communities who may benefit most from knowledge of their pollution exposure. There are also not yet any low-cost instruments available which chemically speciate particulate matter.

Collecting bioindicators of air pollution has been explored both in government and public monitoring efforts. Biomonitoring is still limited in its application, particularly in public science, which may be partially due to the difficulty of identifying the appropriate monitoring species and the unclear role of biological cycling in pollution concentrations in the plants commonly used. Agelenidae webs are easily identifiable and solely collect surface deposited pollutants. I hypothesized that Agelenidae webs would be able to detect fine-scale spatial differences in heavy metal air pollution. To test this, I and a team of volunteers from a variety of backgrounds collected Agelenidae webs from an area of Baltimore city with a history of disproportionately high air pollution and

related health risks. We also collected webs near existing air monitors to compare speciated metal values to an established monitoring system.

While I cannot yet correlate any metal other than iron to our known pollution sources, I was able to detect significant differences across squares, and detect many metals in webs that were less than a month old. I was also able to use Agelenidae webs to detect a significant neighborhood level difference between two small neighborhoods right next to one another which was not being detected by any traditional monitoring methods, although the reasons for this difference are not yet clear. Volunteers were successfully trained to identify and clear metal collecting spiderwebs from a large area. The lessons learned from this research will be applied in future public science projects, including Spidey Senser and Resting Safe, a project which helps people experiencing homelessness in Portland, OR learn about their pollution exposure and develop harm reduction strategies. Due to the limited nature of most monitoring systems, there is a need for fine scale information on air pollution exposure, particularly for marginalized communities who may be especially vulnerable to the negative effects of air pollution. Spiderwebs are easily and cheaply collected and can potentially fill in some of those monitoring gaps.

Appendix

Part A: Summary statistics

Parameter	n=	Mean ug/m3	Standard Deviation	Median ug/m3
Fe ES	269	0.07405056	0.07334396	0.0513
Pb ES	269	0.00318662	0.004151808	0.002
Al ES	269	0.02177788	0.05467215	0.01196
Fe HU	276	0.08027283	0.0760465	0.05615
Pb HU	276	0.00222101	0.003475492	0
Al HU	276	0.02094928	0.04944555	0.0095
PM2.5 BM	645	8.00367	4.496678	6.9
PM2.5 HU	345	6.232754	3.152334	5.6
PM2.5 ES	248	8.219758	4.921223	6.8
2019 PM2.5 BM	33	7.041379	3.95804	6
2020 PM2.5 ES	15	6.8	3.711372	5.8
2020 PM2.5 HU	33	4.863636	2.205649	4.8
October PM2.5 HU	116	5.517241	2.685202	4.85
October PM2.5 ES	89	6.809639	3.982787	5.9
September PM2.5 BM	213	7.78619	3.636807	7.35
October PM2.5 BM	233	7.004444	3.829943	6.2
October Fe HU	98	0.0827875	0.07727619	0.0605
October Pb HU	98	0.00234583	0.003400338	5.00E-04
October Al HU	98	0.01926042	0.02790406	0.008
October Fe ES	96	0.06451319	0.04696631	0.049
October Pb ES	96	0.00289231	0.003530604	0.002
October Al ES	96	0.01312516	0.0167916	0.01
2020 Fe ES	30	0.05816667	0.04919285	0.046
2020 Pb ES	30	0.00376667	0.00394517	0.0035
2020 Al ES	30	0.01314167	0.001271367	0.01261
2020 Fe HU	30	0.06806667	0.05376637	0.046
2020 Pb HU	30	0.00323333	0.003460948	0.003
2020 Al HU	30	0.0194	0.02502495	0.015

Parameter	n=	Mean percent	Standard Deviation	Median percent
HU Pb	312	0.04088606	0.07306387	0
HU Fe	312	1.414322	1.354448	1
HU Al	312	0.3541907	0.7039899	0.1666667
ES Pb	211	0.04137733	0.05550837	0.02424242
ES Fe	211	0.9369976	0.7062727	0.8
ES Al	211	0.2912196	0.55305	0.1530864
2020 Fe ES	15	0.7354838	0.4843993	0.516129
2020 Pb ES	15	0.05541529	0.07679534	0.03846154
2020 Al ES	15	0.2768952	0.2248685	0.2255769
2020 Fe HU	31	1.507232	0.9541915	1.361702
2020 Pb HU	31	0.07021351	0.1052098	0
2020 Al HU	31	0.465503	0.5134191	0.3636364
October Fe HU	112	1.658683	1.825911	1.226087
October Pb HU	112	0.05398905	0.09091146	0.01694915
October Al HU	112	0.4001011	0.6956788	0.1666667
October Fe ES	73	0.8919759	0.4236184	0.8486842
October Pb ES	73	0.03816987	0.05116812	0.01724138
October Al ES	73	0.2074989	0.2508904	0.1495327

Parameter	n=	Mean percent	Standard Deviation	Median percent
R2 Baltimore Al	131	0.005897207	0.04170423	0.00058295
R2 Baltimore Fe	112	0.001247603	0.003310721	0.000331378
R2 Baltimore Pb	115	0.001082662	0.007353105	0.000244627
R2 Curtis Bay Al	57	0.000415199	0.000177832	0.000403471
R2 Curtis Bay Fe	57	0.000296098	0.000135533	0.000274842
R2 Curtis Bay Pb	57	0.000310756	0.000220622	0.000248396
R2 Brooklyn Al	74	0.01011983	0.05527853	0.000872991
R2 Brooklyn Fe	55	0.002233708	0.004534928	0.000402018
R2 Brooklyn Pb	58	0.00184126	0.01033959	0.000233834
R2 HU Beltsville Al	13	0.000829295	0.000417709	0.000797753
R2 HU Beltsville Fe	11	0.002973302	0.0047981	0.000347826
R2 HU Beltsville Pb	8	0.000140148	0.000114323	0.000105144
R2 Essex Al	19	0.00196275	0.000736051	0.001730257
R2 Essex Fe	16	0.000882723	0.000224815	0.000905654
R2 Essex Pb	17	0.000487425	0.000568787	0.000349624

Parameter	n=	Mean Percent	Standard Deviation	Median Percent
R1 Rybak Al	22	0.8196818	0.9450147	0.5562
R1 Rybak Fe	22	0.4365182	0.147749	0.43445
R1 Rybak Pb	22	0.1071318	0.0425545	0.00865
R1 Rybak Zn	22	0.06748636	0.06543705	0.04885
R1 Rybak Cr	22	0.09137273	0.07162281	0.08325
R1 Rybak Cu	22	0.01032727	0.005740811	0.0096
R1 Rybak Ni	22	0.01977273	0.01850884	0.0144
R1 EPA Al	22	0.4587021	0.344502	0.3383763
R1 EPA Fe	22	1.562693	1.290859	1.165316
R1 EPA Pb	22	0.008481332	0.01517767	0.005791271
R1 EPA Zn	22	0.05047865	0.06000784	0.03904316
R1 EPA Cr	22	0.2228251	0.4192596	0.01358741
R1 EPA Cu	22	0.006189178	0.003856924	0.004998258
R1 EPA Ni	22	0.06386214	0.1128189	0.005867183

Part B: Results of Statistical Tests

Both parametric and non-parametric test results are given, along with tests of homogenity of variance. Tests of homogeneity of variance are highlighted in yellow, parametric tests highlighted in red, and non-parametric tests highlighted in green.

Near-monitor webs (n < 30 for all groups)

Parameters	Chi Squared	df	p	t	df	p	W	p
Al/day ~ Site	2.8196	1	0.09312	5.5349	29.222	5.60E-06	231	5.23E-06
Pb/day ~ Site	0.0333	1	0.8851	2.4158	18.553	0.0262	121	0.001126
Fe/day ~ Site	0.44509	1	0.5047	-1.444	10.03	0.1792	127	0.05647

Baltimore Neighborhood Webs

Parameters	Chi-squared	df	p	t	df	p	W	p
%Al/day ~ NB	40.379	1	2.09E-10	1.5102	73.002	0.1353	3514	7.01E-11
%Fe/day ~ NB	16.48	1	4.92E-05	3.1673	54.093	0.002529	2216	0.000162
%Pb/day ~ NB	9.7048	1	0.001838	1.1271	57.053	0.2644	1646	0.971

First vs. Second Round webs (n < 30 for first three groups)

Parameters	F	num df	denom df	p	t	df	p	W	p
Al R2, Al R1	4.6516	19	19	0.001555	-1.1074	26.808	0.278	351	1.34E-05
Pb R2, Pb R1	26.119	18	19	1.96E-09	-1.1274	19.309	0.2734	158	0.3803
Fe R2, Fe R1	0.002066	18	19	<2.2E-16	5.2649	19.083	4.35E-05	380	2.90E-11
Weights R2, Weights R1	8.9725	215	136	<2.2E-16	3.0276	283.37	0.002692	19389	8.89E-07

Baltimore Webs by square (n < 30 for all groups)

Parameters	Chi Squared	df	p	F	df	p	Chi Squared	df	p
%Al/day~Square	66.823	31	0.000197	1.521	31	0.0625	68.253	31	0.000129
%Al/day~Square	39.156	30	0.1223	0.71	30	0.854	64.326	30	0.000267
%Fe/day~Square	47.108	30	0.02428	1.576	30	0.0556	58.699	30	0.001319

Moran's I

Parameters	Moran's I standard deviate	p
R2 Al	-0.50175	0.6921
R2 Pb	0.66006	0.2546
R2 Fe	0.44753	0.3272

Metal Concentration, Weight

Parameters	S	rho	p
R2 Al ppb, mg/ml	103960	0.722523	< 2.2e-16
R2 Pb ppb, mg/ml	59785	0.764123	< 2.2e-16
R2 Fe ppb, mg/ml	107632	0.540301	7.82E-10
R1 Al ppb, mg/ml	660	0.627329	0.002226
R1 Pb ppb, mg/ml	722	0.592321	0.004355
R1 Fe ppb, mg/ml	600	0.661208	0.001076
R1 Cr ppb, mg/ml	1414	0.201581	0.3666
R1 Cu ppb, mg/ml	594	0.664596	0.000996
R1 Zn ppb, mg/ml	778	0.5607	0.007536
R1 Ni ppb, mg/ml	1600	0.6682	0.096556
R2 % Al, Days out	464227	-0.23906	0.00596
R2 % Fe, Days out	256662	-0.09621	0.3129
R2 % Pb, Days out	277790	-0.09599	0.3075

MDE monitors 2020

Parameters	Chi Squared	df	p	t	df	p	W	p
2020 PM2.5 ~ Site	3.5351	1	0.06008	1.8525	19.433	0.07921	126	0.2063
2020 % Al ~ Site	10.436	1	0.001236	-0.3957	37.903	0.6945	179	0.437
2020 % Pb~Site	2.0996	1	0.1473	-0.47593	29.788	0.6376	207.5	0.9593
2020 % Fe~Site	5.9169	1	0.015	-3.4391	40.997	0.001353	94	0.002526
2020 Al~Site	28.252	1	1.07E-07	-0.47858	29.112	0.6358	93	0.8388
2020 Pb~Site	0.36936	1	0.5434	0.7772	57.999	0.4402	90	0.7287
2020 Fe~Site	0.50095	1	0.4791	-0.74408	57.548	0.4599	85.5	0.5812

