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An Assessment of the Feasibility of Environmental Exposure Data for Syndromic Surveillance

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AN ASSESSMENT OF THE FEASIBILITY OF ENVIRONMENTAL EXPOSURE DATA FOR SYNDROMIC SURVEILLANCE

by

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APPROVAL PAGE

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AUTHOR'S STATEMENT PAGE

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ABSTRACT

INTRODUCTION: Syndromic surveillance is a method of rapid disease detection based on categories of syndromes, or signs, experienced before the full onset of disease. It is increasingly being used by government agencies and health departments to identify disease outbreaks in a timely manner. Environmental exposures are known to induce respiratory and gastrointestinal symptoms, tend to have a seasonality component, and adversely affect the health of millions of people.

OBJECTIVE: In this study, we assess the availability of environmental exposure data for air pollution ($PM_{2.5}$, ozone, and NO_2), pollen, and water contaminant exposure for use in a syndromic surveillance project. We also evaluate: 1) the general proximity of HMO populations to monitors, and 2) distribution of SES characteristics of the area populations with respect to monitor locations.

METHODS: We collected exposure data, patient population data, and Census tract SES data for two metropolitan areas where Kaiser Permanente (KP) provides medical services: Atlanta, Georgia and the northern Virginia, District of Columbia (DC), and Baltimore area. Exposure data for air pollution and pollen were collected for 2013-2014. Straight-line distance from a monitor to the nearest KP clinic, and from each Census tract centroid, to the nearest air pollution or pollen monitor was computed using the Euclidean distance formula.

RESULTS:

- Air pollution is routinely monitored by a Federal mandate, is universally available, and easily obtained. Pollen data is collected by private entities, which in some cases hinders access. Water quality data is generally publically available, but it is collected at the source and not easily traceable to water delivery endpoints.
- In both Atlanta and DC, Maryland, and Virginia most of the clinics (78% and 94%, respectively) are located within 10 miles of an air pollution monitor; approximately 83% and 94% of the KP populations were located within 10 miles of an air pollution monitor.
- SES populations differ substantially by race, age, income, and education with respect to the nearest monitor. However, the median and interquartile range of various air pollutants does not differ much across the monitors – indicating that, on average, there is little SES gradient in type of level of air pollution exposure.

CONCLUSIONS: Overall, this study adds knowledge regarding future considerations about the coverage of environmental monitors and to what extent exposure measure estimates can be assigned to certain populations located near monitors.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

1.1 Background

Early detection of disease outbreaks has become a crucial function of public health departments. The World Trade Center terrorist attack in 2001 and the heightened concern of a bioterrorist attack precipitated the necessity for a surveillance system to rapidly identify an increase in symptoms that could suggest the deployment of a nefarious biological or chemical agent[1-5]. Other recent outbreaks involving West Nile virus and SARS, among other diseases, have also prompted the need for improved surveillance of abnormal patterns of symptoms[2].

Syndromic surveillance requires de-identified, pre-diagnostic healthcare data for timely recognition and characterization of unusual pattern of syndromes that could signal an outbreak[1, 6]. Most syndromic surveillance systems use automated encounter data from physician visits (e.g. primary care, infectious disease clinics), emergency department (ED) visits, or hospital admissions[1, 3, 4, 6-10]. Other methods are included but not limited to nurse hot lines and related call center services[5, 11-14] as well as over-the-counter (OTC) medication sales, both of which also operate through computerized systems[15]. In providing automated healthcare data of prodromal symptoms, which appear before the onset of illness, grouped into syndrome groups that is typically available on the next day, it is rational that syndromic data could be linked with routinely collected environmental monitor data.

Exposure data can be obtained through public and private sources. Monitors provide measurements of ambient concentrations on a regular basis. Air pollution is an established source of cardiovascular and respiratory events in vulnerable populations. Particulate matter ($PM_{2.5}$), ozone, and nitrogen dioxide (NO_2) are associated with increased risk of all-cause mortality and cardiovascular mortality[16, 17]. Air pollutants may also exacerbate chronic conditions such as asthma leading to escalating ambulatory care visits[18]. Pollen induces allergic reactions among many sensitive people and is a major health concern for individuals suffering from chronic respiratory diseases such as asthma and hay fever[19]. Temperature increases and heightened levels of CO_2 are expected to increase the duration of allergy seasons and the potency of airborne allergens[19]. These effects due to climate change produce a greater concentration of pollen in the air as well as pollen-related symptoms in the general population. Aeroallergens, including pollen, costs the US $21 billion in direct medical expenses annually [19].

Approximately 11 million physician office visits in 2010 were due to a primary diagnosis of allergic rhinitis [20]. Asthma, accounting for 1.75 million emergency room (ER) visits, places a massive burden on the healthcare system [21]. Monitoring air pollution and pollen can therefore provide a meaningful purpose as an indicator of trends in ambulatory encounters due to triggers of acute reactions in chronic and allergic diseases.

Ultimately, environmental exposures are regularly measured, contribute to a multitude of hospitalizations and deaths each year, and many follow a repeated, annual cycle[16, 19, 22-25]. Air pollution and pollen may be suited for the routine purposes of syndromic surveillance based on these qualities. However less is known regarding how water quality measurements can be used to as indicators for waterborne illness risk, which may impede the use of water contamination exposure in syndromic surveillance.

1.2 Study Objectives

The overall objective of this study is to assess the feasibility of using environmental pollutant data as a means for syndromic surveillance. The data generated in this study will eventually be used as environmental exposure matrices organized by space and time to assess potential syndromic response[26].The availability of existing data will be described along with the level of access- public or private- and how the contaminants are measured. Contaminants include air pollutants ($PM_{2.5}$, ozone, NO_2), pollen, and water. This study will examine populations in the Atlanta, Georgia area and the Washington D.C., Maryland, and Virginia area that are service areas of the Kaiser Permanente in Georgia (KPGA) and Kaiser Permanente in the Mid-Atlantic States (KPMAS) regions, respectively. Policies related to surveillance at various levels of government (federal, state, or local) will be identified to provide a better understanding of where monitors are placed and the frequency of measurements. In order to evaluate the levels of exposure within the area of healthcare facilities, the distance between certain clinics and the nearest monitor will be calculated. Analyzing general demographics- race/ethnicity, age, level of education, and median household income- will produce valuable knowledge on whether or not the level of exposure among vulnerable populations in particular can be reasonably identified by using these monitors for surveillance.

Chapter II

REVIEW OF THE LITERATURE

2.1. Syndromic Surveillance Systems

From the literature review it has been determined that environmental exposure data is not routinely collected for syndromic surveillance. Most research is regarding retrospective analysis and involves events such as wildfires[27] and extreme levels of ambient air pollution [28]. Post-event analyses will link routinely collected air pollution data from environmental monitoring systems with healthcare data (e.g. call records, ED visits, hospital admissions). Pilot studies and proposals have explored developing syndromic surveillance systems that combine air quality or water quality data with healthcare data. Three prominent syndromic surveillance systems are National Health Service (NHS) systems in the United Kingdom (UK), the Electronic Surveillance System for the Early Notification of Community-based Epidemics (ESSENCE) in the US, and systems operated by the New York City Department of Health and Mental Hygiene (NYC DOHMH).

2.1.1 NHS Direct

NHS syndromic surveillance systems were used to identify a rise in respiratory syndromes following two events of poor air quality in 2014. Daily air quality data across regions of England were compared with rates and proportions of respiratory-related calls, consultations, and ED visits to yield a statistically significant increase during both events with particulate matter being the predominant exposure linked in this association[29].

The United Kingdom (UK) has the most established use of telephone data for syndromic surveillance [5, 11-14]. The National Health Service (NHS) operates NHS Direct, a national telephone helpline, to monitor reported syndromes. It is open 24 hours per day for 365 days per year and receives approximately 7 million calls annually from all across England and Wales[5, 11, 30]. Nurses respond to calls received using automated clinical decision support software called the NHS Clinical Assessment System (NHS CAS). NHS CAS contains more than 200 algorithms that models a decision tree structure of questions pertaining to the symptoms of the person whom the call concerns. Based on the algorithm assigned by the nurse and the responses to the questions regarding the patient and the reported symptoms, an outcome results. The call outcome, also known as the disposition, is either advice for self-care, a doctor referral, an ED referral, or a paramedic dispatch. Details of the demographic information and syndrome are recorded for each call [5, 14].

The Health Protection Agency electronically receives daily syndromic data from NHS Direct, which has 23 sites across the UK. The data is analyzed by a small team known as the HPA Real-time Syndromic Surveillance Team (ReSST)[9]. Call data is separated into the following 10 syndromes: cold/"flu", cough, fever, diarrhea, vomiting, difficulty breathing, double vision, eye problems, lumps, and rash [5].

Call data can be analyzed weekly, daily, or hourly. Daily data for each NHS Direct site is reported in two parts. Part 1 illustrates how often an algorithm has been used the dispositions produced. This information is electronically submitted to the Health Intelligence Unit (HIU) of NHS Direct, who then distribute it to the Communicable Disease Surveillance Centre (CDSC) for analysis. Part 2 contains detailed information related to the caller, which includes the call identification (ID) number, age, and postcode of the person for whom the call references. This information remains at the NHS Direct site [14]. Data are categorized by ReSST according to symptom, age group, and disposition among each NHS Direct site. By establishing baselines from historical data, 99.5% upper confidence intervals are set for each of the 10 major syndromes for each NHS Direct site. The confidence limits are calculated as a percentage of daily total calls for each site and are adjusted for seasonal effects [5, 14]. When syndromic calls exceed the 99.5% upper confidence interval, it is designated an 'exceedance'. All exceedances are evaluated by ReSST. Initially, the data is checked for accuracy. The team attempts to identify possible data-related explanations for the exceedance. If no reasonable explanation is uncovered, additional call details are assessed. With the call ID number, duplicate records can be discerned as a possible source. The NHS Direct medical adviser can contact callers for more information about their symptoms or whether their condition has deteriorated. If it is deemed that further investigation is required, the regional epidemiologist is given the call information for follow-up by a public health team(s). Bringing the regional epidemiologist into the investigation triggers an alert. Weekly bulletins containing summaries and graphs of exceedances are released to a range of local and national public health professionals[14].

2.1.2 ESSENCE

In a collaborative project between the Johns Hopkins Applied Physics Laboratory and the Environmental Protection Agency (EPA), a module to connect water quality data and health indicator data was configured in ESSENCE. This project used water quality data from Seattle-King County over a 6-month period beginning in January 2008. Water quality assessed was chemical contamination of drinking water. Neurological and gastrointestinal syndromes were the health events queried. To develop the algorithms this approach included pooling baseline data from environmental sensor data for those with similarities in both magnitude of output and water source characteristics. Overall, this project demonstrated a strategy for integrating both exposure and outcome data and performing spatial analysis within different parts of a large area to enable the detection of abnormalities that could represent a waterborne disease outbreak[31].

In 2001, ESSENCE was adopted by the United States Department of Defense (DoD) to increase the timeliness of outbreak detection[6]. The development of ESSENCE was initiated by perception from health officials that the US was ill-prepared to respond to the release of a biological agent in a hypothetical weapons-of-mass-destruction attack in Denver, Colorado. A system was needed to deliver real-time patient data that incorporated patient counts, location, time, and disease/condition/symptoms related persons affected[4]. ESSENCE captures patient ambulatory data recorded by International Classification of Disease, Ninth Revision (ICD-9) codes as a means of syndromic surveillance. This system draws data from all permanent military treatment facilities (MTFs) to treat active duty military personnel, retirees, and their beneficiaries worldwide. On average, more than 300,000 outpatient primary care and ED visits per week are electronically submitted to ESSENCE. Each patient encounter in the DoD generates a Standardized Ambulatory Data Record (SADR) that matches to patient demographic data. The provider completes the SADR by adding the ICD-9 code to indicate primary symptoms or a diagnosis. Data are submitted through the ESSENCE server every 8 hours and grouped by ICD-9 codes that are classified into syndromes. Reporting of data usually occurs every 1 to 4 days, varying by MTF[4]. There are 9 syndrome groups categorized by ESSENCE based on ICD-9 coded chief complaints: botulism-like, fever, GI, hemorrhagic illness, neurologic, rash, respiratory, and shock/coma [32]. Baseline levels are established for each syndrome group, similar to NHS Direct and other surveillance systems, so that significant increases are identified through data analysis during routine monitoring[4]. ESSENCE uses algorithms to determine the expected number of cases for a given day and location based on the historical data. Exponentially weighted moving average (EWMA) algorithms and regression are combined into a time-series model to detect epidemics. The regression part of the out accounts for effects of differences in holidays and weekends and the days following them. A red alert is triggered when observed cases exceeds expected cases by a significant amount, whereas a yellow alert signifies a marginal exceedance of observed cases. Alerts can be caused by a single event, particularly if it is rare[6]. ESSENCE is increasingly being used to monitor the start and end of influenza season due to the annual cycle of influenza and the economic costs it imposes. The ILI surveillance reports it generates are accurate in comparison to CDC sentinel data and matched trends in positive specimens identified via laboratory testing. ESSENCE has the advantage of more rapid detection in comparison to sentinel- and laboratory-based systems. However, ESSENCE is limited in its inability to detect smaller outbreaks[4].

2.1.3 New York City Syndromic Surveillance

The NYC DOHMH employs a variety of data through its syndromic surveillance system. Efforts have been made to create time-series and spatial models that characterize the heterogeneity of health outcomes in relation to water and air pollution. The rational is that air pollution and weather data are routinely collected near real time and DOHMH collects daily syndromic data [28]. The NYC Community Air Survey (CAS), which was established in December 2008, is the largest urban air monitoring program in the US [33]. NYC also has comprehensive coverage for syndromic data for as of 2012 approximately 95% of all NYC ED visits are included from participating EDs[34].

Syndromic surveillance began in NYC in 1995. Its original purpose was to detect diarrheal illness outbreaks, particularly waterborne diseases such as Cryptosporidium. Originally, the system included nursing home surveillance for diarrheal illness, clinical laboratory surveillance of stool samples, and over-the-counter (OTC) pharmacy sales. Upon evaluating the components of this system, DOHMH transitioned into an electronic reporting system. ED visits were first incorporated into the DOHMH syndromic surveillance system in November 2001. By 2003, data sources included ED visits, OTC pharmacy sales, ambulance dispatch calls, and employee absenteeism in NYC [35]. ED visit data are categorized into syndromes based on chief complaint. There is a hierarchy to these syndromes as follows from most significant to least significant: common cold, sepsis, respiratory, diarrhea, fever, rash, asthma, and vomiting[1]. Participating EDs electronically submit files to DOHMH seven days per week. Each morning, a data analyst retrieves the files and verifies them for completeness and accuracy using SAS software (SAS Institute Inc., Cary, NC). The data are then concatenated into a single SAS dataset. Files contain data for all ED visits from the previous day, Data include the following information: data and time of visit, age, gender, home zip code, and chief complaint. The chief complaint is a free-text field that is filled with the patient's own description of his/her illness. A SAS algorithm assigns a syndrome for a patient record based on the chief complaint. Citywide temporal analyses and spatial clustering analyses are conducted for each syndrome-age category of interest[1, 2].

NYC syndromic surveillance successfully detected an outbreak of diarrheal illness during the 3 days after a power outage in 2003. This was a pivotal event because 4 syndromic data sources identified this outbreak- ED visits, 2 sources of pharmacy sales data, and worker absenteeism. ED visit data exceeded the expected number of visits by 70%. The pharmacy sales data sources- the OTC pharmacy system and National Retail Data Monitor system detected increases in antidiarrheal medication sales the day following the power outage. Daily counts in absences due to GI syndrome increased relative to the 7-day baseline mean set by the worker absenteeism system. The illness was found to be associated with consuming meat or seafood given that power had been lost for an average of 24 hours in peoples' homes. The uptick in GI illness was not detected by traditional methods of surveillance used by health departments, such as routine laboratory reporting and healthcare provider reporting. These surveillance methods are mostly able to indicate unusual disease patterns, but are inept at detecting outbreaks of infectious disease for which a diagnostic test is not normally used. Diarrheal illness poses another issue for traditional surveillance because 1) most people do not seek medical attention for common or mild symptoms like diarrhea and 2) clinicians are less likely to pay attention to such symptoms or report clusters of them. While causal inference between the food and GI illness could not be inferred in this case due to lack of positive stool and food cultures, this illustrated the effectiveness of syndromic surveillance in monitoring for citywide temporal or special increases in nonspecific syndromes to rapidly detect trends in disease relative to traditional methods[15].

2.2. Sources of Environmental Exposure Data for Syndromic Surveillance in the US

2.2.1. Air Pollution

The EPA requires state environmental agencies to report air monitoring data. Monitoring stations are owned and operated by the state environmental agencies, who submit hourly or daily measures of pollutant concentration to the Air Quality System (AQS) of the EPA. The AirData website provides public access to air quality monitor data from each US state, Puerto Rico, and the US Virgin Islands. Data can be downloaded for the six criteria air pollutants for which the EPA sets national air quality standards: ozone, particulate matter (PM_{10} and $PM_{2.5}$), carbon monoxide (CO_2), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and lead (Pb)[22]. The data collected may vary across states (e.g. South Dakota does not monitor Pb). Data can generally be viewed starting from 1980 for CO_2, ozone, NO_2, and SO_2. Particulate matter monitor data generally dates back to 1988 for PM10 and 1989 for $PM_{2.5}$. Downloaded data is in the CSV (comma-separated values) format [36].

The Environmental Protection Agency (EPA) sets national laws and regulations and creates policies and recommendations to protect human health and the environment. The EPA works with federal, state, and tribal entities to monitor and promote compliance with law and regulations. It is divided into ten regions where the EPA Regional Office coordinates programs within its region. Georgia is located in Region 4, which also encompasses the following states: Alabama, Florida, Kentucky, Mississippi, North Carolina, South Carolina, and Tennessee. DC, Maryland, and Virginia are located in Region 3, which also contains: Delaware, Pennsylvania, and West Virginia[37]. Research conducted by the EPA and local, state, academic, and government partner organizations has enabled it to set and amend criteria to reduce harmful pollutants and contaminants in the air and water. The Clean Air Act (CAA) is a federal law that provides the EPA the authority to regulate emissions of air pollutants. Originally enacted in 1963, the CAA was amended in 1970 to give the EPA the authority to set limits to the six criteria air pollutants. Through the CAA, state and local agency plans to reduce air pollution must be approved by the EPA. The EPA can issue sanctions to the state if it does not meet the necessary requirements of the minimum standards established for the amount of air pollutant that can be in the air at a given time. The CAA was last amended in 1990 to provide the EPA with broader authority to regulate the reduction of air pollution. Under the CAA, the EPA is required to set national ambient air quality standards (NAAQS) [38]. Primary standards provide public health protection; secondary standards protect public welfare, which includes decreased visibility and damage to crops among other criteria. If an area contains levels of pollutants that exceed the NAAQS, then it is classified as a nonattainment area[39].

All states are mandated to establish an air quality surveillance system in their State Implementation Plans (SIP). Each system consists of a network of air monitoring stations that include State and Local Air Monitoring Stations (SLAMS), National Air Monitoring Stations (NAMS), Photochemical Assessment Monitoring Stations (PAMS), and Special Purpose Monitors (SPM). SLAMS are the standard monitors required for the six criteria pollutants. The EPA air quality surveillance system regulations do not set a total number of SLAMs sites, although there are minimum numbers of monitors for Pb, SO_2, and $PM_{2.5}$ [40].

The six primary objectives of SLAMS are as follows: (1) determine the expected pollutant concentration in monitored area; (2) determine representative concentrations in densely populated areas; (3) determine the effect of significant pollution sources, or the category of sources, on ambient pollution levels; (4) determine background concentration levels; (5) determine the extent of pollutants transported across region among the populated areas; and (6) determine the welfare-related impacts in more rural and remote areas (such as visibility impairment and effects on vegetation).

SLAMS monitors are expected to be situated in a site where the air quality of the sampled air will be representative of the air quality over the area that the monitoring station is supposed to represent. The scales of representativeness are: microscale (≤ 100m), middle scale (100-500m), neighborhood scale (0.5-4km), urban scale (4-50km), and regional scale (tens to hundreds of km in rural areas). Stations are selected for a given location based on the spatial scale best suited for the monitoring objective of the respective station [40].

NAMS are a subset of SLAMS that must meet more stringent criteria and are directed at urban and multisource areas. Consolidated Metropolitan Statistical Areas/Metropolitan Statistical Areas (CMSA/MSA) with a population greater than 1 million must have at least 1 $PM_{2.5}$ NAMS; a population of at least 1 million must have at least 2 NO2 NAMS; and a population of 200,000 must have at least 2 ozone NAMS. PAMS are also a subset of SLAMS that are required to place in the most problematic ozone nonattainment areas. This type of monitors collects samples of speciated volatile organic compounds (VOCs) including carbonyls, ozone, oxides of nitrogen (NO), and surface (10-meter) x and upper air meteorological parameters such as temperature, precipitation, and wind speed. PAMS must provide a continuous measure of ozone [40].

Ground-level ozone is a parameter of interest because of the adverse respiratory and cardiovascular health effects it is associated with. It is produced by photochemical reactions between oxides of nitrogen (NO_x) and VOC in the presence of sunlight[41]. In larger urban areas, PAMS are strategically placed at different sites to collect information on ozone and its precursors in the following areas: upwind, maximum ozone precursor emissions impact site, maximum ozone concentration site, and the extreme downwind monitoring site. One or two maximum ozone precursor emissions impact sites are placed downwind of the primary site of precursor emissions, which is typically the central business district. This is intended to collect neighborhood scale measurements. In contrast, the other sites obtain urban scale measurements. The maximum ozone concentration site is situated 10 to 30 miles from the urban area limits [42].

The EPA has recent research interests in near-road NO_2 concentrations, as NO_2 is a traffic-related pollutant. Installing and operating near-road NO_2 monitors is a collaboration between the EPA and state and local partner associations, departments of transportation, and the Federal Highway Administration. From the 2009 NO_2 Risk and Exposure Assessment, the EPA has established that roadway-associated exposures contribute the most to peak, ambient NO_2 concentrations. The EPA is revising the NO_2 NAAQS to concentrate on building a near-road NO_2 monitor network to account for the significance of near-road NO_2, and to provide better exposure assessment for populations around roadways [43].

The Air Quality Index (AQI), developed by the EPA, is based on daily air quality standards of criteria pollutants including $PM_{2.5}$. The AQI scale goes from 0 to 500 and is categorized into six levels in regards to the pollutant health effects: (1) 0 to 50 = good, (2) 51 to 100 = moderate, (3) 101 to 150 = unhealthy for sensitive groups, (4) 151 to 200 = unhealthy, (5) 201 to 300 = very unhealthy, and (6) 301 to 500 = hazardous. Although level 3 marks the initial point that air quality is unhealthy for sensitive groups, the definition of the prior level, “moderate”, states that this level may be problematic for a “very small number” of people who are extra sensitive to air pollution [44].

2.2.1.1. Georgia

The Environmental Protection Division (EPD) of the Georgia Department is in charge of monitoring and regulating air, land, and water resources in the state. The Georgia SIP determines the rules and regulations for air quality control. The EPD Air Protection Branch monitors levels of air pollutants via the Ambient Monitoring Program (AMP). AMP is tasked with meeting EPA regulations for monitoring air quality in Georgia by evaluating monitors in the state’s ambient air quality system. Monitor design, site appropriateness, special scale represented, and appropriate new technologies are assessed by AMP [45]. Daily concentrations of ozone, SO_2, CO, NO_2, PM_{10}, and $PM_{2.5}$ can be viewed on AMP for the current day and the past three days. Data for individual monitors are grouped by MSA or general area (e.g. North Georgia Mountains). All exceedances of federal air quality standards can be viewed by year. A summary table of the MSAs and areas where exceedances occurred for each air pollutant is displayed as well as a calendar view that shows the location, pollutant, and pollutant concentration for day of the event. By clicking the link of the exceedance event in either the table or calendar, meteorological data is also provided along with the pollutant concentration by hour over the 24-hour period at the applicable monitors. Monitor data is also submitted to EPA AQS. AQS enables the additional functionality of downloading all available monitor data, not just exceedances, for an entire year [46].

Revisions to the SIP are required for designated nonattainment areas. Fifteen metropolitan Atlanta counties are included in the marginal nonattainment area, which is the least severe classification, according to the 2008 ozone standards. These counties are: Bartow, Cherokee, Clayton, Cobb, Coweta, DeKalb, Douglas, Fayette, Forsyth, Fulton, Gwinnett, Henry, Newton, Paulding, and Rockdale [47].

2.2.1.2. DC, Maryland, Virginia

Air quality and monitoring policies for this region all comply with EPA regulations and AQS. Maryland, Virginia, and DC each complete air quality plans as required by the CAA. As mandated, all air quality monitor data is sent to AQS, where it is available for viewing and downloading. Additionally, the Metropolitan Washington Air Quality Committee (MWAQC) has been commissioned by the mayor of the District of Columbia and the governors of Maryland and Virginia to prepare an air quality plan for the DC-MD-VA MSA. This MSA is a nonattainment area [48]. Other non-attainment areas in this region are: Baltimore, MD and Philadelphia-Wilmington-Atlantic City, PA-DE-MD-NJ [47].

District Department of the Environment (DDOE) enforces environmental laws and regulations in DC. The ambient air quality monitoring network contains 5 monitors that are sited based on population density and distribution, emissions sources, and historic concentrations of pollutants. DDOE checks monitors daily or weekly to perform maintenance or retrieve raw data for quality assurance evaluation. Monitor data is sent to EPA AQS, and then to MWAQC [49].

The Maryland Department of the Environment (MDE) Ambient Air Monitoring Program maintains the state's network of 25 air monitoring sites. Most monitors are concentrated in urban/industrial areas, as is the case with most states. MDE employs a variety of other means of monitoring air quality including but not limited to radar, light detection technology, and ozonesondes. MDE currently contains historical air quality data related to 8-hour ozone exceedance days dating from 2003 to 2013. Data are group by nonattainment area and exceedances outside of these areas referred to as "state-wide" [50]. The Maryland Department of Health and Mental Hygiene in conjunction with MDE, support the Environmental Public Health Tracking program, which has maps and tables on environmental indicators and health outcome indicators. The environmental indicators are $PM_{2.5}$, ozone, and pollen. Users can query indicators separately to attain a layout of measurement data by county across the state. Indicators are displayed by year, measurement, and available advanced options such as gender, age group, and race/ethnicity. Metadata is cited for all indicators [51].

Virginia Department of Environmental Quality (DEQ) houses the air monitoring program for the state. There are 26 monitors in the network which meet federal and state regulations. Monitors are sited and maintained based on same criteria as other states and DC. All except 2 monitors are the responsibility of DEQ. The monitor in Rockbridge County is operated by USDA Forest Service and the monitor in Shenandoah National Park is handled by the National Park Service. Virginia includes additional monitors than the minimum EPA SLAMS requirement. Historical daily data is maintained in AQS. DEQ, however, does offer annual and summary data for $PM_{2.5}$ and PM_{10} starting from 2009 that is available for download [52].

2.2.2. Pollen

There are is no comprehensive, federal policy for monitoring pollen. Daily pollen counts are generally available as well as forecasts similar to temperature and precipitation. Without a federal monitoring policy, however, there is also not a publically available database for daily or continuous pollen count data.

The National Allergy Bureau (NAB) of the American Academy of Asthma Allergy and Immunology (AAAAI) is the premier source for pollen monitor data, pending the availability of monitor locations. NAB is the section of the AAAAI's Aeroallergen Network responsible for reporting current pollen and mold spore levels. There are 84 counting stations located within 31 states across all regions of the US, and DC. NAB stations collect airborne pollen and spores, and then use this information for research purposes. Daily pollen count data is generally categorized by grass, trees, and weeds [53].

The NAB database contains data from 2003 to present. Release of data depends on individual station. Each station has its own policy for data release and may handle requests as they see fit. All approved data requests are formatted into Excel spreadsheets. Data requests sent to the AAAAI Executive Office involving multiple stations follows a strict approval process. Among all stations listed in the request, only those for the desired time period will be contacted for their approval. Data provided by the AAAAI Executive Office are also formatted into Excel spreadsheets [54].

NAB requires members to become certified in order to become pollen counters or mold counters. According to the NAB website, a certified station must collect samples a minimum of three days per week using either a Burkard volumetric spore trap, a Kramer-Collins sampler or a Rotorod sampler. The sampler must be situated on an unobstructed rooftop at least one story above ground with no local pollen and/or mold spore sources [55].

The NAB pollen scale contains 3 main types of pollen- grass, tree, and weed. There are 5 levels of pollen counts: absent, low, moderate, high, and very high. The ranges of counts that correspond to these levels varies between the pollen types. Absent equates to a pollen concentration of 0 for all types. Low levels are concentrations that are less than the 50^{th} percentile or median. Moderate levels are concentrations between the 50th and 75th percentile. High levels are between the 75th and 99th percentile. Very high levels are above the 99th percentile [56].

In urban areas, large populations of vulnerable people are placed at risk for of the adverse health effects of pollen. Many types of tree pollen are considered allergens and that can cause allergic sensitization and exacerbate chronic respiratory conditions such as asthma and allergic rhinitis. There is not much research on local variation of tree pollen exposure as it relates to its independent effect on human health. MSAs typically only have one p

Pollen monitoring station, however research illustrates that there are variations in the amount of pollen deposited varies across small spatial areas within metropolitan areas [57]. Since urban populations experience a mixture of hazards from air pollutant and pollen, it is important to consider pollen in mixed models of air quality indicators. Like air pollutants, traffic may be a factor in increasing the concentration of pollen in urban areas. It was posed that continued highway traffic may re-suspend sedimented pollen. Wind and higher temperature are also variables that favor the pollen as it does air pollution [58].

There are several types of pollen samplers available. The sampler type is important because it affects the time scale and unit of measurements. Three examples of samplers are volumetric, impactor, and gravimetric. Volumetric samplers draw in air at a constant flow rate and allow pollen to impact on a piece of tape secured on a rotating drum. The flow rate enables calculation of pollen concentration in grains/m^3. Impactor samplers consist of a set of greased rods or slides attached to a rotating head such that pollen is impacted on the greased surfaces. This sampler type also measures pollen in grains/m^3. Gravimetric samplers passively sample atmospheric pollen content via gravity. Since this sampling method is passive, pollen counts are reported as influx in grains/cm^2 instead of as a concentration. All of these samplers allow for daily measures of pollen. If there is more than one sampler site in an area, they must be at the same height in order to properly assess homogeneity or variability in pollen concentration at different locations within the study area. Likewise, most pollen types are more concentrated at ground levels [57].

Climate has a major impact on pollen. Pollen flourishes in dry, windy condition because it can travel longer distances with the wind. Conversely, pollen counts are lower during rainy weather because the pollen grains get trapped in the rain droplets, which hinders dispersion [59]. The effect of temperature on pollen is also pronounced, with the increasing yearly temperature and greater days of extreme heat allowing pollen to thrive and grow more potent. This change in climate directly relates to a longer pollination season and more days with peak pollen counts (Measurements of particulate matter and pollen in the city of Berlin). Neophytes (non-native plants) with allergenic pollen grains could multiply and introduce allergens to individuals who had previously been unexposed to them. Also, the increased potency of pollen could evoke allergic symptoms in people who do not currently suffer from seasonal allergies [19, 58].

2.2.2.1. Georgia

Georgia does not have a state policy for monitoring pollen. Consequently, there is no state database of historical daily count data. Predicted pollen counts based on general weather forecasts are available, but these are not actual counts. NAB stations are located in Gainesville, Marietta, and Savannah. These stations are operated by private allergy clinics [60]. The websites of these counting stations provide the daily count data, though not all stations are up to date. The Marietta station, which is located in metro Atlanta, is operated by the Atlanta Allergy and Asthma Clinic. This station displays the daily pollen count as well as counts from the preceding 2 years.

2.2.2.2. DC, Maryland, Virginia

NAB stations are located in DC and Baltimore, MD. The DC station is operated by the US Army Centralized Allergen Extract Lab. The Baltimore station is controlled by a private allergy clinic, Drs. Golden and Matz, LLC. The Maryland Environmental Public Health Tracking portal contains pollen indicators that users can query, however, there was no daily pollen count data nor were the query results downloadable [61]. Virginia does not have an NAB station, and no other source of daily pollen count data could be found upon research for this paper.

2.2.3. Water Quality

The major policies through which the EPA protects water are the Clean Water Act (CWA) and Safe Drinking Water Act (SDWA). The CWA (1972) empowers the EPA to regulate pollution control and enforce quality standards for surface waters. It was originally enacted in 1948, to control the levels of pollutant discharge, but has since been amended for the purposes of water quality. The SDWA (1974) sets standards for the quality of drinking water from actual and potential water sources. Operators or owners of public water use systems must abide by EPA minimum standards [23]. Other federal agencies involved in water quality monitoring include: the U.S. Geological Survey (USGS), U.S. Fish and Wildlife Service, the National Oceanic and Atmospheric Administration, the U.S. Army Corps of Engineers, and the Tennessee Valley Authority [62].

The EPA enforces maximum contaminant levels (MCL), which are the highest levels of contaminants allowed in drinking water. In some cases, a treatment technique (TT) is applied in lieu of an MCL. The microorganisms, some of which are pathogens, which require an MCL or TT are: cryptosporidium, *Giardia lamblia*, heterotrophic plate count (HPC), *Legionella*, total coliforms, turbidity, and enteric viruses. Public water systems are required to disinfect and filter their water. Systems are able to avoid filtration by meeting the criteria to control for the certain contaminants [63].

Nationally, water resources are classified into four levels of hydrologic units: regions, sub-regions, accounting units, and cataloging units. Each hydrologic unit is identified by a unique hydrologic unit code (HUC) that contains 2 digits per level of classification. At the first level of classification the US is divided into 21 regions. Regions contain the drainage area of a major river or the combined drainage areas of a series of rivers. The second level of classification separates regions into 221 sub-regions. The third level of classification, accounting units, are either nested within sub-regions, or are equivalent to sub-regions. Finally, the smallest hydrologic unit is the cataloging unit, of which there are 2,264. Cataloging units are also known as watersheds [64]. A watershed is the area of land where all of the water that is under it or drains off of it goes into the same place [65]. The latest Watershed Boundary Dataset further divides hydrologic units into 5^{th} and 6^{th} levels, making HUC12 (12 digit watersheds) the most distinctive HUC.

STORET (for STOrage and RETrieval) is the EPA repository for water monitoring data. Users can retrieve data after completing a thorough query of the desired geographic location, organization, station name, characteristic, etc. However, the “microbiological” characteristic type, which contains bacteria and viruses, was retired on 1/24/2014 limiting the usefulness of STORET for daily data purposes [66].

How water quality monitoring results can be extrapolated to a targeted population within a geographic area is difficult to determine. A body of water may service multiple counties, for instance, but certain areas within the county may receive their drinking water from a public water system in a different area from other parts of the county. Furthermore, public water systems may draw water from either surface water or ground water. Groundwater is located in aquifers whereas surface water encompasses rivers, lakes, bays, etc. Despite the protections of the SWDA, millions of Americans become ill from contaminated water each year. The EPA and Justice Department are hesitant to enforce fines and other punishments on municipalities that continue to violate water quality standards. There is a fear that the cost of fines will ultimately be passed on to local taxpayers. Many of the violations are among water systems that serve less than 20,000 residents, which may not have the resources to properly meet the SDWA standards [67].

2.2.3.1. Georgia

The Georgia Water Quality Act authorizes EPD to set water quality standards. These standards generally ensure that the state abides by EPA regulations and dictate the criteria for meeting there regulations. Standards. EPD works with USGS, the University System of Georgia and other research institutions, various state agencies, and contractors to assess the availability and quality of water. EPD and its contracts are working on developing a program to integrate existing data and fill in information gaps between governmental and voluntary water monitoring programs [68]. Georgia also has a 305(b)/303(d) List of Waters, which is used to determine whether water meets the water quality criteria based on its designated use (e.g. drinking water, fishing, etc.). This fulfills obligations set forth by the CWA to provide this information biennially [69]. USGS appears to be the most definitive source for historical and real-time water monitoring data for Georgia. USGS monitor sites are located throughout the state and concentrated in the metropolitan Atlanta area. Real-time water quality parameters include the following: temperature, specific conductance, pH, dissolved oxygen, turbidity, nitrate, and discharge. Data are categorized by hydrologic unit code (HUC) within different watersheds.

Over 40 federal, state, local, and academic entities contribute to monitoring Georgia waters. Many bodies of water, however, remain largely unassessed [70]. According to the EPA Georgia Water Quality Assessment Report *Site-specific Targeted Monitoring Summary Results (2012)*, Georgia contains over 70,000 miles of rivers and streams, but only 19.7% are assessed. Of the rivers and rivers and streams designated for the drinking water supply, 52.7% are deemed impaired. Fecal coliform is the primary cause of impairment. This pathogen impacts over 4,600 miles of rivers and streams. The majority of rivers/streams impairment comes from unspecified non-point sources. Lakes, reservoirs, and ponds are also widespread in Georgia, covering approximately 425,000 acres. This collective category of water bodies is highly monitored, with 85% of waters assessed. However, nearly 70% of the drinking water supply is impaired. Unlike rivers and streams, lakes/reservoirs/ponds are mostly impaired by polychlorinated biphenyls (PCBs) in fish tissue; fecal coliform remains the only pathogen cause of impairment and is insignificant relative to other causes. The majority of overall impairment again stems from non-point sources[71].

Georgia possesses over 2,000 total drinking water systems across 52 watersheds based on data from the EPA Safe Drinking Water Information System[72, 73]. There are 154 public surface water systems and 1,936 groundwater systems. Water systems may have multiple sources of drinking water and may serve populations beyond the watershed containing the source of drinking water. For this reason, it is difficult to pinpoint which areas may become affected by contaminated water [72].

The Metropolitan North Georgia Water Planning District includes parts of six major river basins- Chattahoochee, Coosa, Tallapoosa, Flint, Ocmulgee, and Oconee. It encompasses 15 counties within metropolitan Atlanta: Bartow, Cherokee, Clayton, Cobb, Coweta, DeKalb, Douglas, Fayette, Forsyth, Fulton, Gwinnett, Hall, Henry, Paulding, and Rockdale. This area covers just over 4.5 million people, or 50% of Georgia's population. The Chattahoochee River, which flows through this area, is a major body of water used for many purposes including as a drinking water supply for Atlanta residents. It is monitored by government agencies and citizen groups as part of the Chattahoochee River BateriAlert. The partners for the Chattahoochee River BateriAlert are: USGS, GA EPD, the National Park Service, Upper Chattahoochee RiverKeeper, Georgia Conservancy, and Trust for Public Lands. Sampling sites area located off Medlock Bridge Rd. and Paces Ferry Rd. The site at Medlock Bridge Rd. is not widely used, though it is located just a short ways upstream of an area of high recreational use. On the upstream side of the bridge is a storm sewer outfall pipe, which can negatively affect water quality. The Paces Ferry Rd site is highly urbanized with tens of thousands of people using this area of the river. The sampling site is just downstream from major highways I-75 and I-285.