MDE Monitors by year

Parameters	F	num df	denom df	p	t	df	p	W	p
HU Al, ES Al	0.81794	275	268	0.09816	-0.18542	534.55	0.853	36450	0.7086
HU Pb, ES Pb	0.70074	275	268	0.003479	-2.9404	521.86	0.003424	30820	0.000315
HU Fe, ES Fe	1.0751	275	268	0.5519	0.97234	542.94	0.3313	38623	0.4143
2020 ES Al, all ES Al	0.000541	29	268	<2.2E-16	-2.5845	270.55	0.01028	4370	0.4502
2020 ES Pb, all ES Pb	0.90294	29	268	0.7727	0.75975	36.546	0.4523	4524.5	0.2638
2020 ES Fe, all ES Fe	0.44986	29	268	0.01175	-1.5832	44.863	0.1204	3456	0.1977
2020 HU Al, all HU Al	0.25615	29	291	5.08E-05	-0.28412	57.738	0.7773	4440	0.5051
2020 HU Pb, all HU Pb	0.99165	29	275	0.9646	1.5209	35.661	0.1371	4768	0.1399
2020 HU Fe, all HU Fe	0.49988	29	275	0.02714	-1.1269	42.77	0.266	3856.5	0.5386
2020 ES PM2.5, all ES PM2.5	0.56875	14	247	0.224	-1.4086	17.125	0.1769	1579	0.3268
2020 HU PM2.5, all HU PM2.5	0.48956	32	344	0.01628	-3.2614	45.564	0.002103	4468.5	0.04128
2019 BM PM2.5, all BM PM2.5	0.77478	28	653	0.4157	-1.2733	31.292	0.2123	8207.5	0.2201
HU %Al, ES %Al	1.6203	311	210	0.000189	1.1425	509.38	0.2538	34327	0.3957
HU %Pb, ES %Pb	1.7326	311	210	2.25E-05	-0.08724	513.96	0.9305	28825	0.0108
HU %Fe, ES %Fe	3.6777	311	210	<2.2E-16	5.2571	493.27	2.18E-07	40480	8.16E-06
2020 ES %Al, all ES %Al	0.16532	14	210	0.000463	-0.20631	28.28	0.838	1940.5	0.138
2020 ES %Pb, all ES %Pb	1.914	14	210	0.05286	0.69518	15.058	0.4975	1752.5	0.4774
2020 ES %Fe, all ES %Fe	0.47039	14	210	0.1065	-1.5017	18.523	0.15	1201.5	0.1199
2020 HU %Al, all HU %Al	0.53188	30	311	0.03899	1.1081	42.114	0.2741	5725	0.08475
2020 HU %Pb, all HU %Pb	2.0735	30	311	0.002299	1.5161	32.937	0.139	5430.5	0.2199
2020 HU %Fe, all HU %Fe	0.4963	30	311	0.02276	0.49485	43.048	0.6232	5343.5	0.3356

MDE Monitors by month

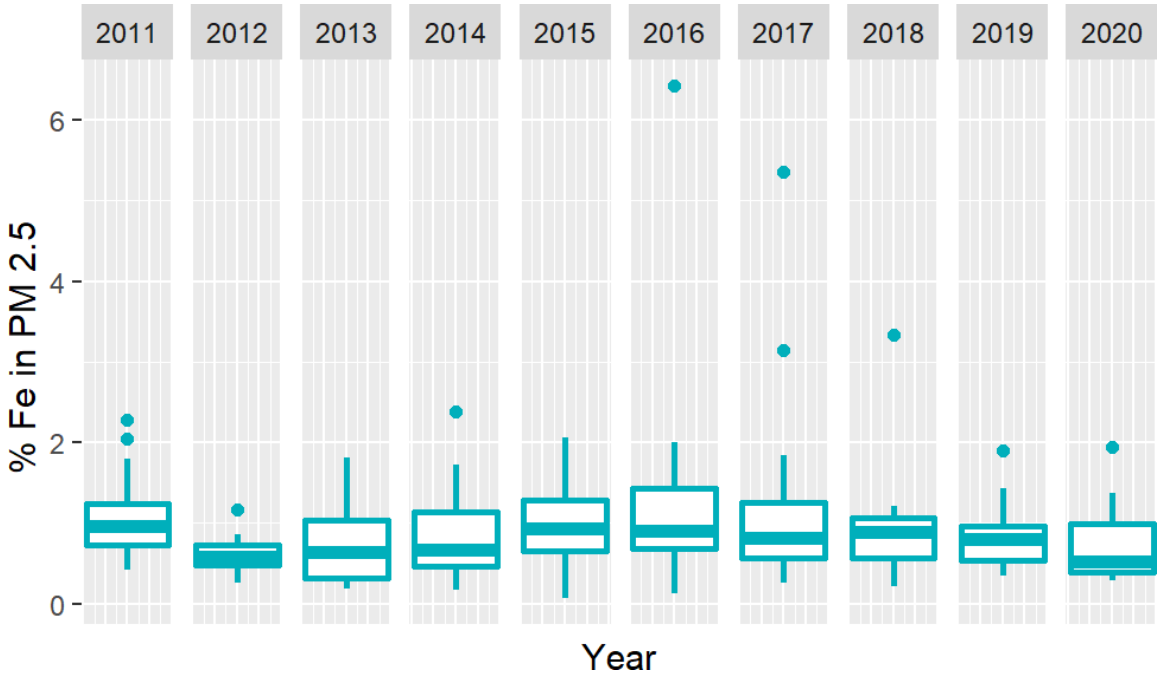
Parameters	F	num df	denom df	p-value	t	df	p-value	W	p-value
%Al ES October, all other months	0.2058	68	210	7.82E-12	-1.7227	250.77	0.08618	6904.5	0.5121
%Pb ES October, all other months	0.84973	68	210	0.4364	-0.44247	124.44	0.6589	7104.5	0.7588
%Fe ES October, all other months	0.35975	68	210	3.08E-06	-0.63895	195.5	0.5236	7574.5	0.614
%Al HU October, all other months	0.97653	110	311	0.8998	0.59526	195.57	0.5524	17443	0.9067
%Pb HU October, all other months	1.5482	110	311	0.003756	1.3693	163.31	0.1728	18702	0.1763
%Fe HU October, all other months	1.8173	110	311	6.57E-05	1.2894	155.18	0.1992	18821	0.1738
Al ES October, all other months	0.09433	90	268	<2.2E-16	-2.2954	355.9	0.02229	10903	0.1111
Pb ES October, all other months	0.72314	90	268	0.07219	-0.65636	180.63	0.5124	11978	0.7539
Fe ES October, all other months	0.41006	90	268	2.19E-06	-1.4339	243.99	0.1529	11861	0.6596
Al HU October, all other months	0.31848	95	275	1.13E-09	-0.40998	294.48	0.6821	13164	0.9246
Pb HU October, all other months	0.95722	95	275	0.8172	0.30803	168.88	0.7584	13678	0.6082
Fe HU October, all other months	1.0326	95	275	0.8273	0.27576	163.38	0.7831	13372	0.8922
PM2.5 HU October, all other months	0.72559	115	344	0.04337	-2.3724	229.78	0.0185	17513	0.04422
PM2.5 ES October, all other months	0.65498	82	247	0.0259	-2.6241	172.28	0.009468	8541	0.02035
PM2.5 BM October, all other months	0.72544	224	653	0.00462	-3.2231	451.97	0.00136	63891	0.003197
PM2.5 BM September, all other months	0.65412	209	653	0.000303	-0.70972	431.29	0.4783	69871	0.7029
PM2.5 BM October vs September	0.90169	209	224	0.4486	2.1835	432.87	0.02953	27470	0.003346

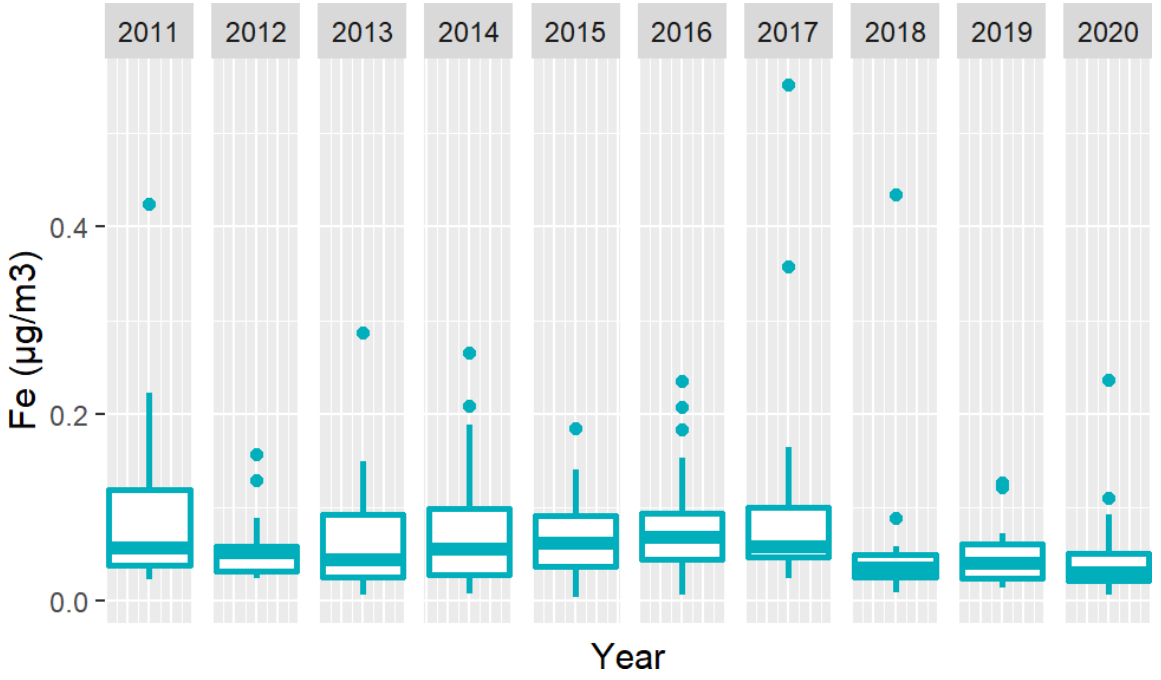
Spearman's Correlation

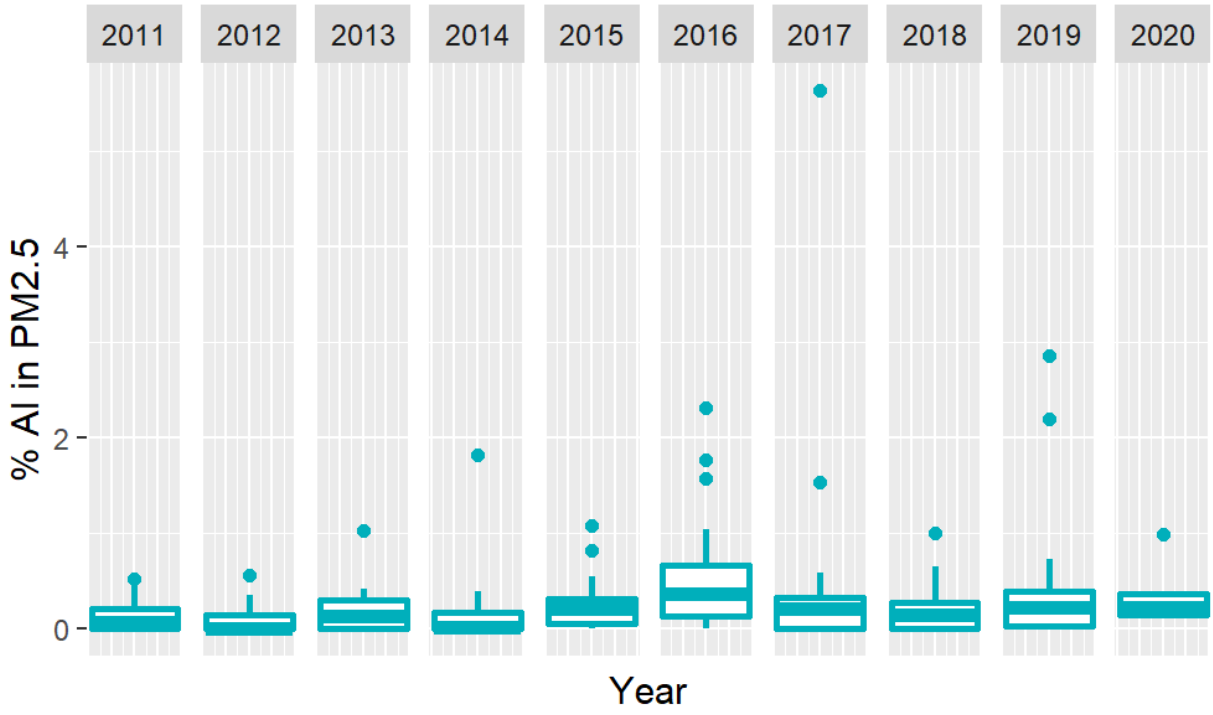
Parameter 1	Parameter 2	cor	p
% Al/day	% Fe/day	0.788115	0
% Al/day	% Pb/day	0.185102	0.047651
% Al/day	Density	0.001979	0.982103
% Al/day	Distance to Adell Plastics	-0.04417	0.616444
% Al/day	Distance to Baltimore Terminal	0.058523	0.506705
% Al/day	Distance to Grace Davidson	0.210518	0.0158
% Al/day	Distance to S&G	0.16182	0.064811
% Al/day	Maximum AADT	0.035105	0.690584
% Al/day	Mean of AADT	-0.02525	0.774659
% Al/day	Sum of AADT	0.002844	0.974279
% Fe/day	% Pb/day	0.239172	0.012256
% Fe/day	Density	-0.1973	0.037059
% Fe/day	Distance to Adell Plastics	-0.01909	0.841622
% Fe/day	Distance to Baltimore Terminal	0.009074	0.924347
% Fe/day	Distance to Grace Davidson	0.14759	0.120439
% Fe/day	Distance to S&G	0.066966	0.482964
% Fe/day	Maximum AADT	0.225488	0.016828
% Fe/day	Mean of AADT	0.208929	0.027053
% Fe/day	Sum of AADT	0.202474	0.032276
% Pb/day	Density	-0.12195	0.194178
% Pb/day	Distance to Adell Plastics	0.149638	0.110454
% Pb/day	Distance to Baltimore Terminal	-0.08182	0.384679
% Pb/day	Distance to Grace Davidson	0.038358	0.684008
% Pb/day	Distance to S&G	0.123397	0.188894
% Pb/day	Maximum AADT	0.073299	0.436269
% Pb/day	Mean of AADT	0.090858	0.334197
% Pb/day	Sum of AADT	0.09678	0.303512
Density	Distance to Adell Plastics	-0.08827	0.316058
Density	Distance to Baltimore Terminal	0.072474	0.410716
Density	Distance to Grace Davidson	0.053844	0.541324
Density	Distance to S&G	-0.03574	0.685245
Density	Maximum AADT	0.147113	0.093585
Density	Mean of AADT	0.025475	0.772715
Density	Sum of AADT	0.044912	0.610489
Maximum AADT	Distance to Adell Plastics	-0.23703	0.006414
Maximum AADT	Distance to Baltimore Terminal	0.250174	0.003953
Maximum AADT	Distance to Grace Davidson	0.237167	0.006381
Maximum AADT	Distance to S&G	0.033356	0.705264
Maximum AADT	Mean of AADT	0.946435	0
Maximum AADT	Sum of AADT	0.949679	0
Mean of AADT	Distance to Adell Plastics	-0.20072	0.02152
Mean of AADT	Distance to Baltimore Terminal	0.238381	0.006109
Mean of AADT	Distance to Grace Davidson	0.221763	0.010908
Mean of AADT	Distance to S&G	0.061274	0.486899
Sum of AADT	Distance to Adell Plastics	-0.26983	0.001828
Sum of AADT	Distance to Baltimore Terminal	0.267526	0.002007
Sum of AADT	Distance to Grace Davidson	0.192693	0.027451
Sum of AADT	Distance to S&G	0.021794	0.804842
Sum of AADT	Mean of AADT	0.897936	0

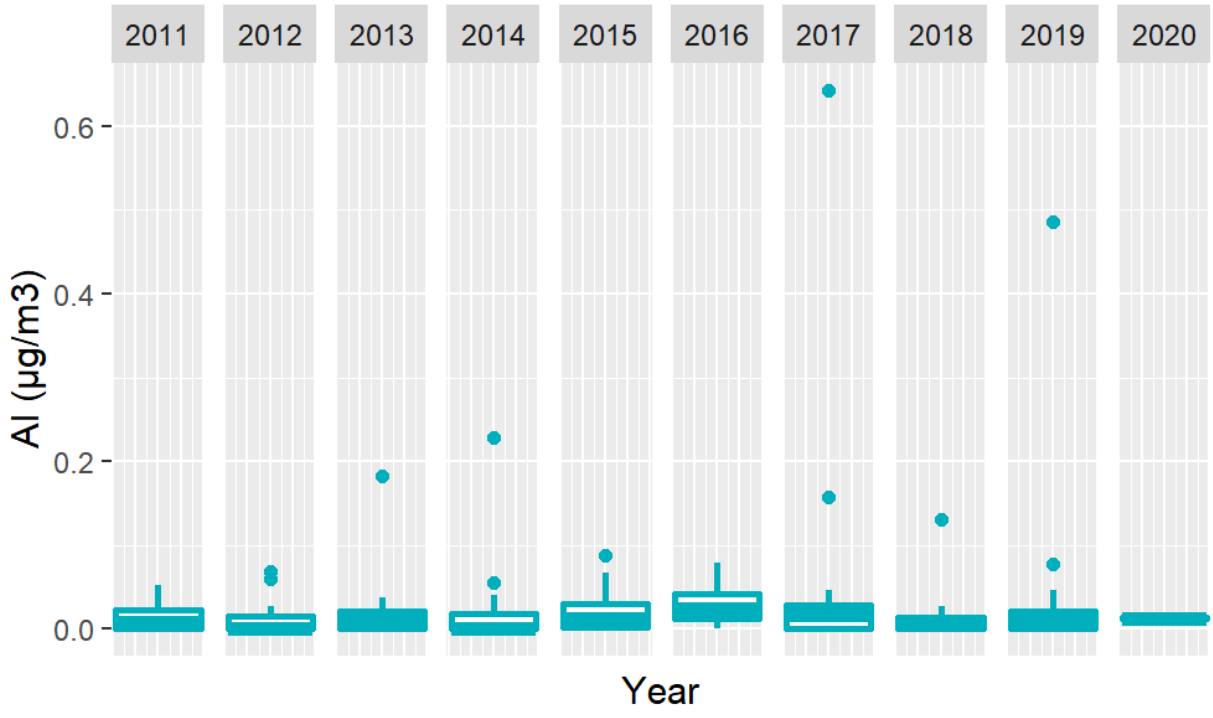
Part C: Monitor Distribution Graphs by Year