The Chattahoochee River BacteriAlert measures turbidity as an indicator of E. coli bacteria counts. Turbidity is the amount of particulate matter that is suspended in water. The EPA has determined that 8 persons per 1,000 are likely to become ill if exposed to E. coli bacteria counts greater than 235 colonies per 100mL. However, there other factors, including the health of the individual, that determine if a person becomes sick. To discover the actual E. coli bacteria count in water, the samples must be tested in a laboratory. Chemicals are added to the water sample and the container is sealed and incubated for about 20 hours. If E. coli is in the water sample, it will fluoresce under ultra-violet light [74]. Turbidity has been identified as a rough proxy of microbial contamination, though a study of water pollution and ED visits for GI disease in Atlanta determined that raw water turbidity was modestly, positively associated with ED visits for GI illness. As expected, filtered water turbidity was not statistically related to GI illness visits[24].

2.2.3.2. Maryland, Virginia, DC

All areas develop Integrated Reports for water quality biennially. These reports are identical to the 305(b)/303(d) List of Waters used by Georgia as they are likewise based off of the CWA requirement.

The MDE, DEQ, and DDOE are all responsible for monitoring water quality and ensuring safe drinking water as established by CWA and SWDA among other state and local policies.

The Chesapeake Bay Program is a regional partnership between the states of Maryland, Pennsylvania, and Virginia; DC; the Chesapeake Bay Commission, a legislative body with representatives from the aforementioned states; the EPA; and citizen advisory groups. It was formed to address the pollution leading to the loss of wildlife in and around the bay. Pollution levels are monitored and total maximum daily load (TMDL) for pollutants including nitrogen, phosphorous, and sediments were established in 2011. TMDL is the 'pollution diet' that sets the maximum loading limit for a pollutant. The Chesapeake Bay TDML is the most extensive and complex, as the Chesapeake Bay covers 64,000 square miles. The maximum loading will be divided among the Bay watershed states and major tributary basins [75, 76].

The Chesapeake Bay is a pivotal water source in the Mid-Atlantic. It is the nation's largest estuary, a mixture of fresh and salt water. Only Maryland and Virginia border it, but the Bay's watershed also covers DC, Delaware, New York, Pennsylvania, and West Virginia. In 2010, 17 million people lived in the Bay watershed. Millions drink the water from the Bay's rivers, streams, and aquifers. However, many of the waters are impaired by human activities (i.e. agriculture, sewage treatment, etc.) that have resulted in excess nutrients in the Bay [77].

Maryland is the only location among the sites in this study to have archived continuous monitoring data available for download. The Maryland Department of Natural Resources Continuous Monitoring Program has approximately 30 monitors throughout the Chesapeake and Coastal Bays. Data are available for all stations from 2000 to 2014. Downloads are in CSV format and for the full year of the dates that water was sampled at a particular station. The parameters included are dissolved oxygen concentration, dissolved oxygen (%), salinity (ppt), temperature (°C), temperature (°F), pH, turbidity, and Chlorophyll a (µg/l) [78].

Maryland has 3,432 total drinking water systems within 24 watersheds[72, 73]. EPA water assessment data for Maryland only show Site-specific Targeted Monitoring Summary Results for 2002. While much of the state's water bodies are assessed, the monitoring results do not group the designated use into specific categories such as "drinking water supply". Virtually all 2,522 square miles of bays and estuaries are assessed, and 90% of these waters were are deemed impaired in this report. Causes of impairment were not provided in 2002, but in the 2010 EPA water assessment nutrients (phosphorous and nitrogen) were the top cause of impairment among Maryland impaired and threated waters, and turbidity and pathogens were a distant 3rd and 5th, respectively. However, unknown was the 2nd greatest cause of impairment, which still presents the possibility of contamination that could elicit acute symptoms in persons exposed to water drawn from any source in Maryland that is insufficiently treated[79].

MDE Water Supply Program provides links for different stakeholders in regards to regulations, resource management, safety, etc. of the water supply. Under the "Information for Consumers" tab, there are links to several Safe Drinking Water Act Compliance Reports that were reported to the EPA. The most recent report listed, from 2012, states that no MCL violations occurred for organic contaminants at the water treatment plant. Few exceedances of MCL for total coliform occurred, and most were in small, transient water systems. Transient non-community water systems (e.g. campgrounds, gas stations, restaurants) are mostly regulated by local county environmental health departments. These systems account for 70% of Maryland's public water systems. MDE Water Supply Program reaffirms that smaller systems have a larger share of MCL and Monitoring/Reporting violations due to fewer resources and less technical expertise. Conversely, MDE directly regulates community water systems (e.g. count and municipal systems, mobile home parks) and non-transient non-community water systems (e.g. businesses, schools) [80].

The Virginia Site-specific Targeted Monitoring Summary Results from 2010 indicates the following assessment of waters: 35% of rivers and streams, 75% of lakes, ponds, and reservoirs, and 94% of bays and estuaries are monitored. Of the approximately 18,000 miles of rivers and streams that are assessed, less than 1,500 miles are used for the public water supply. Although, 94% of the public water supply was deemed good, pathogens are a notable cause of impairment. E. coli contaminates an estimated 7,540 miles of the nearly 18,000 miles of rivers and streams that are monitored, making it the top cause of impairment. Fecal coliform was the 5th highest cause of impairment, adversely affecting nearly 10% of these waters. Over 72,000 acres of lakes, ponds, and reservoirs are used in the public water supply, 100% of which is indicated to be good. Only a small portion of bays and estuaries, 5 square miles, are used for public water, and all were assessed as good. Pathogens account for a low level of impairment in both in lakes/ponds/reservoirs and bays/estuaries, and according to the results do not impact public drinking water drawn from these water sources [81].

Virginia has 53 watersheds and 2,610 total drinking water systems[72, 73]. It shares the Potomac River and Maryland Coastal Bays with Maryland. Additionally Virginia has New River and Albermarle/Pamlico Sounds as part of the American Heritage Rivers and National Estuary Programs, respectively. Each even-numbered year the Virginia DEQ submits a water quality assessment report that is required by the Clean Water Act, to determine whether water meets quality standards. According to this report, known as the 2014 Integrated Report (or 2014 305(b)/303(d) Water Quality Assessment Integrated Report), the state ambient monitoring program for surface waters is the primary data used to evaluate water quality throughout Virginia. This multilayered network of monitors is designed to provide accurate data via consistent monitoring techniques so that results are representative for water quality of all surface waters in the state. According to DEQ, USGS has 127 stations to monitor Virginia waters. Fifty-eight USGS monitors are located around the Potomac/ Shenandoah rivers, and none cover the Chesapeake Bay. It is important to note that DEQ only uses monitor data from non-agency sources that meets DEQ Quality Assurance and Quality Control protocols[82].

The 2012 EPA District Of Columbia Water Quality Assessment Report states that virtually all of DC's waters are monitored, and of assessed waters, all are impaired [83]. DC has 2 watersheds and the Potomac River runs through it as it does Maryland and Virginia. According to DDOE, drinking water comes from the Potomac River upstream from DC. The Anacostia River and Potomac River Monitoring Program measures water conditions of the Anacostia River and Potomac River. DDOE provides the 2014 Integrated Report online as well as reports for several other even-numbered years. Drinking water is not listed as a designated use for any of the 3 categories of water bodies because the drinking water supply is north of the District boundaries. Also, groundwater is monitored on a different basis than surface water, since the surface water of the drinking water supply is outside of DC [84]. While the Anacostia River and Potomac River Monitoring Program provides general ambient measures such as temperature and turbidity, the DDOE Water Quality Division perform testing of drinking water quality. The Water Quality Division tests for total chlorine and total coliform [85]. DDOE does not list any historical data on ambient water conditions or contaminant measurements online, though real-time ambient monitoring data is available for three stations.

CHAPTER III

APPROACH

This project is intended to demonstrate an integrated approach that connects environmental monitor data and syndromic data. The research goals are as follows:

1. Identify the availability of environmental monitor data with regards to existing data sources, the consistency of data collection, and inherent limitations.
2. Evaluate variation in KP population characteristics according to proximity to the nearest monitor.
3. Evaluate the differential exposure of area populations by SES in relation to the nearest monitor.

Among the comparison between the study areas, locations were chosen based on services provided by KPGA and KPMAS. This analysis examines trends in air pollution and pollen monitor data and the Euclidean distance of KP membership with respect to the closest monitor using the clinic location as a proxy for member residence. SES factors of populations are assessed based on the nearest census tracts to each monitor. Although the purpose of this study includes identifying water quality data, this was excluded in the analysis due to the difficulty of linking water quality indicators with populations that consume water from specific sources of drinking water.

3.1 Study Settings

This study compares the areas of Atlanta, Georgia and DC, Maryland, and Virginia. These locations were chosen because the KP Medical Care Program includes facilities in both Georgia and the mid-Atlantic region. KPGA provides comprehensive care to members residing in the metropolitan Atlanta area, where there are more than 230,000 members enrolled. KPMAS covers members in DC, Maryland, and Virginia. As of December 31, 2014, KPMAS has 530,275 members enrolled, which is more than twice the amount of KPGA enrollees. The Georgia locations of interest representative of KPGA has been narrowed down to an 11-county metropolitan area of Atlanta because this is the area where most KP clinics reside. The counties of the Atlanta metro area are: Cherokee, Clayton, Cobb, Dekalb, Douglas, Fayette, Forsyth, Fulton, Gwinnett, Henry, and Rockdale. The KPMAS facilities included in this study cover populated counties in Maryland and Virginia in addition to DC. The Maryland counties are Anne Arundel, Baltimore City, Frederick, Howard, Montgomery, and Prince George's. The Virginia counties, all located in northern part of the state near DC, are Fairfax, Loudoun, Prince William, and Spotsylvania. Five of the eight Virginia KPMAS facilities in this study are located in Fairfax County.

3.2 Data Sources

3.2.1. Environmental Exposure Data

3.2.1.1 Air Pollution Data

The Air Quality System (AQS) is the repository of EPA ambient air quality data. Data are accessible to the public through AirData, the website containing AQS air quality monitor data. This data can be visualized through various maps and plots, and can be downloaded as daily data or raw data.

3.2.1.2. Pollen Count Data

There are two pollen counting stations in the KPMAS area and one in the KPGA area. Data for only one station was available at the time of this study, despite attempts to collect pollen data from all three stations. Monthly reports of pollen counts for 2013 and 2014 were provided by the US Army Centralized Allergen Extract Lab in DC. Reports contain the 3 types of pollen identified by NAB pollen monitoring stations- grass, tree, and weed. Dates that pollen counts were conducted are located across the horizontal axis. The first column lists the pollen types as well as any subtypes for tree and weed. Counts are listed for each count date and a total count for each week is listed. Following the "sum" column containing the row total for that week is a column of the average pollen count for each row. At the top of this column is the number of days counts were conducted. The value in the "sum" column is divided by this number to attain the value of the average weekly pollen count.

This pollen monitoring station uses a Rotorod sampler. Two greased polystyrene rods spin 1 out of every 10 minutes in a 24 hour period to collect pollen. After this period, the pollen samples are identified, and technicians perform a pollen count measured in grains per cubic meter [86].

3.3. Methods

3.3.1. Goal 1: Identify the availability of environmental monitor data with regards to existing data sources, the consistency of data collection, and inherent limitations.

Daily data were downloaded for $PM_{2.5}$, ozone, and NO_2 for 2012-2014. All monitoring sites were included in the download, and exceptional events data were included. Data for the same three air pollutants was then downloaded for all three locations. CSV files, one for each query, were imported into SAS 9.4 (SAS Institute Inc., Cary, NC).

Monthly pollen count data from files provided by the US Army Centralized Allergen Extract Lab were manually reconfigured into a SAS-ready format. Columns were made for the date and the different types of pollen- grass, weed, tree, and unknown.

3.3.2. Goal 2: Evaluate variation in KP population characteristics according to proximity to the nearest monitor.

SAS datasets were created for KPMA primary care clinics and for all of the EPA air pollution monitors located in DC, Maryland, and Virginia. Both datasets contained latitude and longitude coordinates. Recent membership totals per clinic supplied by both KPGA and KPMAS were imputed into the datasets. The coordinates for monitors were already provided in the EPA AirData Now info. The coordinates for the KPMA clinics were obtained from Google Maps by entering the address for each clinic. In order to merge the two datasets, a dummy variable was developed. Then, the Euclidean (or straight line) distance formula was used to calculate the distance from each clinic to the nearest monitor. This process was then repeated to generate the distance from each clinic to the nearest pollen monitor, with Google Maps used to get the latitude and longitude of both pollen monitors in the study area. Datasets were ordered by ascending distance from clinic to nearest monitor to evaluate the cumulative frequency of membership by proximity.

3.3.3. Goal 3: Evaluate the differential exposure of area populations by SES in relation to the nearest monitor.

The SES characteristics included in this analysis are as follows: Black (Non-Hispanic), households with individuals age 65 and older, individuals with a high school education or less, and median household income. These characteristics were chosen because race, age, level of education, and income present widely recognized barriers to access of healthcare services. Demographic and socioeconomic data were gathered from American Fact Finder (AFF). AFF is a portal developed by the US Census Bureau that contains data tables of population characteristics identified through census data. Data were downloaded for Georgia and DC/Maryland/Virginia from the following tables: Profile of General Population and Housing Characteristics: 2010; SEX BY AGE BY EDUCATIONAL ATTAINMENT FOR THE

POPULATION 18 YEARS AND OVER; and MEDIAN HOUSEHOLD INCOME IN THE PAST 12 MONTHS (IN 2013 INFLATION-ADJUSTED DOLLARS) (Table 1). The first table listed uses census data because data were collected during a census year. The other tables were developed from American Community Survey data. The option for five year estimates was chosen because the longer time length enables more accurate data for smaller levels of geography such as census tracts [87]. Table 1 lists the years and population characteristics for each AFF data table. Data was downloaded by census tract for each location. The files are in CSV format.

Table 1. American Fact Finder data tables with demographic and socioeconomic variables used.

ID	Title	Year(s)	Characteristics used for analysis
B15001	SEX BY AGE BY EDUCATIONAL ATTAINMENT FOR THE POPULATION 18 YEARS AND OVER	2009-2013	High school graduate; 9th to 12th grade, no diploma; Less than 9th grade
B19013	MEDIAN HOUSEHOLD INCOME IN THE PAST 12 MONTHS (IN 2013 INFLATION-ADJUSTED DOLLARS)	2009-2013	Median household income
DP-1	PROFILE OF GENERAL POPULATION AND housing characteristics: 2010 (2010 SF1 100% Data)	2010	Hispanic or Latino and Race; Households with individuals 65 and over

The AFF files were truncated into only columns containing the desired characteristics and other general information using Microsoft Excel. The general information kept included column with the GEOID, population totals, households with individuals under age 18, other education levels, and other race/ethnicity categories. The files were then imported into SAS and, for each location, merged into a single dataset by the GEOID variable.

In order to calculate the median percent of individuals with high school education or less, the variables in AFF Table B15001 for “High school graduate (or equivalency)”, “9th to 12th grade, no diploma”, and “Less than 9th grade” were summed together and each was divided by the population total from AFF Table DP-1, which is 2010 Census SF1 data (Table 1). The quotient was then multiplied by 100 to generate a percent.

The air pollution monitors dataset was merged to the combined dataset of the census tracts and population characteristics. The Euclidean distance was calculated for the merged datasets to assess how close each census tract is to each monitor is to each census tract by using the internal point, or centroid, of the census tract. The closest monitor to each census tract was kept in the final dataset, so that all census tracts identified as being nearest a monitor relative to other monitors in each study area were incorporated into the monitor catchment area based off distance between monitor location and the census tract centroid. The same procedure was done for pollen monitors to census tracts.

To evaluate the SES characteristics of interest for each monitor, the interquartile range and median were produced. The number of census tracts that were calculated to be closest to the particular monitor was also generated from these procedures. The median and interquartile range of the 2014 data for each air pollutant were generated by SAS, and merged with the summary datasets of each SES variable to assess concentrations among census tract nearest to each monitor.

ESRI TIGER shapefiles were downloaded for each location to map the distributions of SES. TIGER shapefiles are geographic boundaries developed for GIS. ArcGIS 10.1 was used to display these boundaries. The shapefiles were re-projected to UTM Zone 18. The GEOID column in the AFF files is essential in order to join them to the shapefiles in ArcGIS, or whichever GIS program is used. The format of the GEOID column in the AFF files was changed to the "text" format to match the format of the GEOID column in the shapefiles, which is necessary for a successful join. After joining the two layers (i.e the DC shapefile to a table containing DC AFF data), each census tract, contained the variables from the table of all of the AFF data that was created in SAS. This allowed maps to be created to illustrate the distribution of characteristics across census tracts.

BatchGeo, a free online mapping service, was used to create a KML file of the monitor and clinic locations. The name and address were entered in an Excel file and copied into BatchGeo. The KML file generated was uploaded to ArcMap 10.1 as a layer by employing the "KML To Layer" tool. This was added to the data frame containing the TIGER shapefile layers to plot the monitors into a map of the census tracts.

Chapter IV

FINDINGS

4.1 Euclidean Distance from KP Clinics to Nearest Monitor

4.1.1. Atlanta

There are nine KPGA clinics in the metropolitan Atlanta study area included in this study that provide primary-care services. Seven of the clinics are located within 10 miles of the closest air pollution monitor (Figure 1). Clinic location was used as a proxy measure because KP members typically utilize healthcare services from the facility closest to their residence. By means of this proxy, approximately 78% of membership from these clinics are covered by these monitors. The clinics within 10 miles account for 83% of the nine KP clinic populations. Among these seven clinics, four clinics- TownPark, Southwood, TownCenter, and Cumberland- are 5 miles or less from a monitor.

Atlanta Asthma and Allergy Clinic is the location of the sole pollen monitor for Atlanta. Only two clinics, TownPark and Cumberland, are within 10 miles of this monitor (Figure 2). Five clinics are 20 miles or more from this pollen monitor, which may not provide an accurate representation of pollen concentration within the greater metropolitan area. Among these further clinics, Southwood and Henry are roughly 32 miles and 40 miles away, respectively.