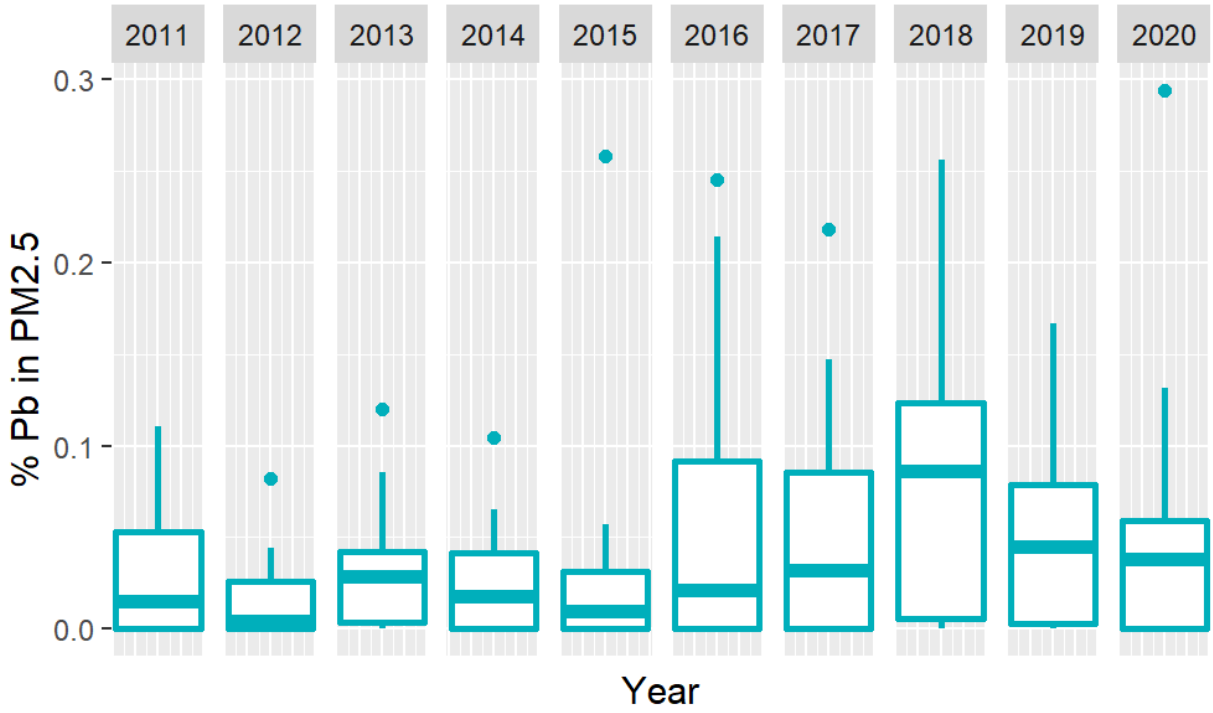
Essex Monitor

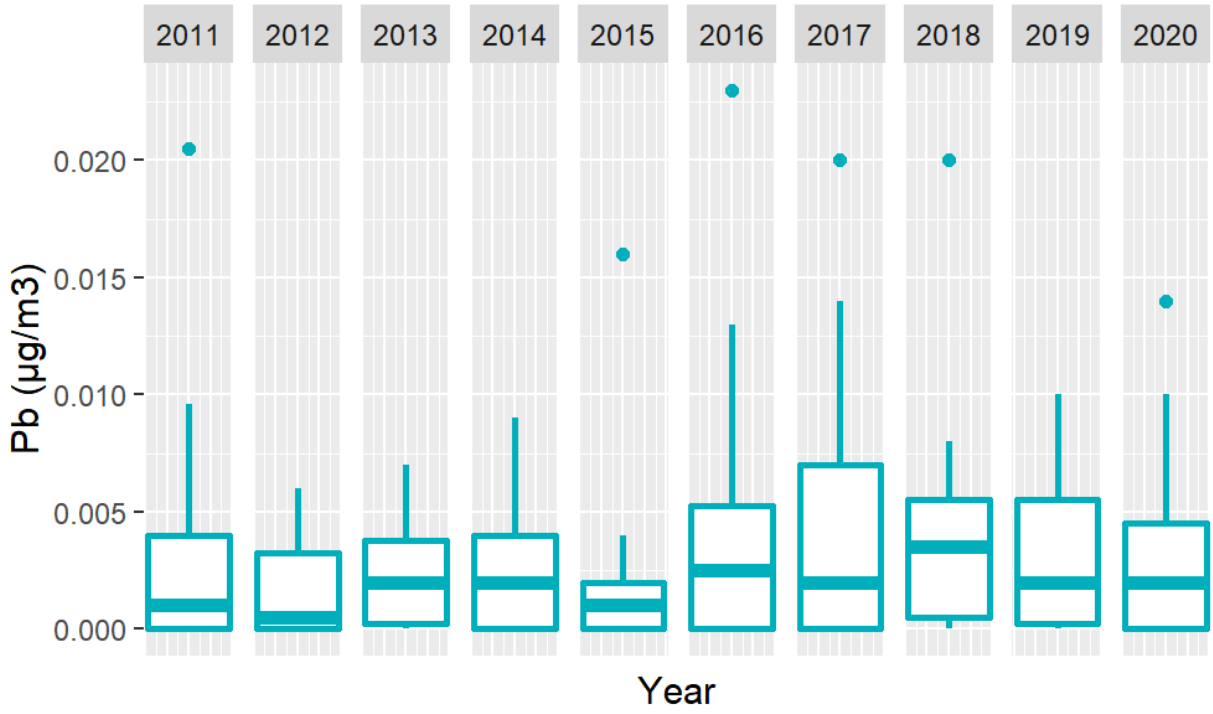


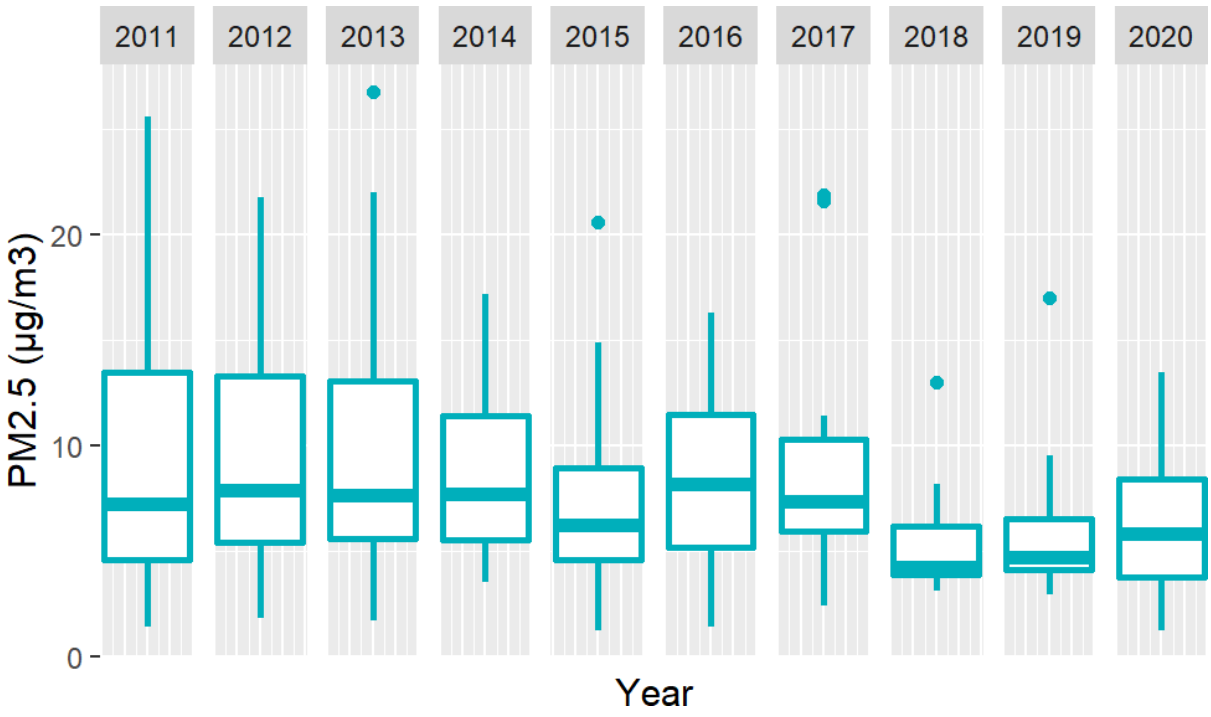



2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
% Al in PM2.5
4
2
0
Year

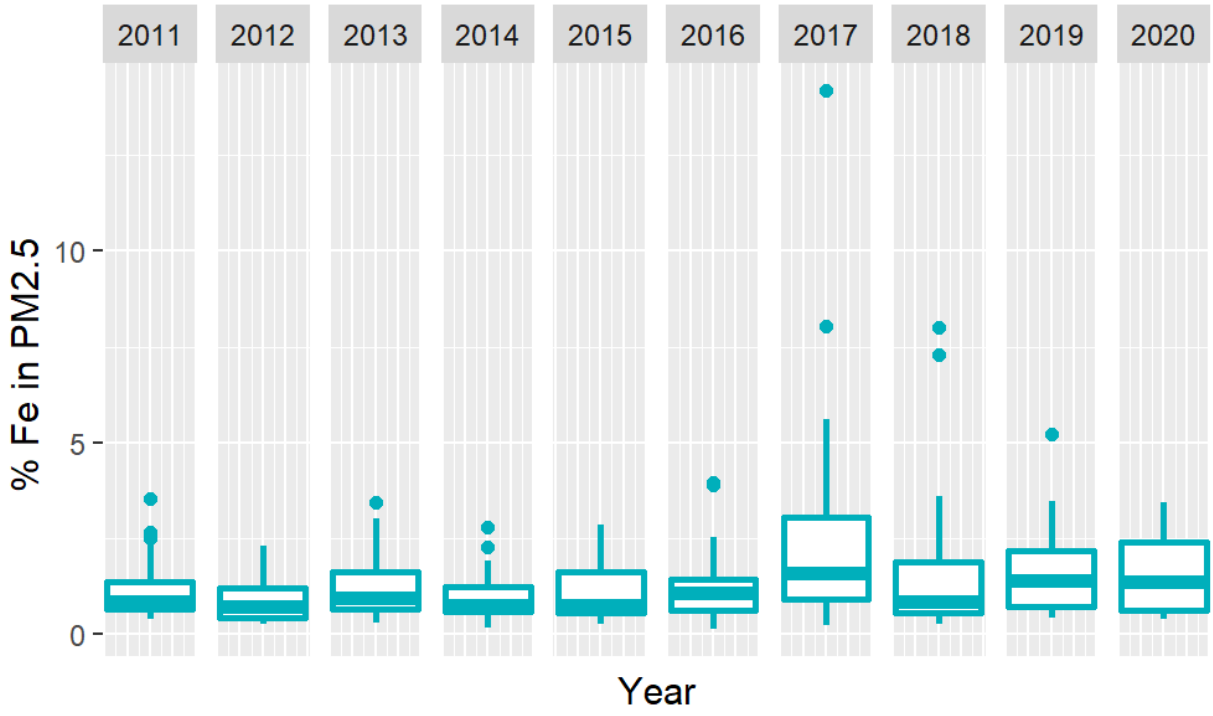

2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
Al (µg/m3)
0.6
0.4
0.2
0.0
Year

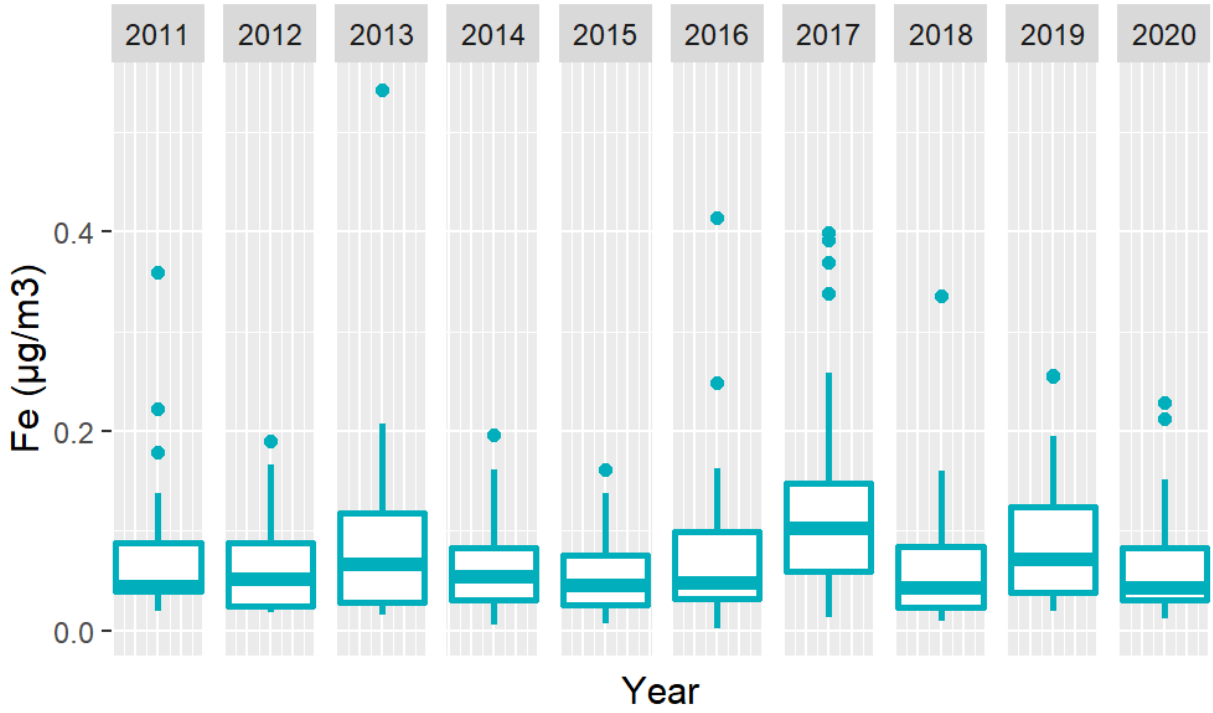

2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
0.3
0.2
0.1
0.0
% Pb in PM2.5
Year

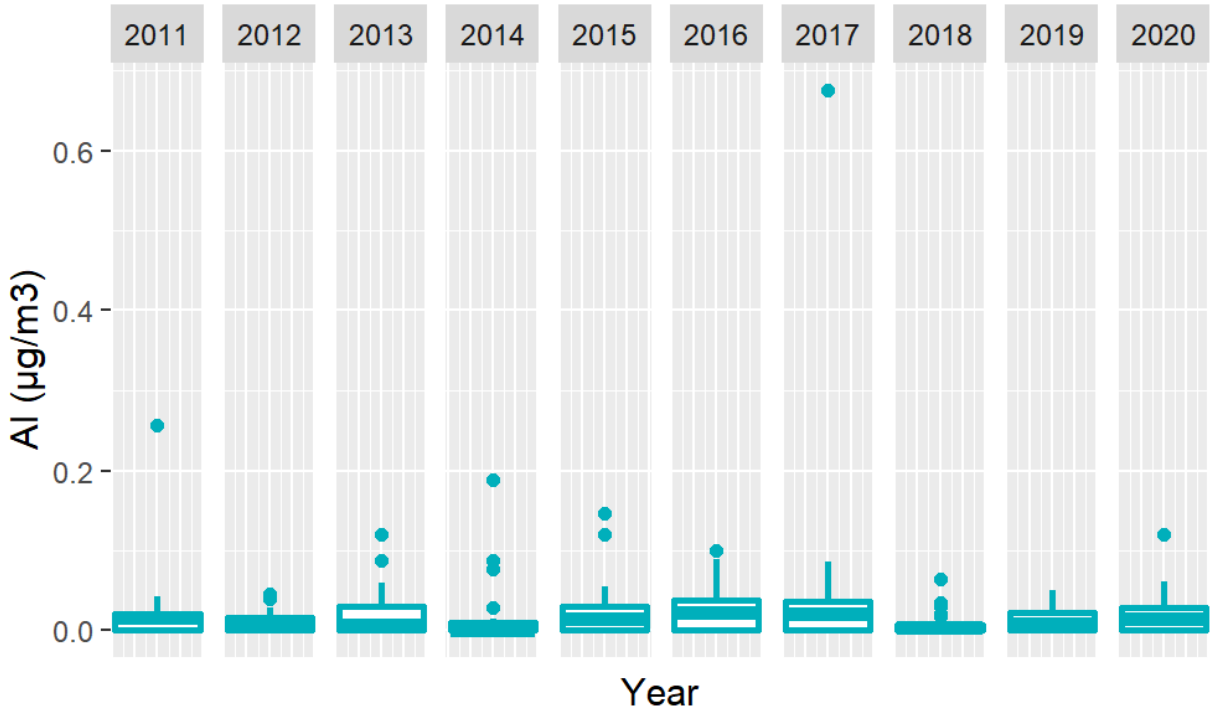

2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
0.020
0.015
0.010
0.005
0.000
Pb (µg/m3)
Year

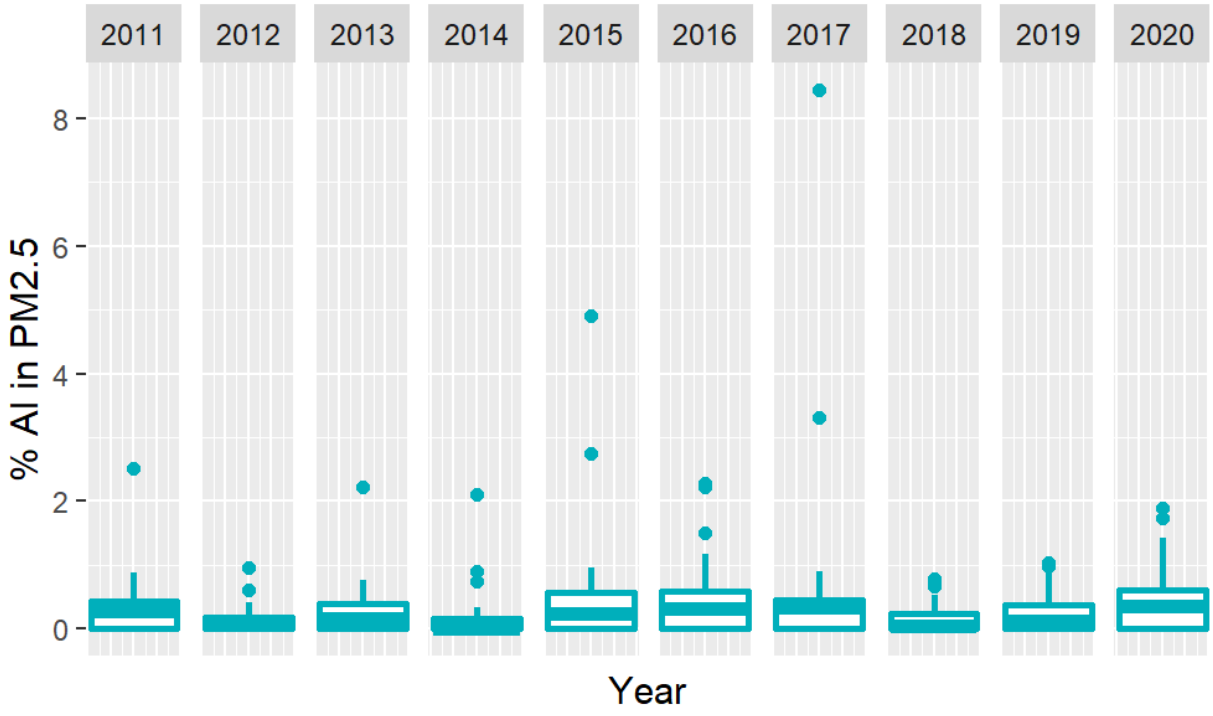

2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
PM2.5 (µg/m3)
0
10
20
Year