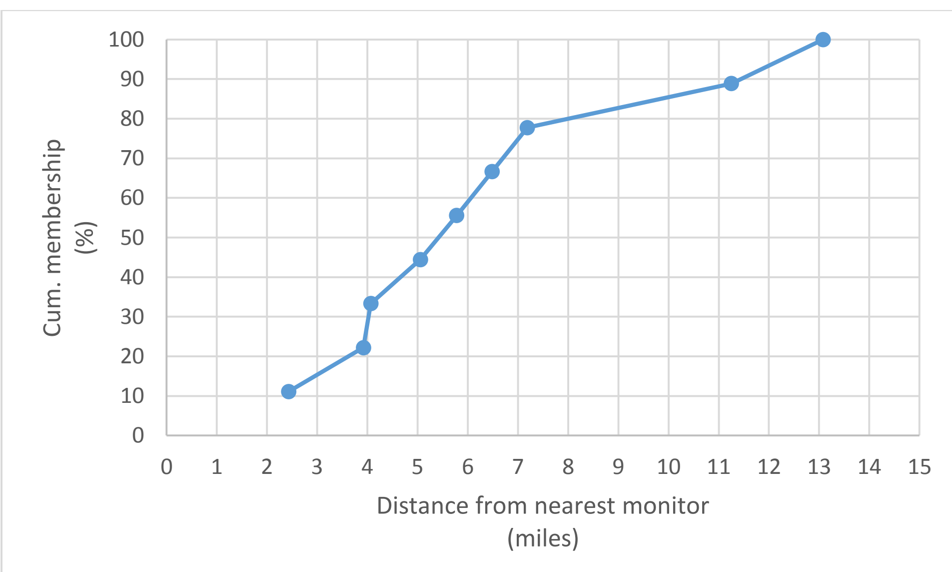


Figure 1. Distance between KPGA facility and nearest air pollution monitor as a proxy of cumulative membership covered by monitor measurements.

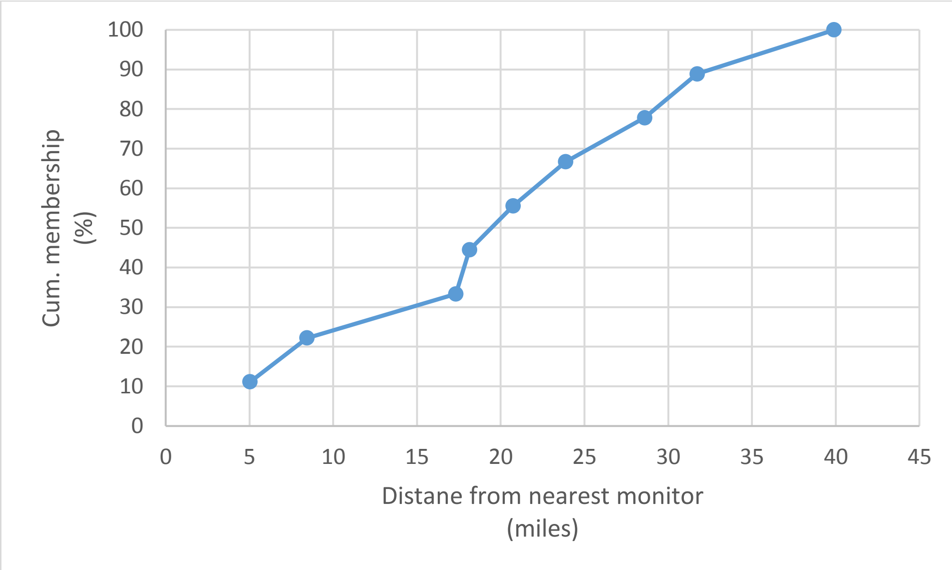


Figure 2. **Distance between KPGA facility and nearest pollen monitor as a proxy of cumulative membership covered by monitor measurements.**

4.1.2. DC, Maryland, Virginia

Eighteen KPMAS clinics were identified as primary-care medical offices. Many of the clinics were located in and around the DC metropolitan area. Eight clinics are less than 5 miles from the nearest air pollution monitor (Figure 3). Two of these clinics, the Northwest DC Medical Office Building in DC and the City Plaza Medical Center in Baltimore, are less than 1 mile from a monitor. All but one clinic are approximately 10 miles or less from the closest monitor. By this proxy, 94% of membership are covered by KP clinics within 10 miles of an air pollution monitor. These clinics account for 94% of the eighteen KP populations. The Stevenson Park monitor situated on the Virginia side of the DC metro area is the closest air pollution monitor for 4 of the clinics- the Springfield Medical Center, the Falls Church Medical Center, the Fair Oaks Medical Center, and the Burke Medical Center. All 4 facilities are in Virginia, and the Springfield Medical Center and Falls Church Medical Center have two of the largest membership populations among the selected clinics.

Only two pollen monitors exist in the study area- the US Army Centralized Allergen Extract Lab in DC and the Drs. Golden and Matz LLC pollen counting station in Baltimore. For distance to nearest pollen monitor, all but one were closest to the DC pollen monitor. The one clinic closest to the Baltimore monitor is the City Plaza Medical Center in Baltimore. This clinic also has the smallest membership population of the 18 clinics with less than 5,000 members. Contrary to distance between clinics and air pollution monitors, only 5 clinics are about less than 10 miles from the nearest pollen monitor (Figure 4). This includes the City Plaza Medical Center. Six more clinics were more than 20 miles from the closest monitor, the one in DC, with the Frederick Medical Center being the furthest away from its nearest pollen monitor at approximately 35 miles.

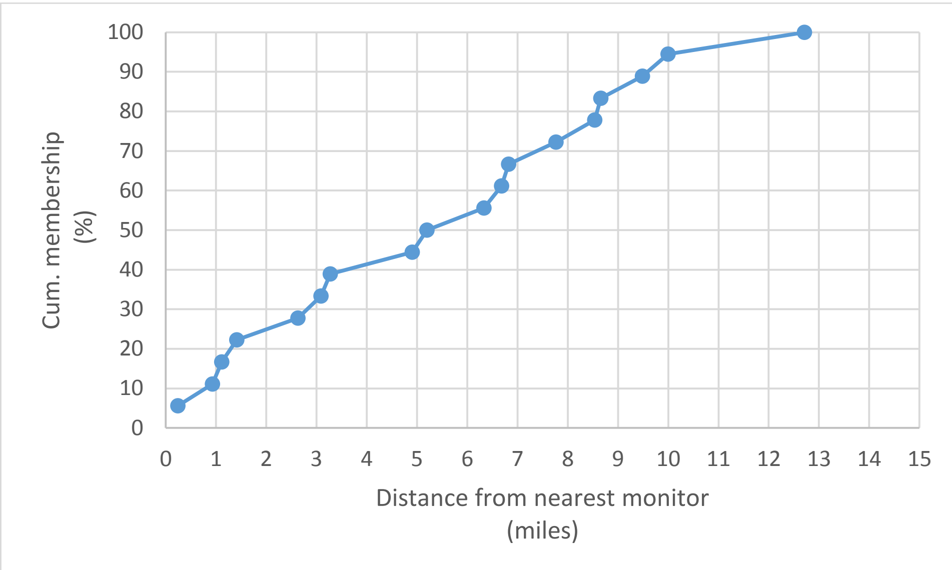


Figure 3. Distance between KPMAS facility and nearest air pollution monitor as a proxy of cumulative membership covered by monitor measurements.

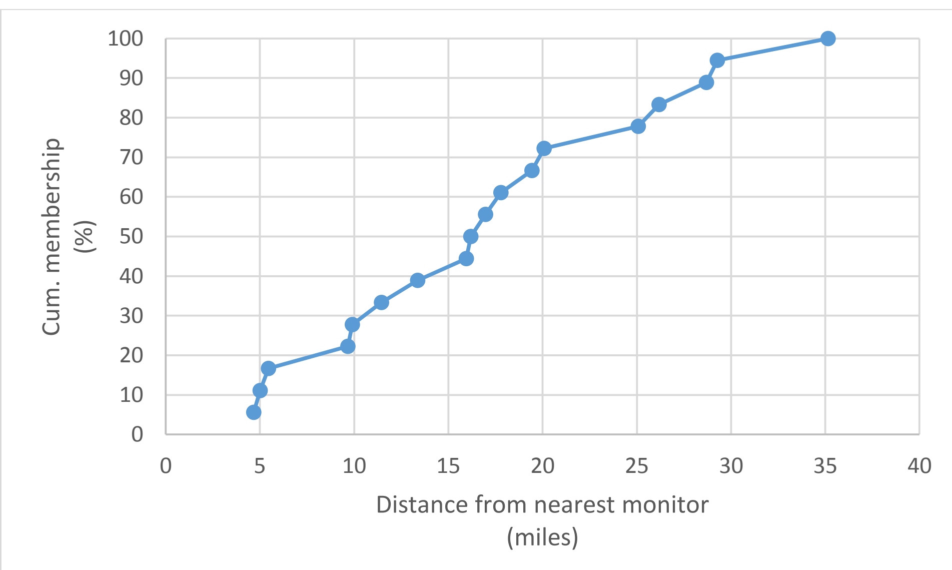


Figure 4. Distance between KPMAS facility and nearest pollen monitor as a proxy of cumulative membership covered by monitor measurements.

4.2 Descriptive Analysis of Air Quality Data

4.2.1. Atlanta

Ozone exceeded air quality standards most frequently relative to $PM_{2.5}$ and NO_2 from 2012-2014 (Table 2). The greatest AQI value for ozone was 203, which occurred in June 2012. Ozone levels reached maximum AQI values June through August. There were only three $PM_{2.5}$ exceedances during this time period. The max AQI for 2012 occurred in January and March of 2014, with no exceedances in 2013. NO_2 remained below hazardous AQI levels.

Mean $PM_{2.5}$ concentrations were generally higher in the warmer months with annual peaks in July 2012 (12.2 μg/m^3), September 2013 (12.2 μg/m^3), and July 2014 (12.2 μg/m^3) (Figure 5). However, there were inconsistencies between the years studied including a rise in mean concentration in November 2012 and sharp drops in July 2013 and September 2014. On average ozone concentrations, were also elevated during warmer parts of the year, particularly March-May (Figure 6). During 2012, there was a peak mean concentration in June (53 ppb), whereas 2013 and 2014 both had springtime and summertime peaks, which maximum mean concentrations in April of both years (45.6 ppb and 47.2 ppb, respectively). NO_2 generally declined during the warmer months (Figure 7). There was a steady decrease during 2012 and a steep drop in 2013, in which there was a nadir in mean NO_2 concentration in July. In 2014, there were dual drops in mean concentration that nearly coincided to the rises in ozone concentrations. Peak mean NO_2 concentrations for each year were during January and November of 2012 (16 ppb), January and February of 2013 (15 ppb), and November 2014 (18.3 ppb).

Table 2. Number of days air pollutants exceeded moderate air quality*, Atlanta, GA, 2012-2014.

Year	$PM_{2.5}$		OZONE		NO_2	
	# of days	Max AQI (month)	# of days	Max AQI (month)	# of days	Max AQI (month)
2012	2	134 (jan)	17	203 (jun)	-	-
2013	-	-	3	151 (jul)	-	-
2014	1	104 (mar)	8	135 (aug)	-	-

*AQI greater than 100

4.2.2. DC, Maryland, Virginia

Air quality most often exceeded an AQI of 100 for ozone for DC, Maryland, and Virginia (Tables 3-5). The maximum AQI value for ozone occurred June through August for all locations. This matched the trend in maximum AQI in the Atlanta area with the greatest annual value in June 2012, July 2013, and August 2014. In 2012, max AQI values for ozone and the number of exceedances were exceptionally greater than in 2013 or 2014. In Maryland, for instance there were 30 such exceedance in 2012, compared to 9 exceedances and 5 exceedances, for 2013 and 2014, respectively. Also, the max AQI value of 2012, 195, was of a higher AQI level than max values in the other years. $PM_{2.5}$ concentrations were rarely, if at all, above moderate air quality. In 2014, DC and Maryland did not experience any high levels of $PM_{2.5}$, and Virginia only did so once. NO_2 never reached above moderate air quality for any location in any of the years examined.

Table 3. Number of days air pollutants exceeded moderate air quality*, DC, 2012-2014.

Year	$PM_{2.5}$		OZONE		NO_2	
	# of days	Max AQI (month)	# of days	Max AQI (month)	# of days	Max AQI (month)
2012	3	105 (Jun/Dec)	11	156 (Jun)	-	-
2013	-	-	-	-	-	-
2014	-	-	1	116 (Jun)	-	-

*AQI greater than 100

Table 4. Number of days air pollutants exceeded moderate air quality*, Maryland, 2012-2014.

Year	$PM_{2.5}$		OZONE		NO_2	
	# of days	Max AQI (month)	# of days	Max AQI (month)	# of days	Max AQI (month)
2012	1	108 (Dec)	30	195 (Jun)	-	-
2013	4	126 (Dec)	9	119 (Jul)	-	-
2014	-	-	5	124 (Aug)	-	-

*AQI greater than 100

Table 5. Number of days air pollutants exceeded moderate air quality*, Virginia, 2012-2014.

Year	$PM_{2.5}$		OZONE		NO_2	
	# of days	Max AQI (month)	# of days	Max AQI (month)	# of days	Max AQI (month)
2012	1	107 (Dec)	20	177 (Jul)	-	-
2013	1	115 (Dec)	2	124 (Jul)	-	-
2014	1	108 (May)	3	129 (Jun)	-	-

*AQI greater than 100

Mean $PM_{2.5}$ levels trended positively beginning in the spring and peaking in July in all locations each year (Figure 8). The largest peaks were in July for 2012, however, the greatest mean concentration occurred in colder months for 2013 (January and December) and 2014 (February) for this area. Ozone was typically highest during the warmer part of the year (April through August) with peak mean concentrations during either June or July (Figure 9). NO_2 appears to be negatively correlated with ozone. In all locations, it was greatest during the colder months (November through February), and declined during the warmer months with a nadir in July (Figure 10). This was directly inverse to the trends in ozone. A correlation of air pollutants and pollen confirmed that NO_2 and ozone were significantly negatively correlated (Table 6). Throughout 2012-2014 for each air pollutant, concentrations in DC and Maryland were normally greater relative to those in Virginia. The only exception to this trend was for ozone during the non-peak times of year (January-March and October-December). It is possible that this is due to these locations are smaller than Virginia, especially DC, and have more densely populated areas. Such areas are associated with more sources of pollution, and thus have higher concentrations of air pollution. During a 2-year period, DC air pollutants were found to be significantly correlated with one another.

Table 6. Mean values, ranges, and Spearman's rank correlation coefficients for air quality and pollen variables, DC, 2013-2014.

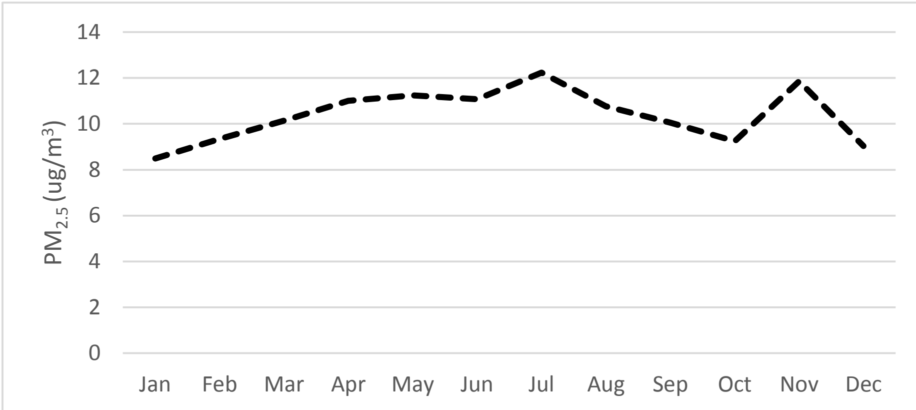
				Spearman's rank correlation coefficient			
	Mean	**Range**		**24-hour $PM_{2.5}$ (μg/m³)**	**8-hour ozone (ppb)**	**1-hour NO_2 (ppb)**	**Tree pollen (grains/m³)**
24-hour $PM_{2.5}$ (μg/m³)	9.64 (4.64) †	0	31	1.00			
8-hour ozone (ppb)	37.26 (14.19)	2	82	0.07*	1.00		
1-hour NO_2 (ppb)	23.89 (11.31)	4	72	0.27*	-0.21*	1.00	
Tree pollen (grains/m³)	104.21 (297.41)	0	2871	-0.14*	-0.01	0.13*	1.00

*$p < 0.05$.
†Numbers in parentheses, standard deviation.

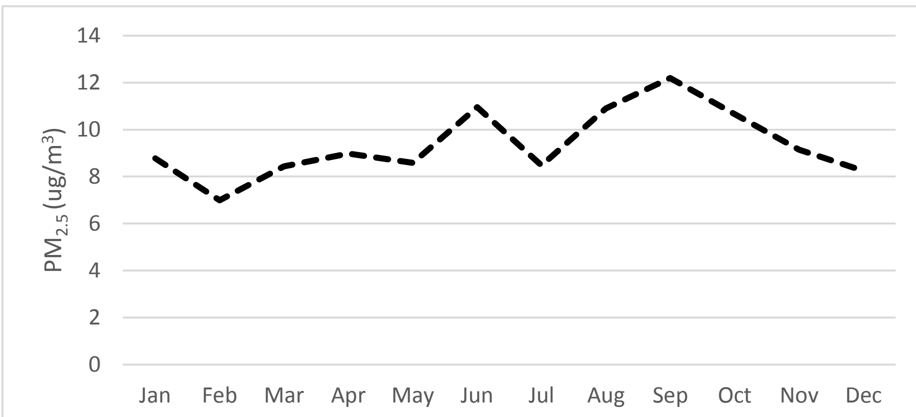
4.3 Descriptive Analysis of Pollen Data

DC pollen counts were low to non-existent during the colder months (Figure 11). Peak concentrations for grass occurred in May for both 2013 and 2014. Tree pollen was most concentrated in April and May for 2013 and 2014, respectively. Weed pollen counts were greatest in September for both years. Tree pollen counts are significantly larger than grass and weed, as expected from the pollen index. Peak tree pollen counts were more than 600 grains/m^3. Mean concentrations for grass and weed did not surpass 20 grains/m^3. Tree pollen was significantly correlated with ozone. A significant correlation was also found between tree pollen and $PM_{2.5}$ albeit to a smaller extent.

2012



2013



2014

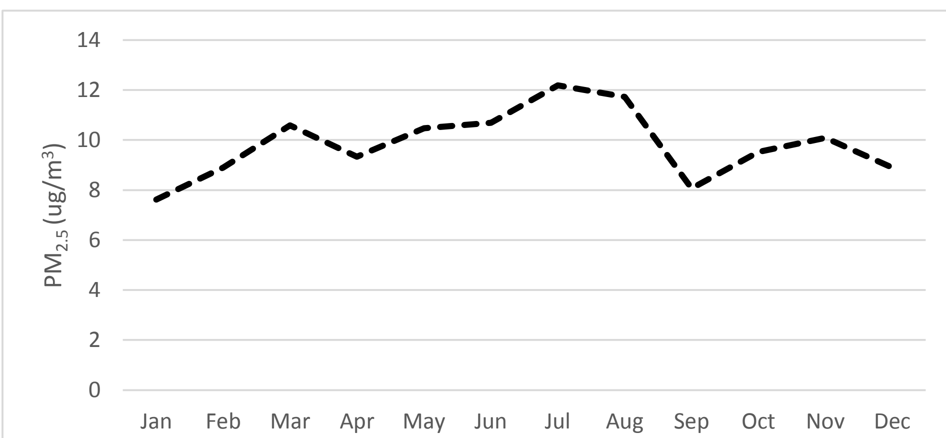
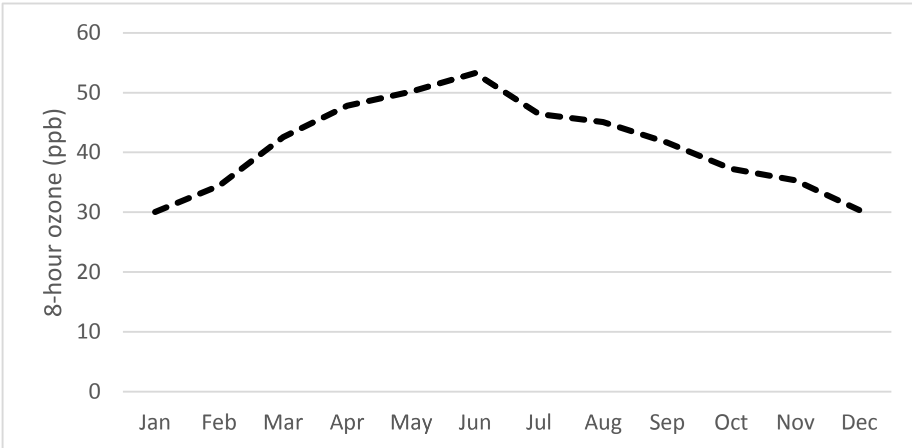


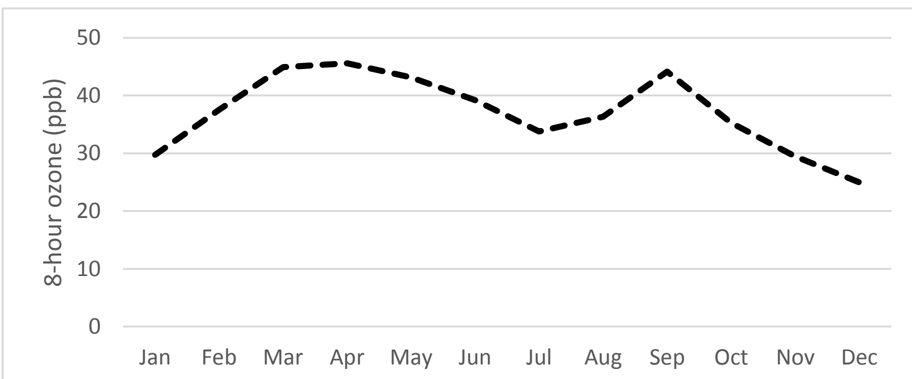
Figure 5. Mean $PM_{2.5}$ concentrations for Atlanta, GA, 2012-2014.*

*see Appendix for table of concentrations.

2012



2013



2014

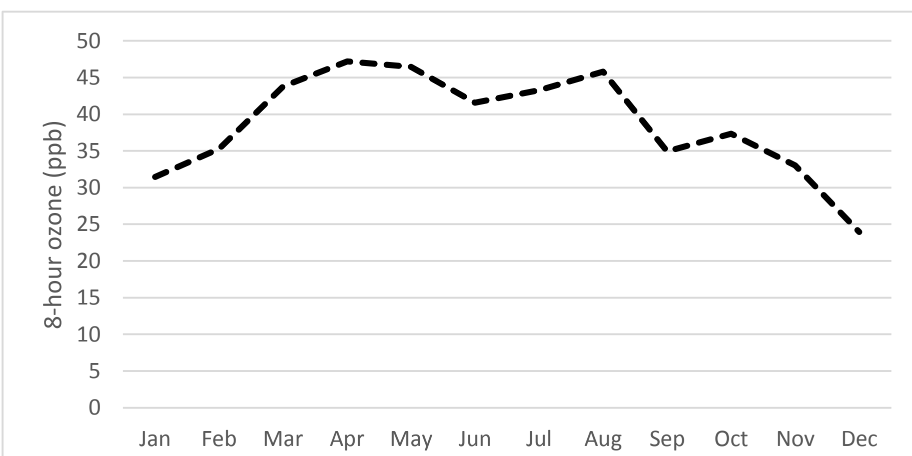
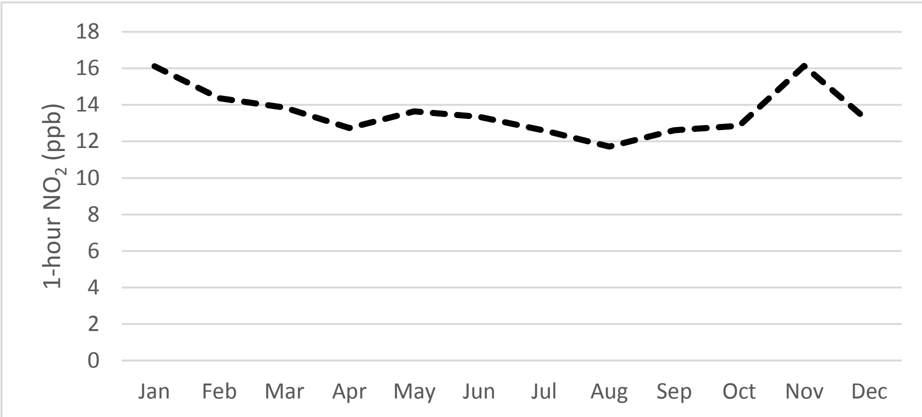


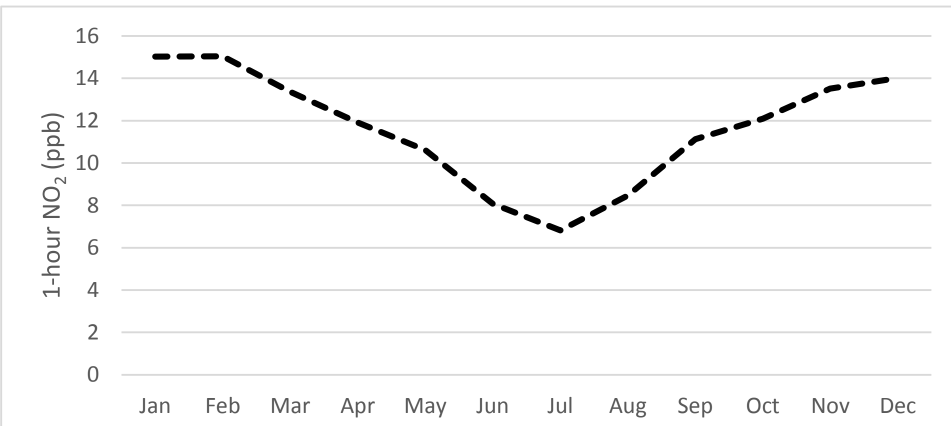
Figure 6. Mean ozone concentrations for Atlanta, GA, 2012-2014.*

*see Appendix for table of concentrations.

2012



2013



2014

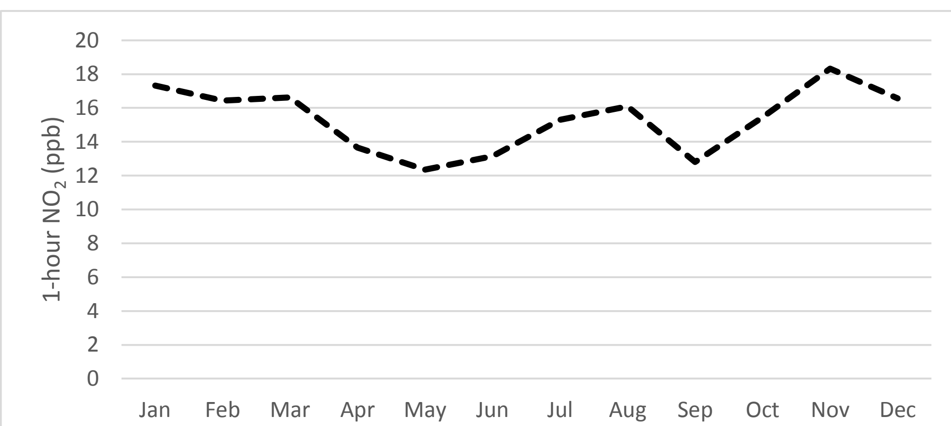
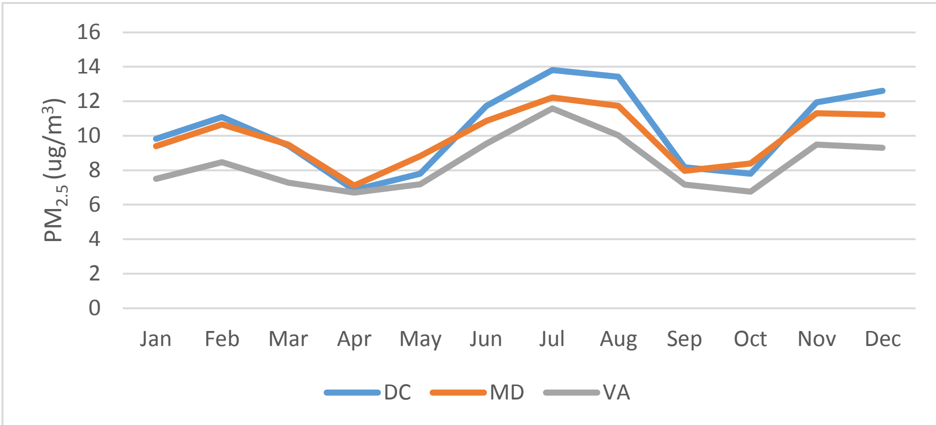


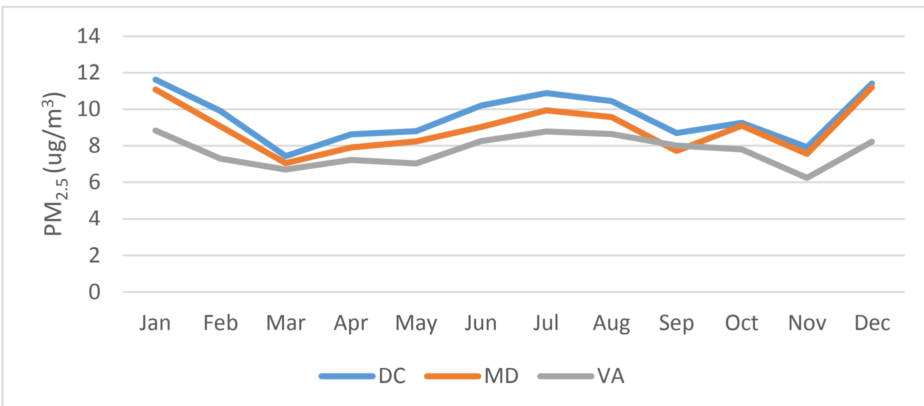
Figure 7. Mean NO_2 concentrations for Atlanta, GA, 2012-2014.*

*see Appendix for table of concentrations.

2012



2013



2014

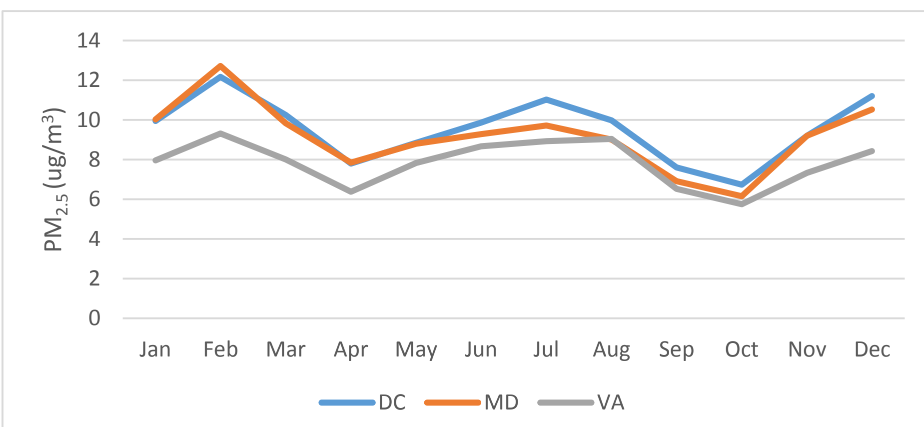
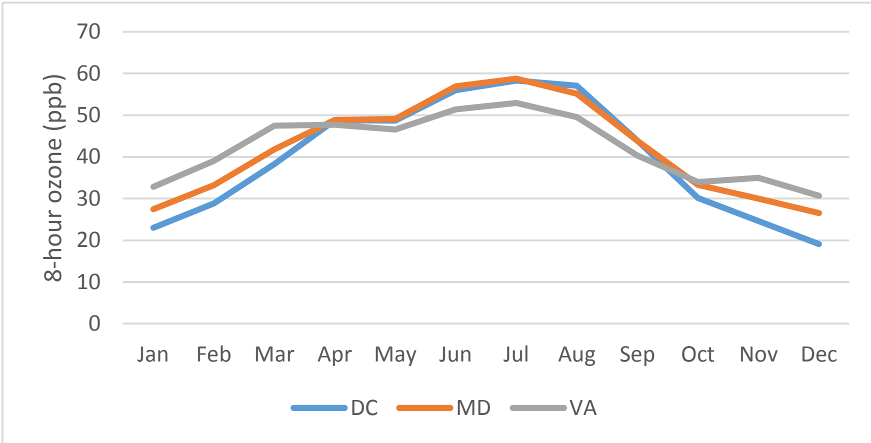


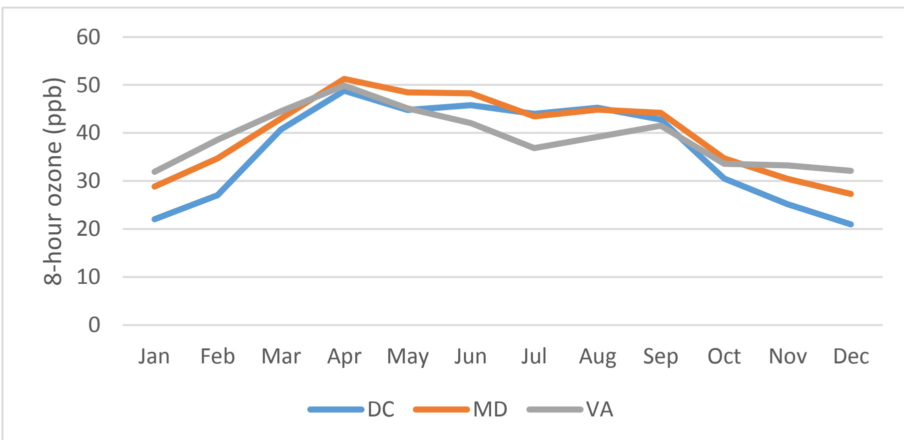
Figure 8. Mean PM$_{2.5}$ concentrations for DC, Maryland, and Virginia, 2012-2014.*

*see Appendix for table of concentrations.

2012



2013



2014

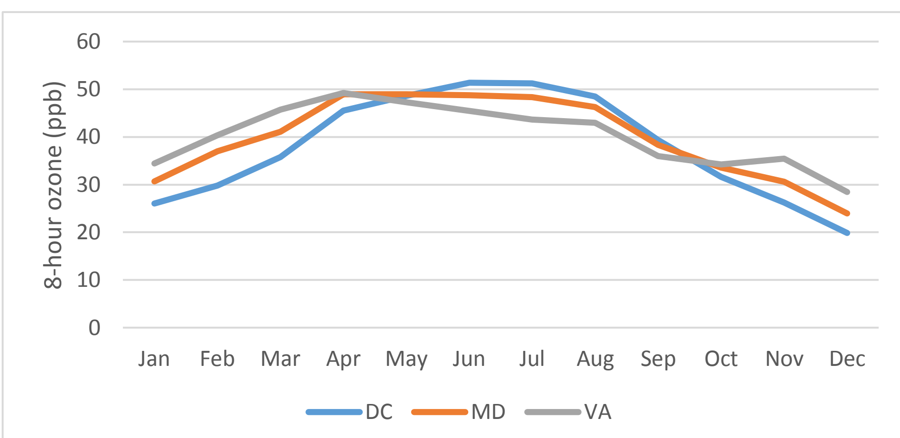
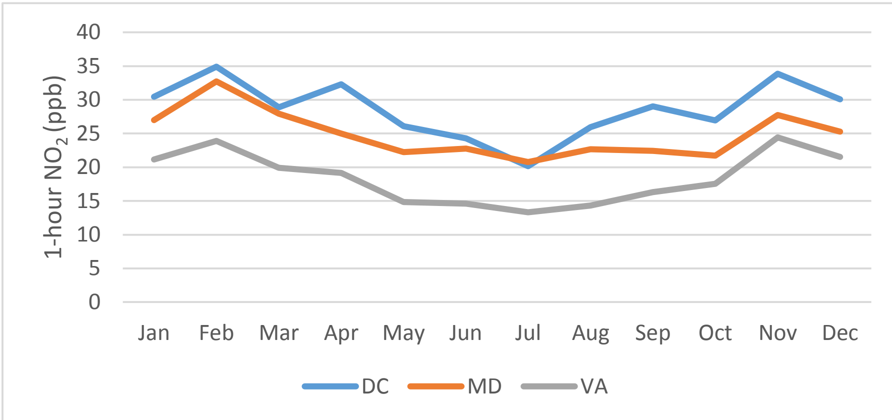


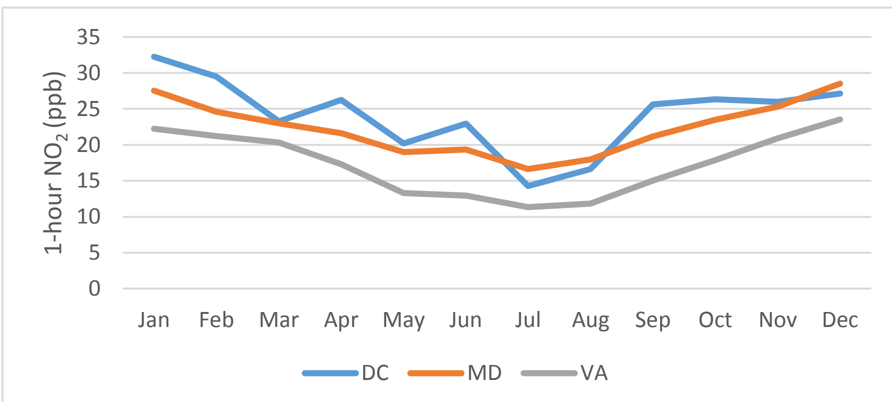
Figure 9. Mean ozone concentrations for DC, Maryland, and Virginia, 2012-2014.*

*see Appendix for table of concentrations.

2012



2013



2014

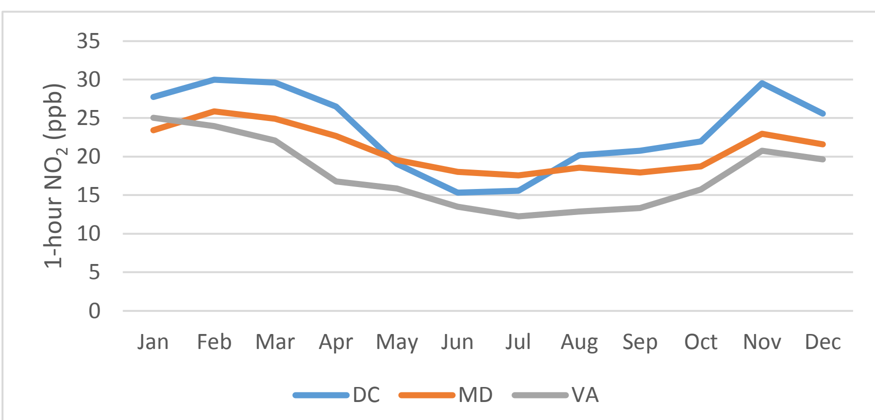


Figure 10. Mean NO_2 concentrations for DC, Maryland, and Virginia, 2012-2014.*

*see Appendix for table of concentrations.