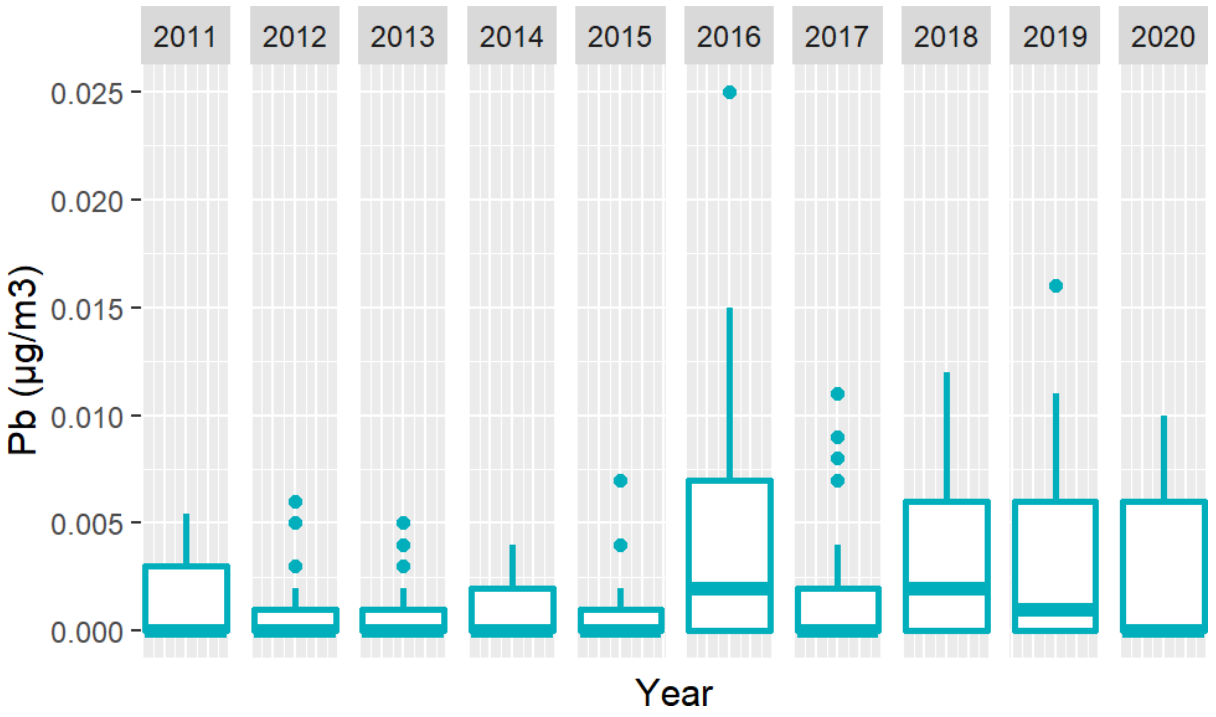
HU Beltsville Monitor

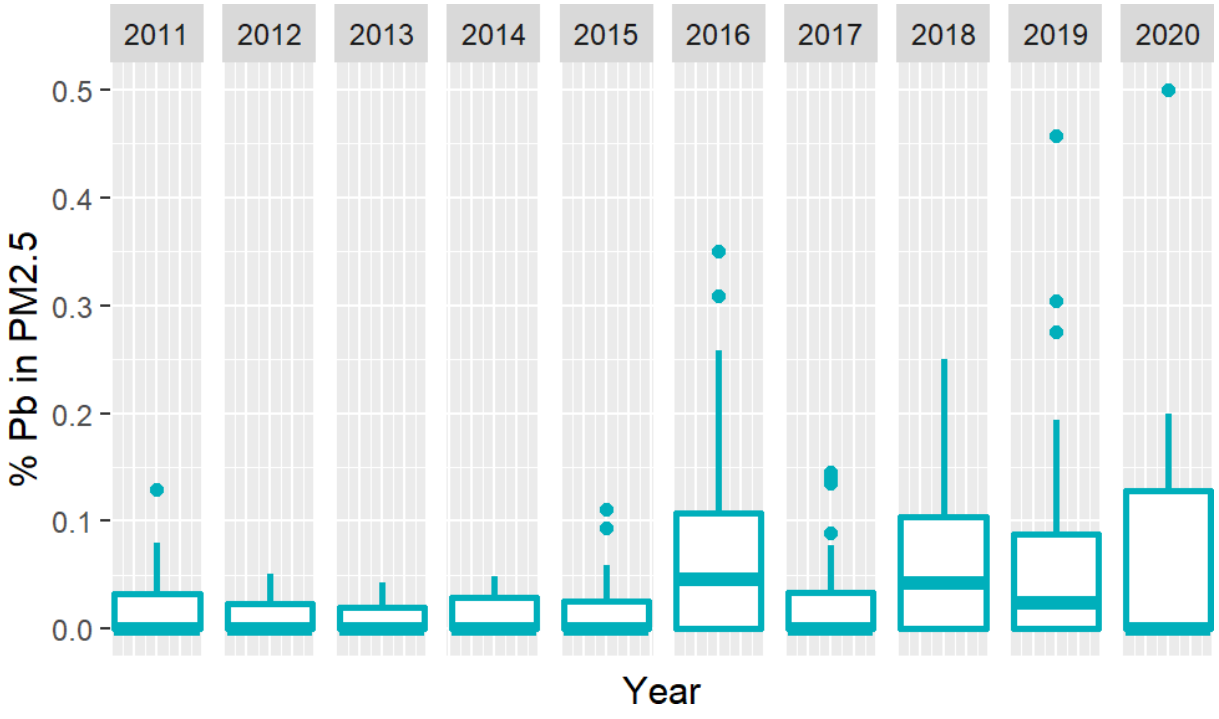


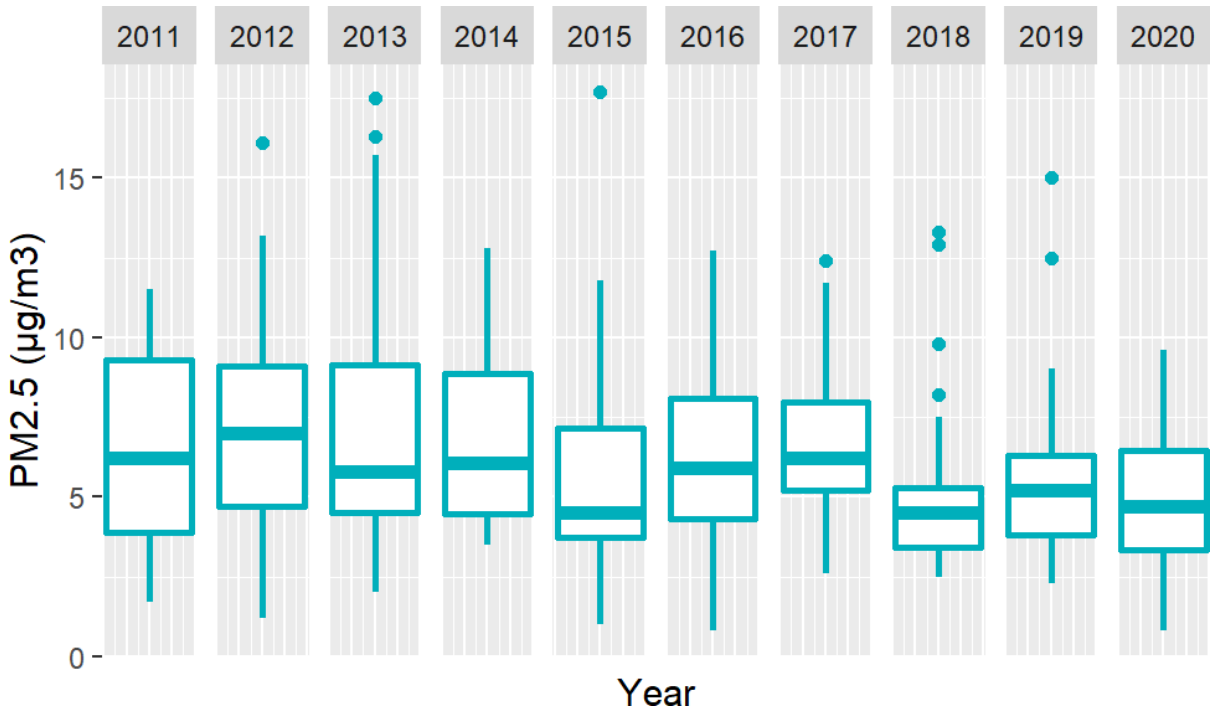



2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
0.6
0.4
0.2
0.0
Al (µg/m3)
Year

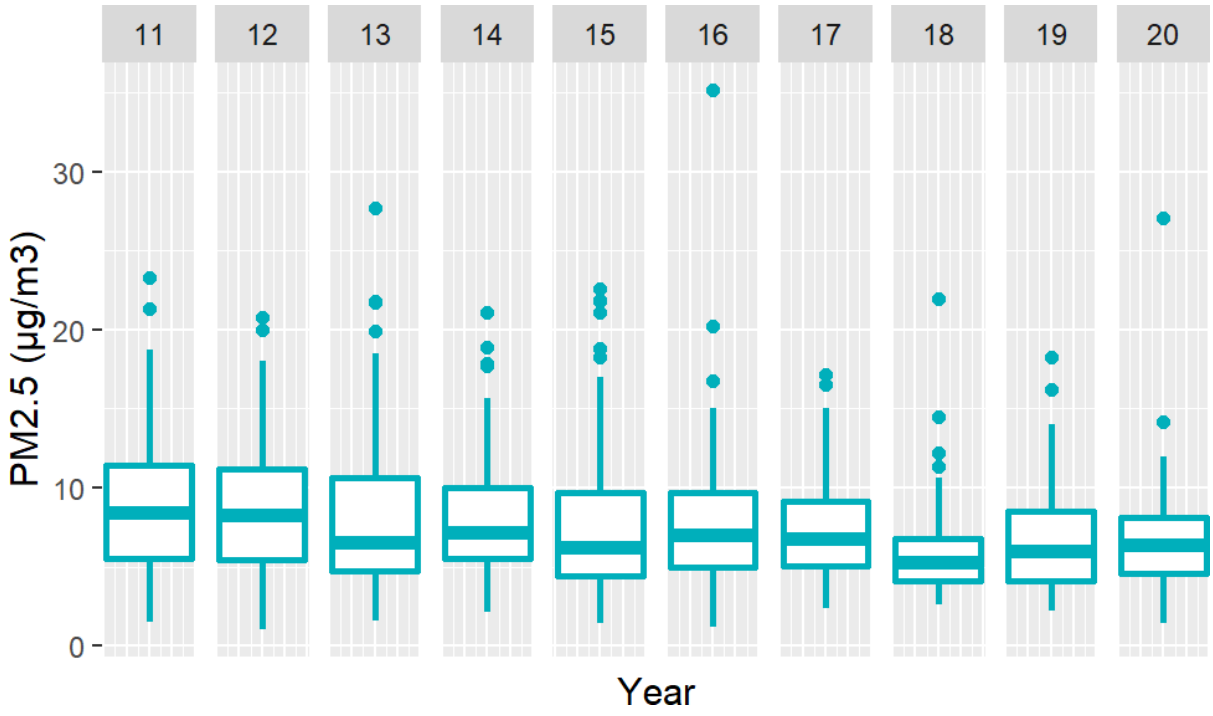

2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
8
6
4
2
0
% Al in PM2.5
Year


2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
0.025
0.020
0.015
0.010
0.005
0.000
Pb (µg/m3)
Year


2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
0.5
0.4
0.3
0.2
0.1
0.0
% Pb in PM2.5
Year


2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
PM2.5 (µg/m3)
0
5
10
15
Year

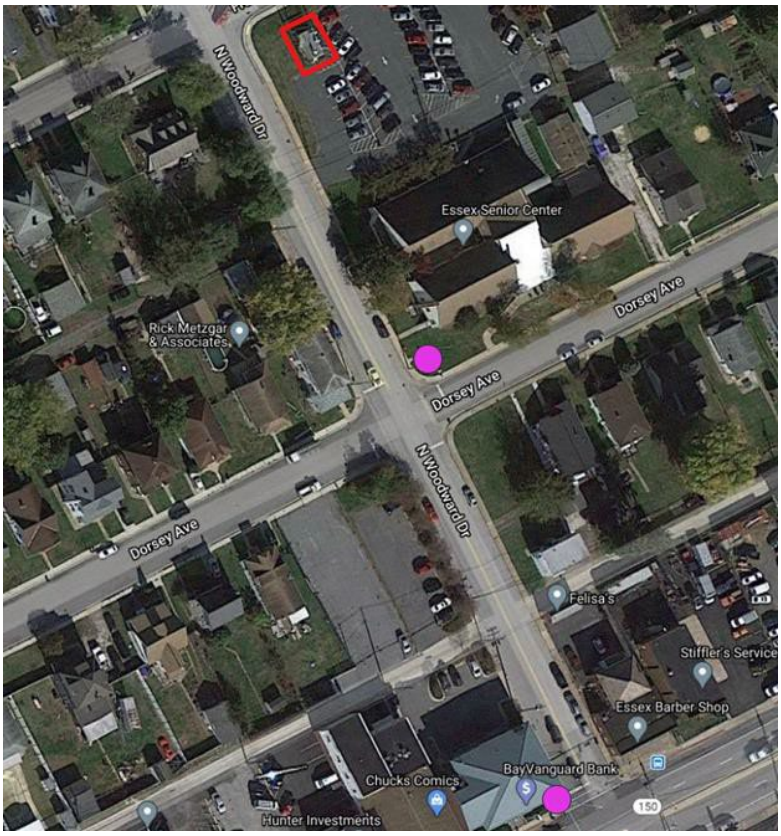
Baltimore Oldtown Monitor



Part D: Metal Speciating Monitor Sites

HU Beltsville

Essex



Bibliography

1. Ahmann, Chloe. 2018. "'IT'S EXHAUSTING TO CREATE AN EVENT OUT OF NOTHING': Slow Violence and the Manipulation of Time." *Cultural Anthropology* 33 (1): 142–71. https://doi.org/10.14506/ca33.1.06.

2. Alikina, Inga, and Oleg Dolgikh. 2020. "Aerogenous Exposure to Aluminium and Disbalance of the Clinical and Laboratory Indicators Values of the Immune Profile in Children with Compromated Respiratory System." *Proceedings of the International Multidisciplinary Scientific GeoConference SGEM*, December, 49–54. https://doi.org/10.5593/sgem2020V/6.2/s08.07.

3. Allaby, Michael. 1999. *A Dictionary of Zoology*. New York: Oxford University Press.

4. Agency for Toxic Substances and Disease Registry (ATSDR). *Toxicological profile for Chromium.* Atlanta, GA: U.S. Department of Health and Human Services, Public Health Service, 2008. https://www.atsdr.cdc.gov/toxprofiles/tp7.pdf (accessed September 7 2021).

5. Agency for Toxic Substances and Disease Registry (ATSDR). *Toxicological profile for Lead.* Atlanta, GA: U.S. Department of Health and Human Services, Public Health Service, 2020.https://www.atsdr.cdc.gov/toxprofiles/tp13.pdf (accessed September 7 2021).