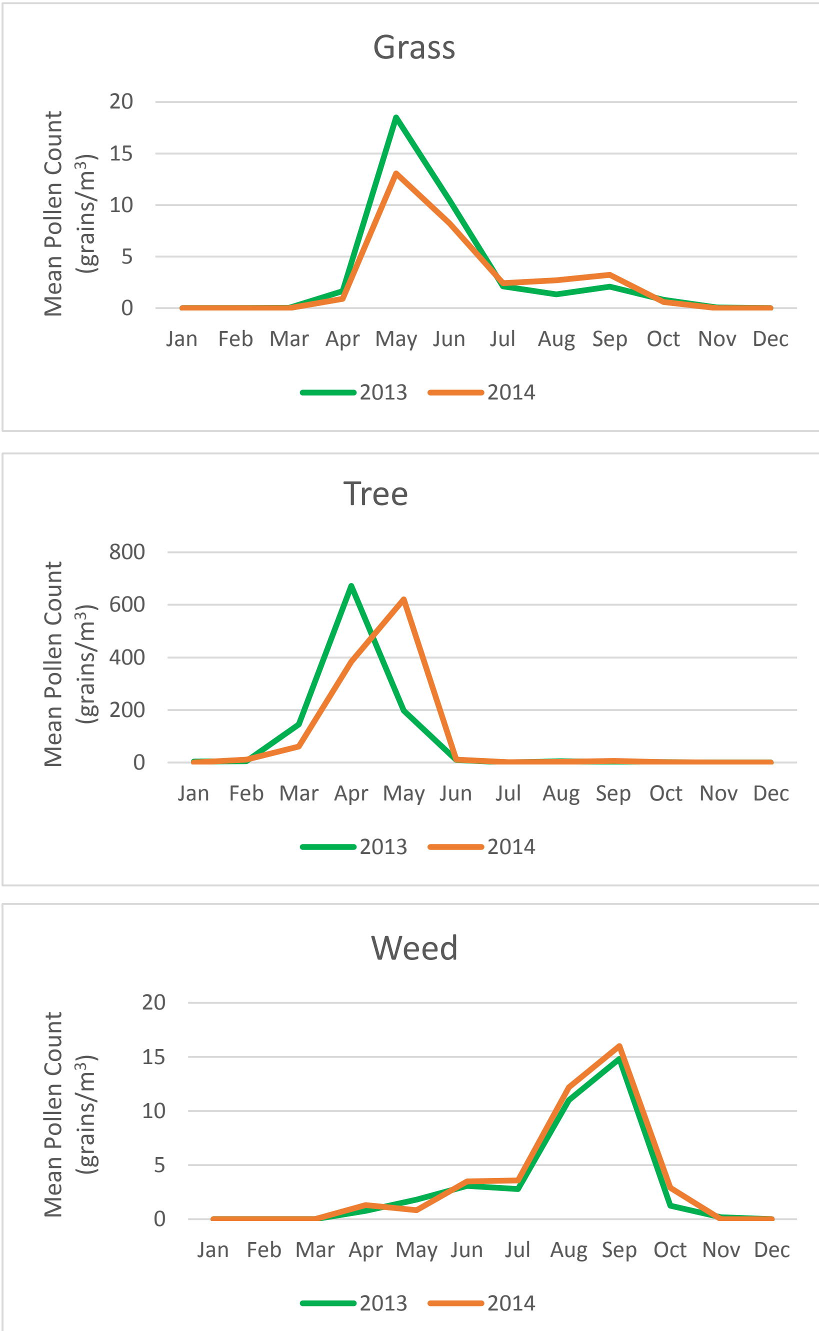


Figure 11. Mean pollen counts for grass, tree, and weed, DC, 2013-2014.

4.4 Descriptive Analysis of SES Characteristics at the Census Tract Level

4.4.1. Atlanta

4.4.1.1. Population Characteristics

Black

In Atlanta there is a general residential segregation by race, with the Black population clustered in the southern parts of the metro area. The South Dekalb monitor has a median percent Black persons of 89% among census tracts closest to this monitor. Conversely, the census tracts nearest to the National Guard monitor and Gwinnett Tech monitor located in the northwest and northeast of this study area, only possess a proportion of 4.6% and 5.9% of Black residents in the census tracts nearest to those monitors, respectively.

Households with individuals age 65 and older

Older individuals typically reside further outside of the city of Atlanta in the metro area. The Monastery monitor in Rockdale County covers census tracts where more than 1 in 5 households contains individuals age 65 and older. Midtown and North Atlanta parts of Fulton County contain a lower percentage of households with elderly persons. The Georgia Tech-Near Road monitor is closest to these census tracts with a median percent of 13.6% of residents 65 and older.

Individuals with high school education or less

Similar to the racial gradient of the Black population, there is also a North-South divide in education level. The monitors in northern parts of the metro area cover lower percentages of individuals with a high school education or less. The Georgia Tech Near-Road monitor has the lowest median percent of these individuals at 17.6%. The monitors in the south- south Dekalb, south Fulton, Clayton County, Henry County, and Rockdale County- all cover census tracts with a median between 30% and 33% of people with or without a high school degree as their highest level of education.

Median household income

Median household income is higher in northern areas of Atlanta. The census tracts closest to the National Guard has the greatest median, over $73,000, followed by the surrounding area of the Gwinnett Tech monitor at approximately $70,000. There is large concentration of Atlanta with a median household income of less than $45,000. The areas close to the Confederate Ave and Georgia DOT monitors have medians of $34,925 and $42,665 respectively.

4.4.1.2. Exposures

Figure 12 shows the median and interquartile range (IQR) of NO_2 for the three monitors where this measure is collected. Figures 13 and 14 show the median and IQR for monitors that measure ozone and $PM_{2.5}$, respectively. Figures 15-23 illustrate the median and IQR for NO_2, ozone, and $PM_{2.5}$ for households with individuals age 65 and older, individuals with high school education or less, and median household income. With one exception- the Monastery monitor- air pollution exposure is relatively consistent across monitor catchment areas with high versus low percentage of Blacks, high versus low households with individuals age 65 and older, individuals with high school education or less, and median household income among census tracts nearest to each monitor. The Monastery monitor, however, with a catchment area characterized by an intermediate level of Blacks as well as the highest medians of households with individuals age 65 and older, individuals with high school education or less, and median household income has substantially lower ambient exposure of NO_2.

4.4.1.3. Summary

There is a statistically significant correlation between Black and all three air pollutants (Table 7). Black-$PM_{2.5}$ is a weak, positive correlation and is the strongest among all correlations between SES and air pollution in this study area. Black-ozone and Black-NO_2 are weak, negative correlations. There is a very weak, positive correlation between households with individuals age 65 and older and NO_2. High school education or less is weakly, negatively correlated to NO_2. Median household income has a very weak, positive correlation to $PM_{2.5}$. Due to the prominent residential segregation by race in the Atlanta metropolitan area, and consistency in $PM_{2.5}$ exposure for among low to high median percent of Blacks in monitor catchment areas, the Black-$PM_{2.5}$ relationship merits close surveillance. The link between SES and NO_2 is meaningful for the inverse relationship with median daily NO_2 and several SES variables in the Monastery monitor catchment area.

Table 7. Mean values, ranges, and Spearman's rank correlation coefficients for air quality variables, Atlanta, GA, 2014.

				Spearman's rank correlation coefficient		
	Mean	**Range**		**24-hour $PM_{2.5}$ (µg/m^3)**	**8-hour ozone (ppb)**	**1-hour NO_2 (ppb)**
Black (%)	36.51 (31.42) †	0.20	97.70	0.32*	-0.28*	-0.20*
Households with individuals age 65 and older (%)	17.72 (8.34)	0	100	0	-0.09	0.15*
High school education or less (%)	27.25 (13.00)	1.81	71.83	0.01	0.02	-0.25*
Median household income (USD)	$62, 592 ($29,775)	$7,872	$176,818	-0.1*	0.03	0.02

*p < 0.05.
†Numbers in parentheses, standard deviation.

4.4.2 DC, Maryland, Virginia

4.4.2.1. Population Characteristics

4.4.2.1.1. DC

Black

In DC, non-Hispanic Black individuals were highly prevalent in most census tracts. They were concentrated in eastern part of the city. The River Terrace Site monitor is the closest monitor for 124 census tracts of which the median proportion of Blacks is 89%. Two other DC monitors, Hains Point and McMillan Reservoir, also have a median above 50%, at approximately 81% and 54%, respectively.

Households with individuals age 65 and older

Census tracts with households with individuals age 65 and over appear evenly distributed. Most DC census tracts have a median of households with elderly persons of 30% or less.

Individuals with high school education or less

The western part of DC contain few individuals with only a high school education or less. The Verizon Telephone monitor was nearest census tracts with a median of 0-10% for such persons. This value was lowest among all monitors in the study locations.

Medan Household Income

Northwest DC was the most affluent area of the city. These census tracts contained a median household income of $105,000 or greater. Among this income level, virtually all of the few tracts with a median household income of $150,000 or greater were in this area. The Verizon Telephone monitor, which is furthest west in DC, therefore is nearest areas with the highest median household income as it accounts for affluent areas of both within DC and its affluent suburbs in Maryland and northern Virginia.

4.4.2.1.2. Maryland

Black

Black persons in Maryland are concentrated near DC and in Baltimore. Outside of these area, most of Maryland is less than 10% Black. The PG Equestrian Center and Oldtown monitors, located outside of DC and in Baltimore respectively, are among the monitors in areas with the largest concentration of Blacks. Median Black (%) were 74% and 80% for census tracts around these monitors.

Households with individuals age 65 and older

Larger proportions of households with individuals age 65 and over were in less urban areas. Almost none of the areas in Baltimore or adjacent to DC had a median less than 20%. The Piney Run monitor had the highest median at households with individuals age 65 and over at 32%. This monitor is location in the northwest corner of the state. The Horn Point monitor, also within an area with many elderly persons, is situated to the east of the Chesapeake Bay on the land that is separated from the main body of Maryland.

Individuals with high school education or less

Rural areas are also where individuals with a high school education or less live. Horn Point and monitors closer to the Atlantic coast measure air pollution levels for these areas with more vulnerable elderly people. The monitors closest to the coastal Maryland are the Fair Hill and Millington monitors. Bethesda, MD, which is an affluent suburban area north of DC area contains a high median household income. The Rockville monitor, north of Bethesda, is nearest this area. Another area of concentrated wealth is situated west of Baltimore and further north of DC. Baltimore contained areas of lower overall median household income. All Baltimore census tracts were less than $75,000, and multiple ones were less than $45,000. Most of the Maryland area east of DC also has a combined median household income of less than $45,000.

4.4.2.1.3. Virginia

Black

Census tracts with a larger proportion of Blacks were located in southern and eastern Virginia. Certain monitors in and around Richmond, the MSIC and Charles City County monitors, had the highest median percent of Blacks with 69% and 40%, respectively.

Households with individuals age 65 and older

Most of the state has areas with a median percent of households with persons 65 and over that is 30% or higher. Monitors in the DC area or just outside of it in Alexandria, have lower median values, some of which are the lowest of all monitors in the study locations. These are the Alexandria Transport, Stevenson Park, Aurora Hills Visitor Center, and Lee District Park- Fairfax County monitors.

Individuals with high school education or less

There is a fairly even distribution of the median percent of persons with a high school education or less across the state. Although, monitors with the lowest median of these individuals are those located in northern Virginia near DC. The monitors- Alexandria Transport, Ashburn, Aurora Hills, and Stevenson- have a median percent of people with no more than a high school education of less than 20%.

Median household income

Wealth is concentrated in northern Virginia outside of DC. The Ashburn monitor is nearest households with a combined median household income of approximately $120,000. This monitor and the Stevenson Park and Lee District Park ones are in areas with a combined median household income over $100,000. These affluent census tracts in northern Virginia are where most of the KPMAS facilities included in this study area located. The greater median household income in theses northern Virginia census tracts parallels the much lower medians of Blacks, elderly persons, and those with a lower level of education relative to other areas of the state.

4.4.2.2. Exposures

Figures 24-35 show the median and IQR for the aforementioned SES characteristics of NO_2, ozone, and $PM_{2.5}$ monitors. NO_2 exposure is inconsistent across monitor catchment areas whereas ozone and $PM_{2.5}$ is generally consistent. Among the NO_2 monitors, the Howard County Near-Road, Oldtown, and River Site Terrace monitors measured higher mean concentrations than other NO_2 monitors. These mean concentrations were 28-31 ppb. However, within the SES characteristics, the Oldtown and River Site Terrace monitors were generally similar whereas the Howard County Near-Road monitor was not. The Long Park, NASA Langley, and Piney Run monitors measured the lowest NO_2 concentrations relative to other monitors. These mean concentrations of these three monitors were less than 10 ppb. These monitors were typically far different in SES factors. Overall, NO_2 monitor catchment areas would have to be more closely examined in relation SES due to irregularities not observed among other air pollutants.

4.4.2.3. Summary

There is a statistically significant correlation between Black and all three air pollutants (Table 8). Black-$PM_{2.5}$ is a very weak, positive correlation, and Black-$PM_{2.5}$ is a weak, positive correlation. Black-ozone is a moderate, negative correlation and is the strongest SES-air pollutant correlation in this study area. This could be due to the large concentration of Blacks in DC and neighboring parts of Maryland in contrast with the lack of a robust industrial area in DC and successful efforts to improve air quality in metropolitan DC. There are very weak, negative correlations between households with individuals age 65 and older and both $PM_{2.5}$ and NO_2. High school education or less and median household income were both very weakly, negatively correlated to $PM_{2.5}$. These two SES variables were also very weakly and weakly correlated to ozone, respectively. Monitors with lower median household income catchment areas consistently have catchment areas with higher medians of Blacks, households with elderly persons, and those with a high school education at most as the highest level of educational attainment.

Table 8. Mean values, ranges, and Spearman's rank correlation coefficients for air quality variables, DC, Maryland, and Virginia, 2014.

				Spearman's rank correlation coefficient		
	Mean	Range		24-hour $PM_{2.5}$ ($\mu g/m^3$)	8-hour ozone (ppb)	1-hour NO_2 (ppb)
Black (%)	26.24 (28.03) †	0	100	0.14*	-0.52*	0.35*
Households with individuals age 65 and older (%)	23.54 (9.88)	0	100	-0.15*	-0.03	-0.1*
High school education or less (%)	30.69 (18.08)	0	98.72	-0.04*	-0.18*	0.03
Median household income (USD)	$74,187 ($37,746)	$4,808	$244,013	0.18*	0.30*	0.01

*p < 0.05.
†Numbers in parentheses, standard deviation.

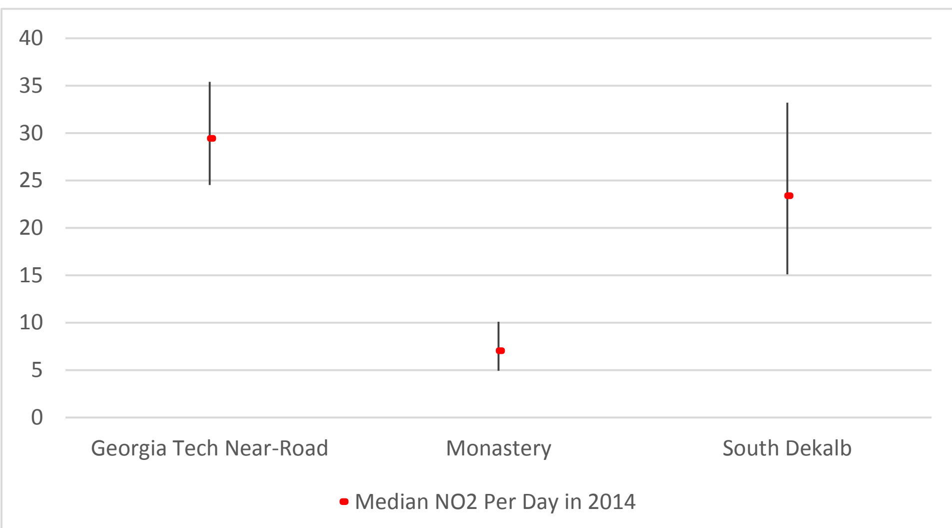


Figure 12. Median and Interquartile Range for NO_2 Monitors Ordered by Lowest to Highest Median Percent of Blacks in Census Tracts Nearest to Monitors, Atlanta, GA, 2014.

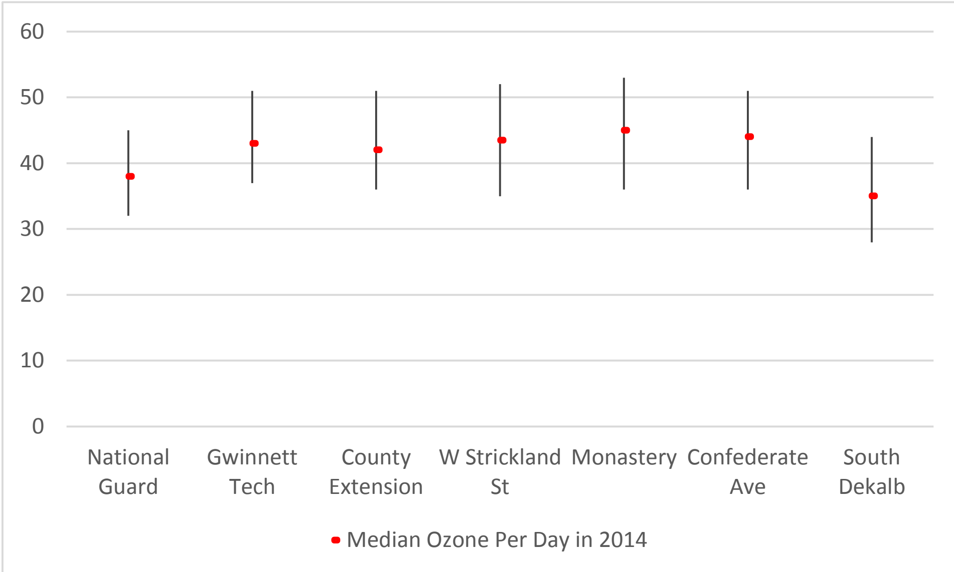


Figure 13. Median and Interquartile Range for Ozone Monitors Ordered by Lowest to Highest Median Percent of Blacks in Census Tracts Nearest to Monitors, Atlanta, GA, 2014.

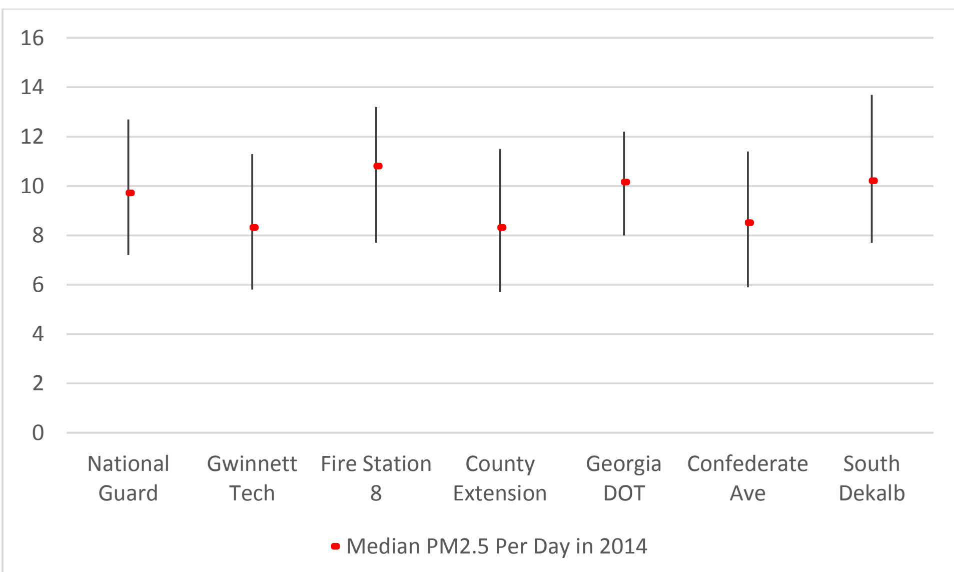


Figure 14. Median and Interquartile Range for $PM_{2.5}$ Monitors Ordered by Lowest to Highest Median Percent of Blacks in Census Tracts Nearest to Monitors, Atlanta, GA, 2014.