6. Ballard, Heidi L., Colin G. H. Dixon, and Emily M. Harris. 2017. "Youth-Focused Citizen Science: Examining the Role of Environmental Science Learning and Agency for Conservation." *Biological Conservation*, The role of citizen science in biological conservation, 208 (April): 65–75. https://doi.org/10.1016/j.biocon.2016.05.024.

7. Baltimore City Health Department. *Baltimore City 2017 Neighborhood Health Profile: Brooklyn/Curtis Bay/Hawkins Point.* 2017. https://health.baltimorecity.gov/sites/default/files/NHP%202017%20-%2004%20Brooklyn-Curtis%20Bay-Hawkins%20Point%20(rev%206-9-17).pdf (accessed September 7, 2021).

8. Boone, Christopher G., Michail Fragkias, Geoffrey L. Buckley, and J. Morgan Grove. 2014. "A Long View of Polluting Industry and Environmental Justice in Baltimore." *Cities* 36 (February): 41–49. https://doi.org/10.1016/j.cities.2013.09.004.

9. Boquete, M.T., J.R. Aboal, A. Carballeira, and J.A. Fernández. 2017. "Do Mosses Exist Outside of Europe? A Biomonitoring Reflection." *Science of The Total Environment* 593–594 (September): 567–70. https://doi.org/10.1016/j.scitotenv.2017.03.196.

10. Bremer, S., M. Mahfujul Haque, Saifullah Bin Aziz, and S. Kvamme. 2019. "'My New Routine': Assessing the Impact of Citizen Science on Climate Adaptation in Bangladesh." *Environmental Science & Policy* 94 (April): 245–57. https://doi.org/10.1016/j.envsci.2018.12.029.

11. Briffa, Jessica, Emmanuel Sinagra, and Renald Blundell. 2020. "Heavy Metal Pollution in the Environment and Their Toxicological Effects on Humans." *Heliyon* 6 (9): e04691. https://doi.org/10.1016/j.heliyon.2020.e04691.

12. Cao, Rong, Bai Li, Zhanyong Wang, Zhong-Ren Peng, Shikang Tao, and Shengrong Lou. 2020. "Using a Distributed Air Sensor Network to Investigate the Spatiotemporal Patterns of PM2.5 Concentrations." *Environmental Pollution* 264 (September): 114549. https://doi.org/10.1016/j.envpol.2020.114549.

13. Charlesworth, S., E. De Miguel, and A. Ordóñez. 2011. “A Review of the Distribution of Particulate Trace Elements in Urban Terrestrial Environments and Its Application to Considerations of Risk.” *Environmental Geochemistry and Health; Kew* 33 (2): 103–23. http://dx.doi.org.proxy-bc.researchport.umd.edu/10.1007/s10653-010-9325-7.

14. Clapp, Justin T., Jody A. Roberts, Britt Dahlberg, Lee Sullivan Berry, Lisa M. Jacobs, Edward A. Emmett, and Frances K. Barg. 2016. “Realities of Environmental Toxicity and Their Ramifications for Community Engagement.” *Social Science & Medicine* 170 (December): 143–51. https://doi.org/10.1016/j.socscimed.2016.10.019.

15. Clements, Andrea L., William G. Griswold, R. S. Abhijit, Jill E. Johnston, Megan M. Herting, Jacob Thorson, Ashley Collier-Oxandale, and Michael Hannigan. 2017. “Low-Cost Air Quality Monitoring Tools: From Research to Practice (A Workshop Summary).” *Sensors (14248220)* 17 (11): 2478. https://doi.org/10.3390/s17112478.

16. Code of Federal Regulations (CFR). “40 CFR Appendix D to Part 58 - Network Design Criteria for Ambient Air Quality Monitoring.” *Code of Federal Regulations,* title 40 (2012): 279-294. https://www.govinfo.gov/app/details/CFR-2012-title40-vol6/CFR-2012-title40-vol6-part58-appD (accessed September 9, 2021)

17. Commodore, Adwoa, Sacoby Wilson, Omar Muhammad, Erik Svendsen, and John Pearce. 2017. “Community-Based Participatory Research for the Study of Air Pollution: A Review of Motivations, Approaches, and Outcomes.” *Environmental Monitoring and Assessment* 189 (8). https://doi.org/10.1007/s10661-017-6063-7.

18. Cooper, Caren B. 2016. *Citizen Science : How Ordinary People Are Changing the Face of Discovery*. New York: The Overlook Press.

19. Cooper Environmental Services. *Overview of Airborne Metals Regulations, Exposure Limits, Health Effects, and Contemporary Research*. Portland: Environmental Protection Agency, 2010. https://www3.epa.gov/ttnemc01/prelim/otm31appC.pdf (accessed August 8, 2021).

20. Dance, Scott. 2017. “How a Trash Incinerator — Baltimore’s Biggest Polluter — Became ‘green’ Energy.” *The Baltimore Sun.* November 7 https://www.baltimoresun.com/news/environment/bs-md-trash-incineration-20171107-story.html (accessed October 14, 2020).

21. deSouza, Priyanka, and Patrick L. Kinney. 2021. “On the Distribution of Low-Cost PM2.5 Sensors in the US: Demographic and Air Quality Associations.” *Journal of Exposure Science & Environmental Epidemiology* 31 (3): 514–24. https://doi.org/10.1038/s41370-021-00328-2.

22. Emch, Michael, Elizabeth Dowling Root, and Margaret Carrel. 2017. *Health and Medical Geography.* New York: Guilford.

23. Environmental Protection Agency. Robert Goyer. *Issue Paper on the Human Health Effects of Metals*, Environmental Protection Agency: Washington, DC 2004. https://www.epa.gov/sites/default/files/2014-11/documents/human_health_effects.pdf (accessed August 30, 2021)

24. Environmental Protection Agency. EPCRA Section 313 Questions & Answers

2019 Consolidation Document. Environmental Protection Agency: Washington, DC 2019. https://ordspub.epa.gov/ords/guideme_ext/guideme_ext/guideme/file/2019qa.pdf. (Accessed October 20, 2021).

25. Environmental Protection Agency. *Determination of Metals by Inductively Coupled Plasma (ICP) Methods.* EPA/SW-846 Methods 3015/3050B/6010B. 2006. https://clu-in.org/s.focus/c/pub/i/2025/ (accessed September 7, 2021).

26. Falla, Jaïro, Philippe Laval-Gilly, Michel Henryon, Dominique Morlot, and Jean-françois Ferard. 2000. "Biological Air Quality Monitoring: A Review." *Environmental Monitoring and Assessment* 64 (3): 627–44. https://doi.org/10.1023/A:1006385924945.

27. Fears, Darryl. "This Baltimore 20-Year-Old Just Won a Huge International Award for Taking out a Giant Trash Incinerator." *Washington Post*. April 18, 2016. https://www.washingtonpost.com/news/energy-environment/wp/2016/04/18/this-baltimore-20-year-old-just-won-a-huge-international-award-for-taking-out-a-giant-trash-incinerator/ (accessed 7 September 2021).

28. Gaber, Nadia. 2019. "Mobilizing Health Metrics for the Human Right to Water in Flint and Detroit, Michigan." *Health and Human Rights* 21 (1): 179.

29. Ginzburg, Helen, Xiaobo Liu, Michael Baker, Robert Shreeve, R. K. M. Jayanty, David Campbell, and Barbara Zielinska. 2015. "Monitoring Study of the Near-Road PM2.5 Concentrations in Maryland." *Journal of the Air & Waste Management Association* 65 (9): 1062–71. https://doi.org/10.1080/10962247.2015.1056887.

30. Goddard, Jerome. 2012. *Physician's Guide to Arthropods of Medical Importance*. Florida: CRC Press.

31. Grainger, Corbett, and Andrew Schreiber. 2019. "Discrimination in Ambient Air Pollution Monitoring?" *AEA Papers & Proceedings* 109 (May): 477–82. https://doi.org/10.1257/pandp.20191063.

32. Hawksworth, D. L., and F. Rose. 1970. "Qualitative Scale for Estimating Sulphur Dioxide Air Pollution in England and Wales Using Epiphytic Lichens." *Nature* 227 (5254): 145–48. https://doi.org/10.1038/227145a0.

33. Hoek, Gerard, Rob Beelen, Kees de Hoogh, Danielle Vienneau, John Gulliver, Paul Fischer, and David Briggs. 2008. "A Review of Land-Use Regression Models to Assess Spatial Variation of Outdoor Air Pollution." *Atmospheric Environment* 42 (33): 7561–78. https://doi.org/10.1016/j.atmosenv.2008.05.057.

34. Hose, G.C, J.M James, and M.R Gray. 2002. "Spider Webs as Environmental Indicators." *Environmental Pollution* 120 (3): 725–33. https://doi.org/10.1016/S0269-7491(02)00171-9.

35. Ito, Kazuhiko, Sarah Johnson, Iyad Kheirbek, Jane Clougherty, Grant Pezeshki, Zev Ross, Holger Eisl, and Thomas D. Matte. 2016. "Intraurban Variation of Fine Particle Elemental Concentrations in New York City." *Environmental Science & Technology* 50 (14): 7517–26. https://doi.org/10.1021/acs.est.6b00599.

36. Kampa, Marilena, and Elias Castanas. 2008. "Human Health Effects of Air Pollution" *Environmental Pollution* 151(2): 362-67. https://doi.org/10.1016/j.envpol.2007.06.012

37. Kelly, Leah, Robbie Orvis, and Abel Russ. *Air Quality Profile of Curtis Bay, Brooklyn and Hawkins Point, Maryland*. Washington, D.C.: Environmental Integrity Project, 2012. https://www.environmentalintegrity.org/wp-content/uploads/2016/11/2012-06_Final_Curtis_Bay.pdf (accessed May 1, 2020).

38. Kelly, Leah, Troy Sanders, Courtney Bernhardt, and Kira Burkhart. *Citizen Air Quality Monitoring in Curtis Bay, Baltimore*. Washington, D.C.: Environmental Integrity Project, 2016. https://environmentalintegrity.org/wp-content/uploads/2016/11/PM2.5Report.pdf (accessed May 1, 2020)

39. Kelly, Leah, Kira Burkhart. *Asthma and Air Pollution in Baltimore City*. Washington, D.C.: Environmental Integrity Project, 2017. https://www.environmentalintegrity.org/wp-content/uploads/2017/12/Baltimore-Asthma.pdf (accessed May 30, 2021).

40. Kraus, Thomas, Karl Heinz Schaller, Jürgen Angerer, Ralf-Dieter Hilgers, and Stephan Letzel. 2006. "Aluminosis – Detection of an Almost Forgotten Disease with HRCT." *Journal of Occupational Medicine and Toxicology* 1 (1): 4. https://doi.org/10.1186/1745-6673-1-4.

41. Lave, Rebecca. 2015. "The Future of Environmental Expertise." *Annals of the Association of American Geographers* 105 (2): 244–52. https://doi.org/10.1080/00045608.2014.988099.