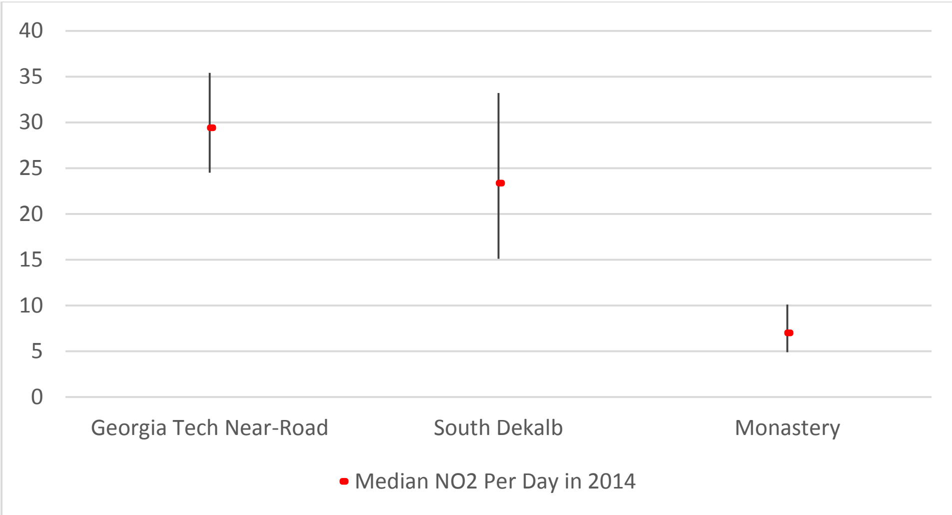


Figure 15. Median and Interquartile Range for NO_2 Monitors Ordered by Lowest to Highest Median Percent of Households with Individuals Age 65 and Older in Census Tracts Nearest to Monitors, Atlanta, GA, 2014.

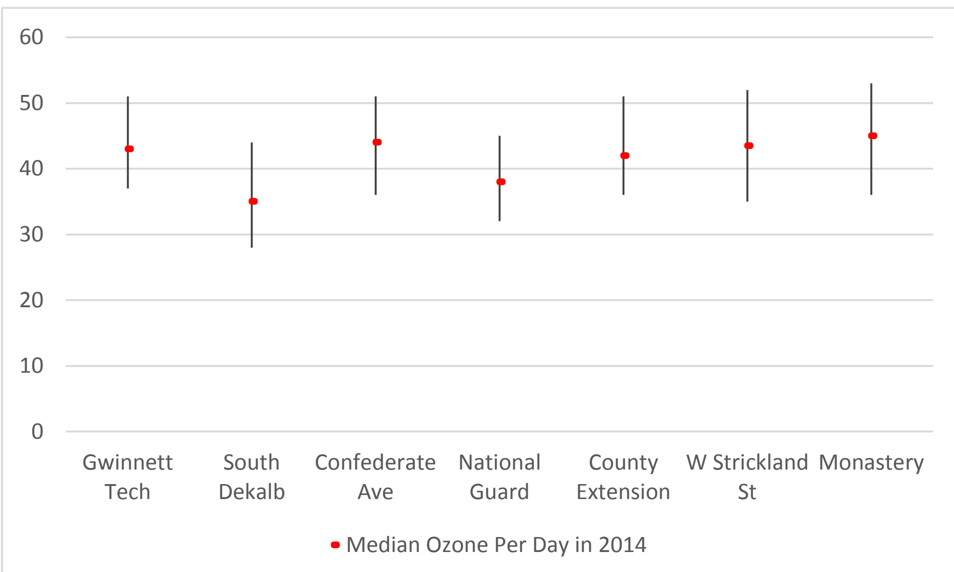


Figure 16. Median and Interquartile Range for Ozone Monitors Ordered by Lowest to Highest Median Percent of Households with Individuals Age 65 and Older in Census Tracts Nearest to Monitors, Atlanta, GA, 2014.

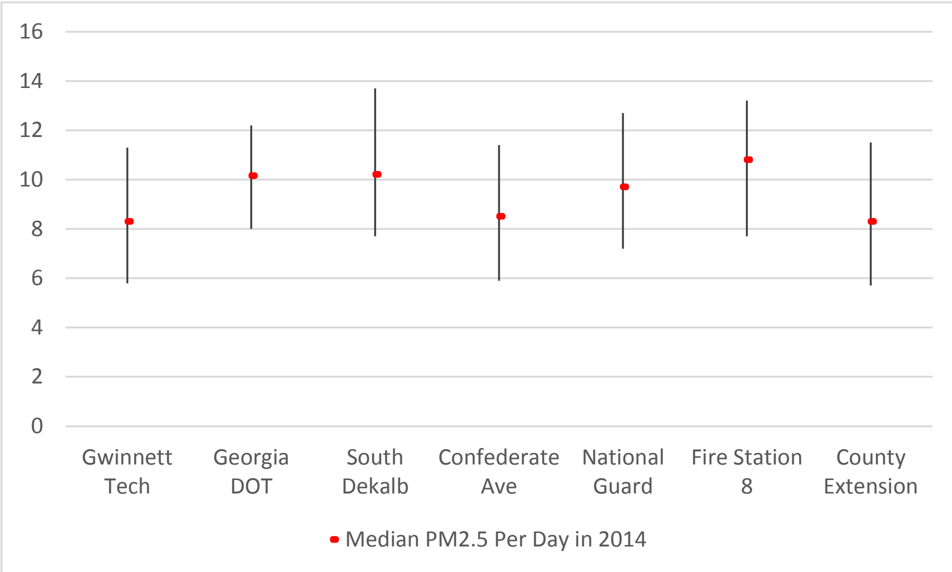


Figure 17. Median and Interquartile Range for $PM_{2.5}$ Monitors Ordered by Lowest to Highest Median Percent of Households with Individuals Age 65 and Older in Census Tracts Nearest to Monitors, Atlanta, GA, 2014.

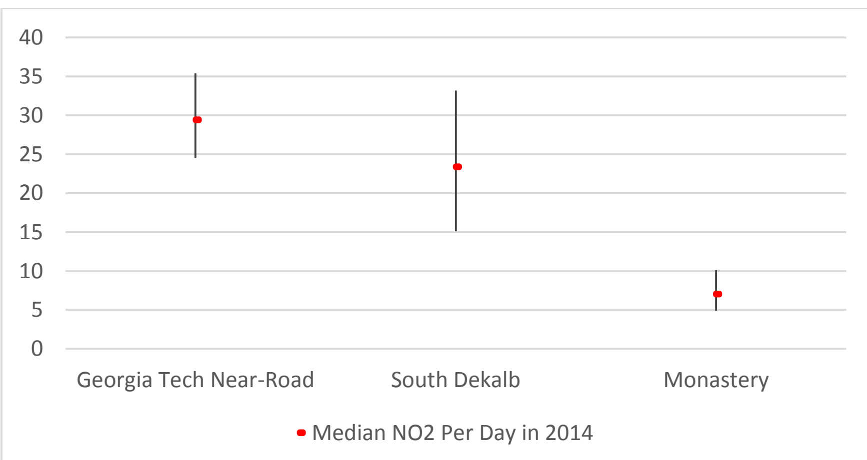


Figure 18. Median and Interquartile Range for NO_2 Monitors Ordered by Lowest to Highest Median Percent of Individuals with High School Education or Less in Census Tracts Nearest to Monitors, Atlanta, GA, 2014.

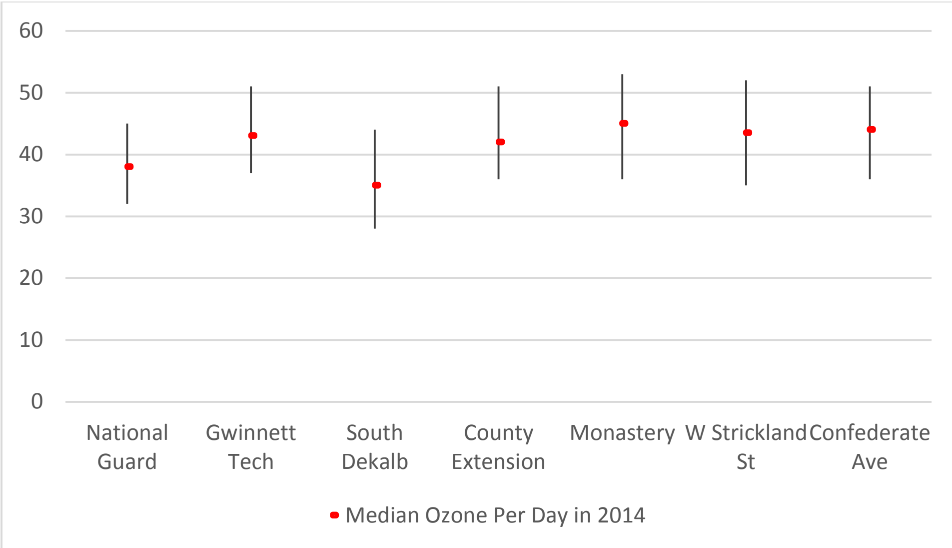


Figure 19. Median and Interquartile Range for Ozone Monitors Ordered by Lowest to Highest Median Percent of Individuals with High School Education or Less in Census Tracts Nearest to Monitors, Atlanta, GA, 2014.

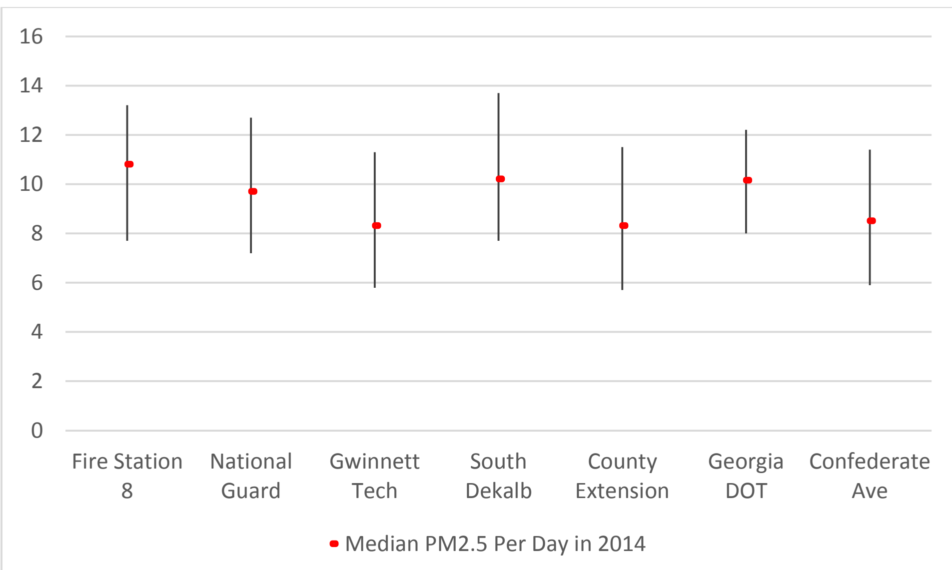


Figure 20. Median and Interquartile Range for $PM_{2.5}$ Monitors Ordered by Lowest to Highest Median Percent of Individuals with High School Education or Less in Census Tracts Nearest to Monitors, Atlanta, GA, 2014.

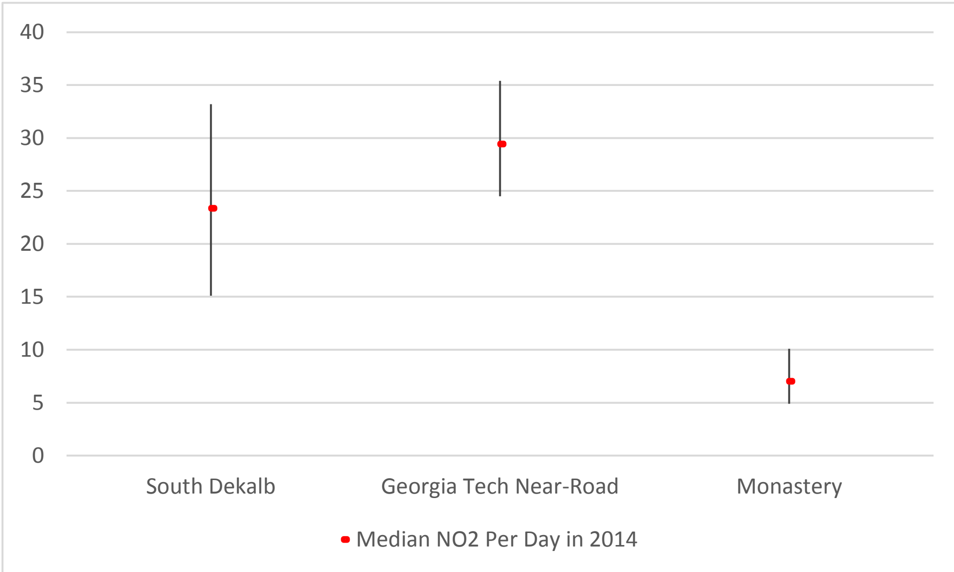


Figure 21. Median and Interquartile Range for NO_2 Monitors Ordered by Lowest to Highest Median Household Income in Census Tracts Nearest to Monitors, Atlanta, GA, 2014.

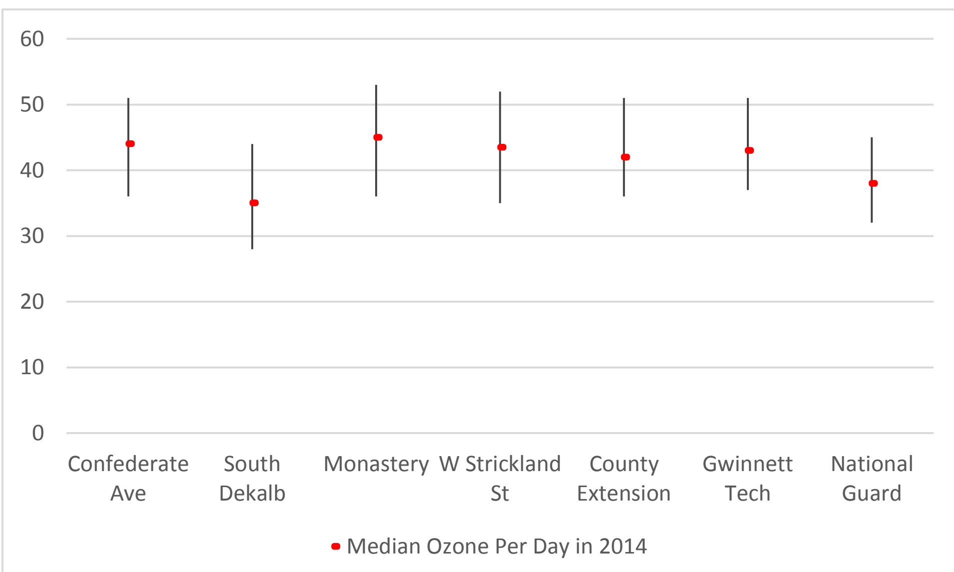


Figure 22. Median and Interquartile Range for Ozone Monitors Ordered by Lowest to Highest Median Household Income in Census Tracts Nearest to Monitors, Atlanta, GA, 2014.

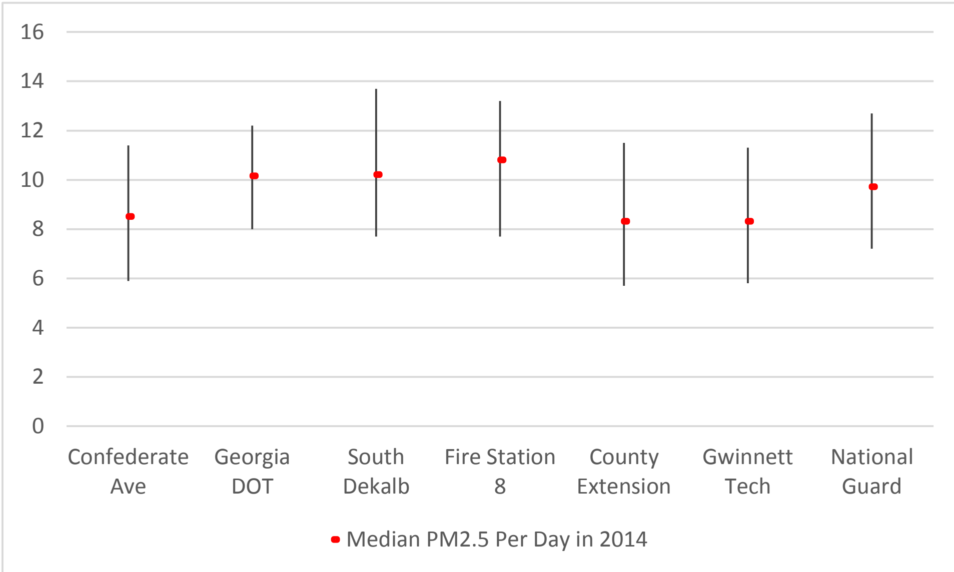


Figure 23. Median and Interquartile Range for $PM_{2.5}$ Monitors Ordered by Lowest to Highest Median Household Income in Census Tracts Nearest to Monitors, Atlanta, GA, 2014.

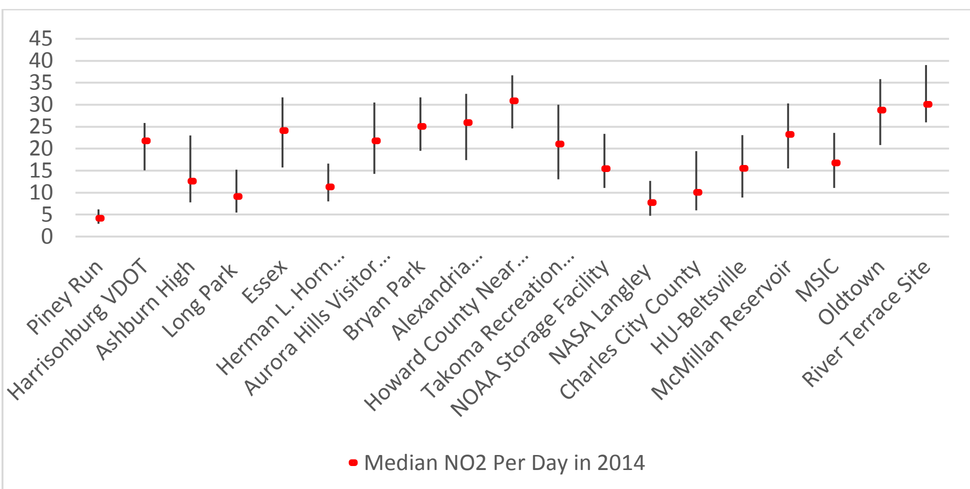


Figure 24. Median and Interquartile Range for NO_2 Monitors Ordered by Lowest to Highest Median Percent of Blacks in Census Tracts Nearest to Monitors, DC, Maryland, and Virginia, 2014.