42. Maryland Department of the Environment, *Ambient Air Monitoring Network Plan for Calendar Year 2020*, Baltimore, Maryland: Maryland Department of the Environment, 2019. https://mde.state.md.us/programs/Air/AirQualityMonitoring/Documents/MDNetworkPlanCY2020.pdf (accessed September 9, 2021)

43. McKinley, Duncan C., Abe J. Miller-Rushing, Heidi L. Ballard, Rick Bonney, Hutch Brown, Susan C. Cook-Patton, Daniel M. Evans, et al. 2017. "Citizen Science Can Improve Conservation Science, Natural Resource Management, and Environmental Protection." *Biological Conservation*, The role of citizen science in biological conservation, 208 (April): 15–28. https://doi.org/10.1016/j.biocon.2016.05.015.

44. Miller-Rushing, Abraham, Richard Primack, and Rick Bonney. 2012. "The History of Public Participation in Ecological Research." *Frontiers in Ecology and the Environment* 10 (6): 285–90. https://doi.org/10.1890/110278.

45. Morawska, Lidia, Phong K. Thai, Xiaoting Liu, Akwasi Asumadu-Sakyi, Godwin Ayoko, Alena Bartonova, Andrea Bedini, et al. 2018. "Applications of Low-Cost Sensing Technologies for Air Quality Monitoring and Exposure Assessment: How Far Have They Gone?" *Environment International* 116 (July): 286–99. https://doi.org/10.1016/j.envint.2018.04.018.

46. NARSTO. *Particulate Matter Science for Policy Makers: A NARSTO Assessment.* Edited by Peter McMurry, Marjorie Shepherd, and James Vickery. Cambridge, England: Cambridge University Press, 2004.

47. Orozco, Daniel, Ruben Delgado, Daniel Wesloh, Richard J. Powers, and Raymond Hoff. 2015. "Aerosol Particulate Matter in the Baltimore Metropolitan Area: Temporal Variation over a Six-Year Period." *Journal of the Air & Waste Management Association* 65 (9): 1050–61. https://doi.org/10.1080/10962247.2015.1067653.

48. Pedersen, Marie, Ulrike Gehring, Rob Beelen, Meng Wang, Lise Giorgis-Allemand, Anne-Marie Nybo Andersen, Xavier Basagaña, et al. 2016. “Elemental Constituents of Particulate Matter and Newborn’s Size in Eight European Cohorts.” *Environmental Health Perspectives* 124 (1): 141–50. https://doi.org/10.1289/ehp.1409546.

49. Piscitello, Amelia, Carlo Bianco, Alessandro Casasso, and Rajandrea Sethi. 2021. “Non-Exhaust Traffic Emissions: Sources, Characterization, and Mitigation Measures.” *Science of The Total Environment* 766 (April): 144440. https://doi.org/10.1016/j.scitotenv.2020.144440.

50. Pulido, Laura. 2017. “Geographies of Race and Ethnicity II: Environmental Racism, Racial Capitalism and State-Sanctioned Violence.” *Progress in Human Geography* 41 (4): 524–33. https://doi.org/10.1177/0309132516646495.

51. Rachwał, Marzena, Justyna Rybak, and Wioletta Rogula-Kozłowska. 2018. “Magnetic Susceptibility of Spider Webs as a Proxy of Airborne Metal Pollution.” *Environmental Pollution* 234 (March): 543–51. https://doi.org/10.1016/j.envpol.2017.11.088.

52. Ramirez-Andreotta, Monica D., Mark L. Brusseau, Janick F. Artiola, Raina M. Maier, and A. Jay Gandolfi. 2014. “Environmental Research Translation: Enhancing Interactions with Communities at Contaminated Sites.” *Science of The Total Environment* 497–498 (November): 651–64. https://doi.org/10.1016/j.scitotenv.2014.08.021.

53. Rindy, Jenna E., Alexandra G. Ponette-González, Tate E. Barrett, Rebecca J. Sheesley, and Kathleen C. Weathers. 2019. “Urban Trees Are Sinks for Soot: Elemental Carbon Accumulation by Two Widespread Oak Species.” *Environmental Science & Technology* 53 (17): 10092–101. https://doi.org/10.1021/acs.est.9b02844.

54. Rohr, Annette C., and Ronald E. Wyzga. 2012. “Attributing Health Effects to Individual Particulate Matter Constituents.” *Atmospheric Environment* 62 (December): 130–52. https://doi.org/10.1016/j.atmosenv.2012.07.036.

55. Ryan, Patrick H., and Grace K. LeMasters. 2007. “A Review of Land-Use Regression Models for Characterizing Intraurban Air Pollution Exposure.” *Inhalation Toxicology* 19 (August): 127–33. https://doi.org/10.1080/08958370701495998.

56. Rybak, Justyna, Izabela Spówka, and Anna Zwoździak. 2012. “Preliminary Assessment of Use of Spider Webs for the Indication of Air Contaminants.” *ENVIRONMENT PROTECTION ENGINEERING* 38 (3): 175–81. https://doi.org/10.5277/EPE120315.

57. Rybak, Justyna. 2015. “Accumulation of Major and Trace Elements in Spider Webs.” *Water, Air, & Soil Pollution* 226 (4). https://doi.org/10.1007/s11270-015-2369-7.

58. Rybak, Justyna, Izabela Spówka, Anna Zwoździak, Magdalena Fortuna, and Krystyna Trzepla-Nabagło. 2015. “Evaluation Of The Usefulness Of Spider Webs As An Air Quality Monitoring Tool For Heavy Metals.” *Ecological Chemistry and Engineering S* 22 (3). https://doi.org/10.1515/eces-2015-0021.

59. Rybak, Justyna, Wioletta Rogula-Kozłowska, Izabela Jureczko, and Radosław Rutkowski. 2019. “Monitoring of Indoor Polycyclic Aromatic Hydrocarbons Using Spider Webs.” *Chemosphere* 218 (March): 758–66. https://doi.org/10.1016/j.chemosphere.2018.11.174.

60. Rybak, Justyna, Wioletta Rogula-Kozłowska, Krzysztof Loska, Kamila Widziewicz, and Radosław Rutkowski. 2019. “The Concentration of Cu and Pb in the Funnel Spider

Eratigena Atrica (C. L. Koch 1843) (Araneae: Agelenidae) and Its Web." *Chemistry & Ecology* 35 (2): 179–90. https://doi.org/10.1080/02757540.2018.1546295.

61. Signorelli, Salvatore Santo, Gea Oliveri Conti, Antonella Zanobetti, Andrea Baccarelli, Maria Fiore, and Margherita Ferrante. 2019. "Effect of Particulate Matter-Bound Metals Exposure on Prothrombotic Biomarkers: A Systematic Review." *Environmental Research* 177 (October): 108573. https://doi.org/10.1016/j.envres.2019.108573.

62. Sun, Yele, Guoshun Zhuang, Ying Wang, Lihui Han, Jinghua Guo, Mo Dan, Wenjie Zhang, Zifa Wang, and Zhengping Hao. 2004. "The Air-Borne Particulate Pollution in Beijing—Concentration, Composition, Distribution and Sources." *Atmospheric Environment* 38 (35): 5991–6004. https://doi.org/10.1016/j.atmosenv.2004.07.009.

63. Tahir, Hafiz Muhammad, Hammad Aamir, and Junaid Nadeem. 2018. "Use of Spider Webs as Indicators of Air Quality Assessment of Lahore City: Spider Web as Indicators of Air Quality." *Water and Environment Journal* 32 (2): 292–300. https://doi.org/10.1111/wej.12327.

64. Targino, Admir Créso, Mark David Gibson, Patricia Krecl, Marcos Vinicius Costa Rodrigues, Maurício Moreira dos Santos, and Marcelo de Paula Corrêa. 2016. "Hotspots of Black Carbon and PM2.5 in an Urban Area and Relationships to Traffic Characteristics." *Environmental Pollution* 218 (November): 475–86. https://doi.org/10.1016/j.envpol.2016.07.027.

65. Tregidgo, Daniel J., Sarah E. West, and Mike R. Ashmore. 2013. "Can Citizen Science Produce Good Science? Testing the OPAL Air Survey Methodology, Using Lichens as Indicators of Nitrogenous Pollution." *Environmental Pollution* 182 (November): 448–51. https://doi.org/10.1016/j.envpol.2013.03.034.

66. U.S. Census Bureau, "Population Estimates, July 1, 2019 (V2019) -- Baltimore City, MD," *Quick Facts*. (2019) https://www.census.gov/quickfacts/fact/table/baltimorecitymaryland,US/PST045219 (accessed May 12, 2020)

67. U.S. Census Bureau. *Household Income: 2019* by Gloria G. Guzman. American Community Survey Briefs, 2020. https://www.census.gov/content/dam/Census/library/publications/2020/acs/acsbr20-03.pdf (accessed September 9, 2021).

68. Vann-Sander, Sarah, Julian Clifton, and Euan Harvey. 2016. "Can Citizen Science Work? Perceptions of the Role and Utility of Citizen Science in a Marine Policy and Management Context." *Marine Policy* 72 (October): 82–93. https://doi.org/10.1016/j.marpol.2016.06.026.

69. Williams, Ron, Vasu Kilaru, Emily Snyder, Amanda Kaufman, Timothy Dye, Andrew Rutter, Ashley Russell, and Hilary Hafner. *Air Sensor Guidebook.* Washington, DC.: US Environmental Protection Agency, 2014. https://cfpub.epa.gov/si/si_public_record_Report.cfm?Lab=NERL&dirEntryId=277996 (accessed September 12, 20201).

70. World Health Organization. "Health Risks of Heavy Metals from Long-Range Transboundary Air Pollution," Copenhagen, Denmark: WHO regional office for Europe, 2007. https://www.euro.who.int/__data/assets/pdf_file/0007/78649/E91044.pdf (accessed September 2, 2021).

71. Xiao-li, S., P. Yu, G.C. Hose, C. Jian, and L. Feng-xiang. 2006. “Spider Webs as Indicators of Heavy Metal Pollution in Air.” *Bulletin of Environmental Contamination and Toxicology* 76 (2): 271–77. https://doi.org/10.1007/s00128-006-0917-y

72. Xie, Xingzhe, Ivana Semanjski, Sidharta Gautama, Evaggelia Tsiligianni, Nikos Deligiannis, Raj Thilak Rajan, Frank Pasveer, and Wilfried Philips. 2017. “A Review of Urban Air Pollution Monitoring and Exposure Assessment Methods.” *ISPRS International Journal of Geo-Information* 6 (12): 389. https://doi.org/10.3390/ijgi6120389

73. Ye Dongni, Mitchel Klein, James A. Mullholand, Armistead G. Russell, Rodney Weber, Eric S. Edgerton, Howard H. Chang, Jeremy A. Sarnat, Paige E. Tolbert, and Stefanie Ebelt Sarnat. 2018. “Estimating Acute Cardiovascular Effects of Ambient PM2.5 Metals.” *Environmental Health Perspectives* 126 (2): 027007-1-10. https://doi.org/10.1289/EHP2182.