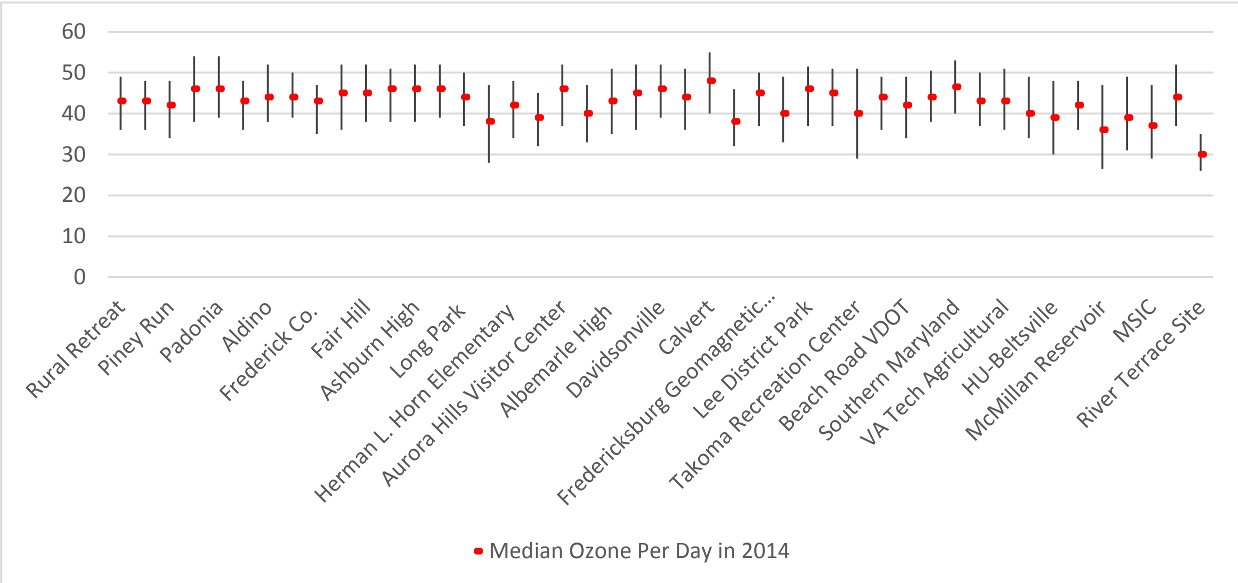


Figure 25. Median and Interquartile Range for Ozone Monitors Ordered by Lowest to Highest Median Percent of Blacks in Census Tracts Nearest to Monitors, DC, Maryland, and Virginia, 2014.

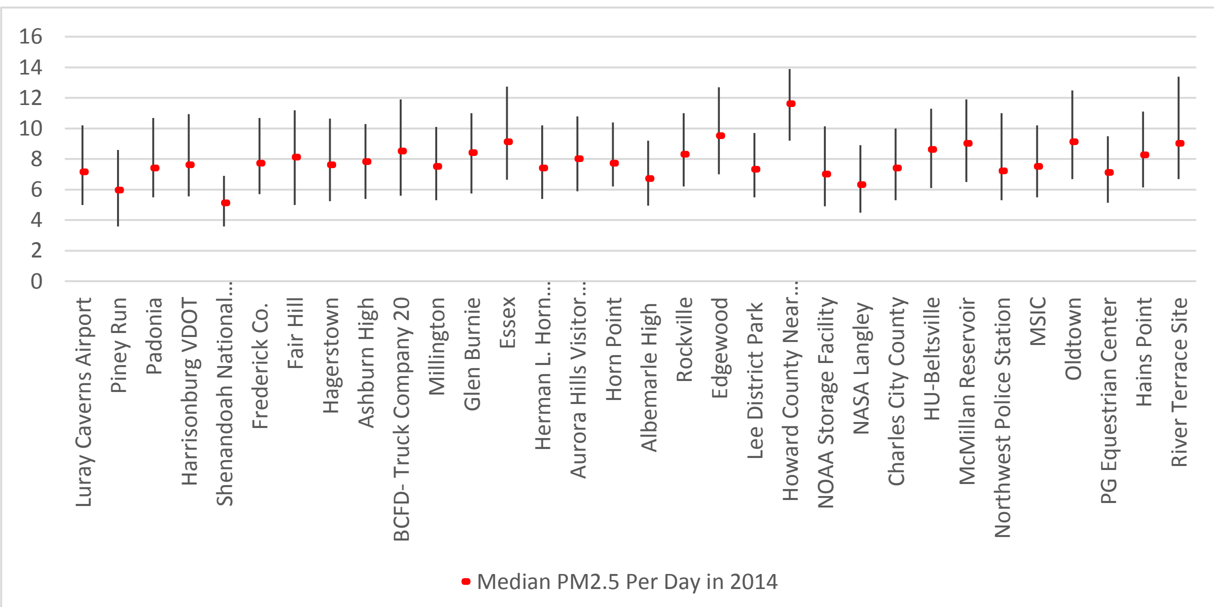


Figure 26. Median and Interquartile Range for $PM_{2.5}$ Monitors Ordered by Lowest to Highest Median Percent of Blacks in Census Tracts Nearest to Monitors, DC, Maryland, and Virginia, 2014.

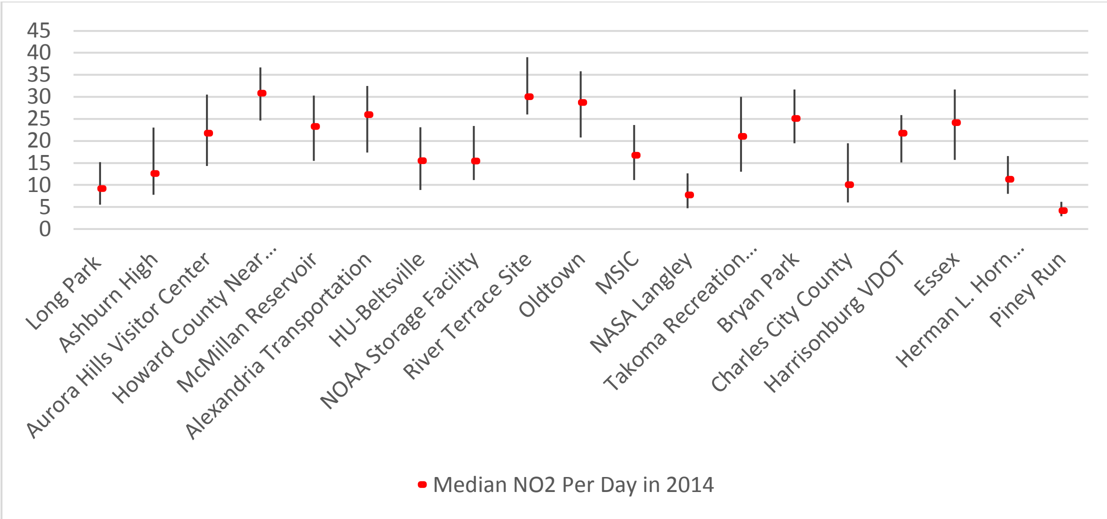


Figure 27. Median and Interquartile Range for NO_2 Monitors Ordered by Lowest to Highest Median Percent of Households with Individuals Age 65 and Older in Census Tracts Nearest to Monitors, DC, Maryland, and Virginia, 2014.

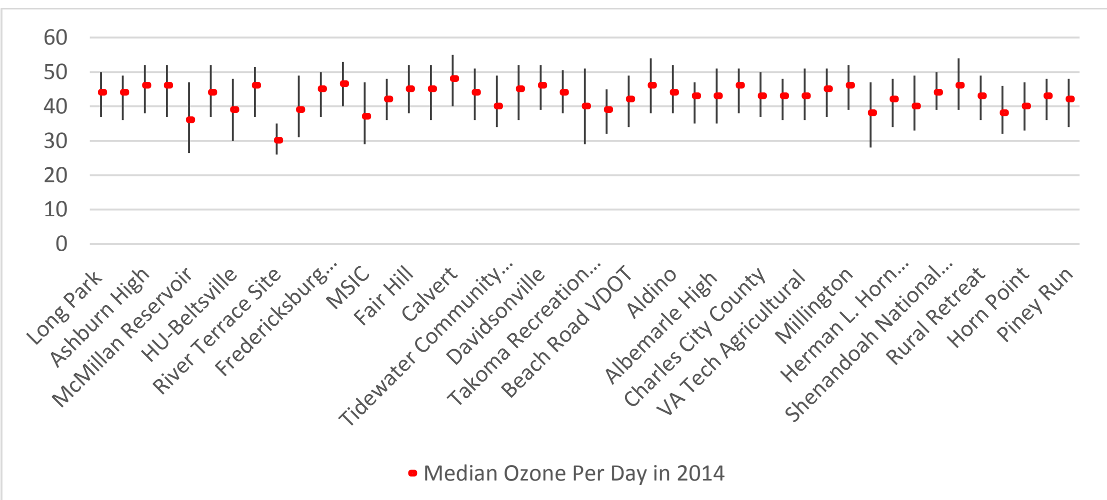


Figure 28. Median and Interquartile Range for Ozone Monitors Ordered by Lowest to Highest Median Percent of Households with Individuals Age 65 and Older in Census Tracts Nearest to Monitors, DC, Maryland, and Virginia, 2014.

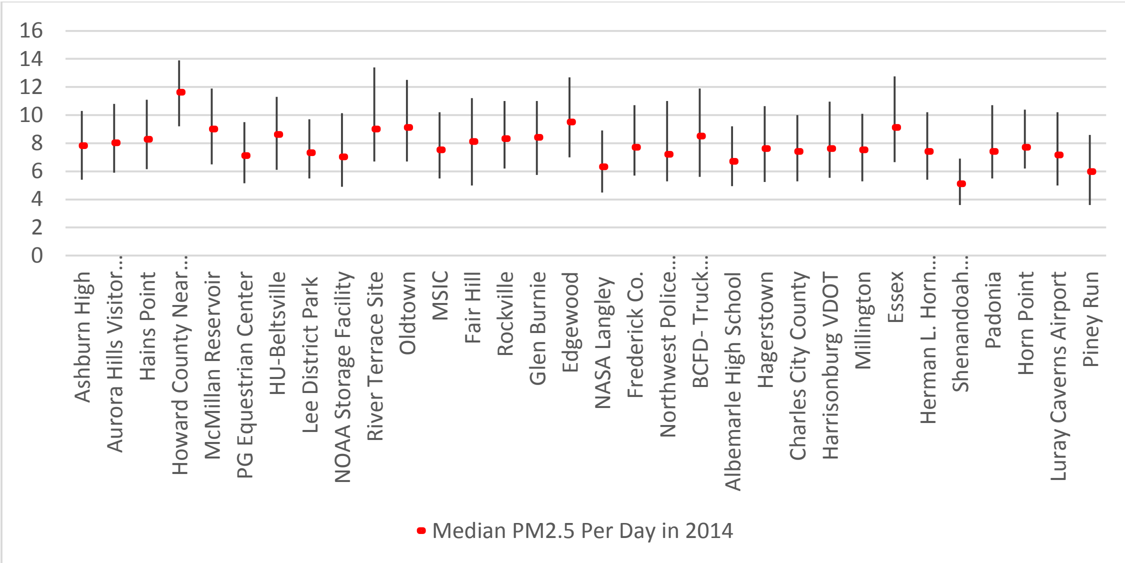


Figure 29. Median and Interquartile Range for $PM_{2.5}$ Monitors Ordered by Lowest to Highest Median Percent of Households with Individuals Age 65 and Older in Census Tracts Nearest to Monitors, DC, Maryland, and Virginia, 2014.

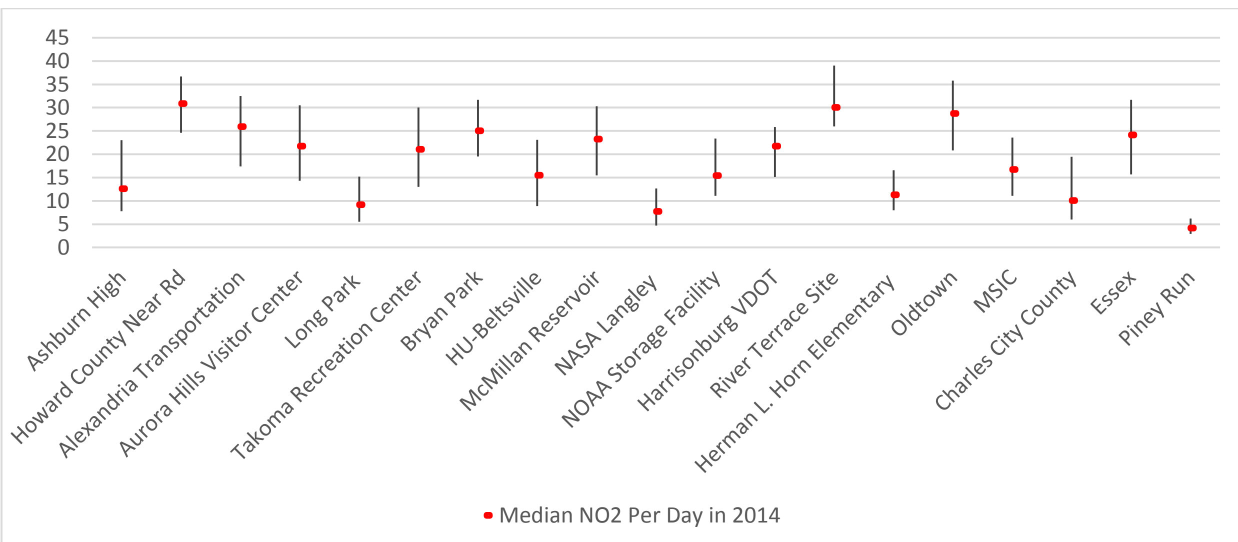


Figure 30. Median and Interquartile Range for NO_2 Monitors Ordered by Lowest to Highest Median Percent of Individuals with High School Education or Less in Census Tracts Nearest to Monitors, DC, Maryland, and Virginia, 2014.

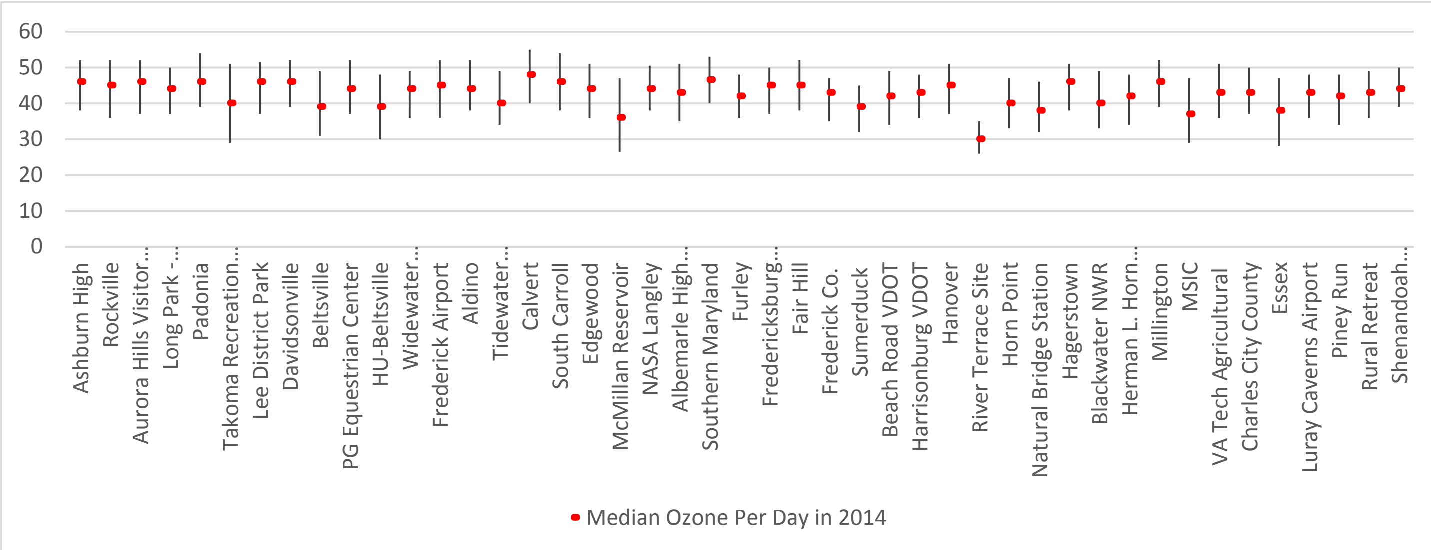


Figure 31. Median and Interquartile Range for Ozone Monitors Ordered by Lowest to Highest Median Percent of Individuals with High School Education or Less in Census Tracts Nearest to Monitors, DC, Maryland, and Virginia, 2014.

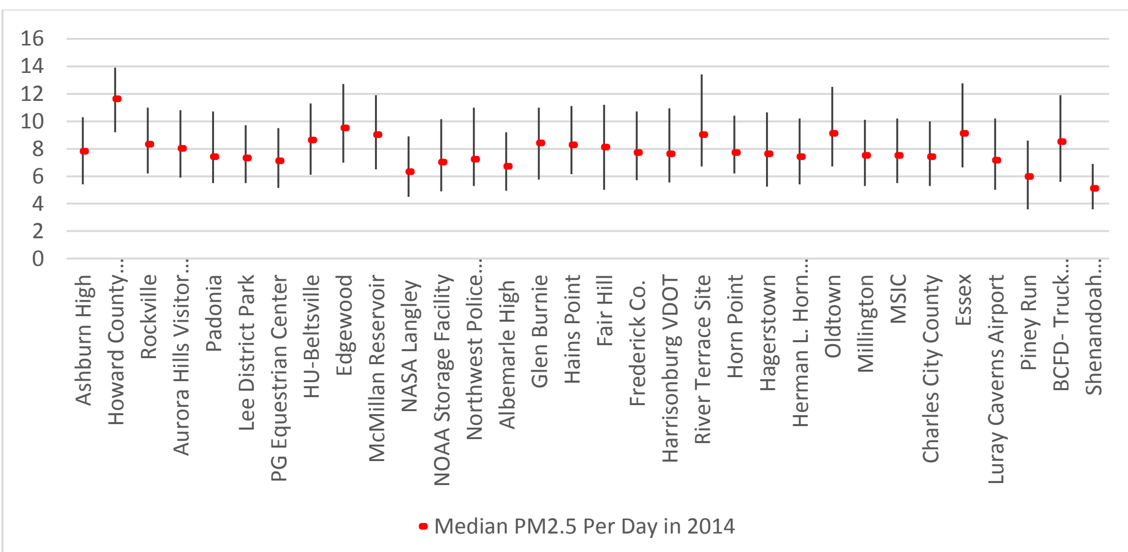


Figure 32. Median and Interquartile Range for $PM_{2.5}$ Monitors Ordered by Lowest to Highest Median Percent of Individuals with High School Education or Less in Census Tracts Nearest to Monitors, DC, Maryland, and Virginia, 2014.

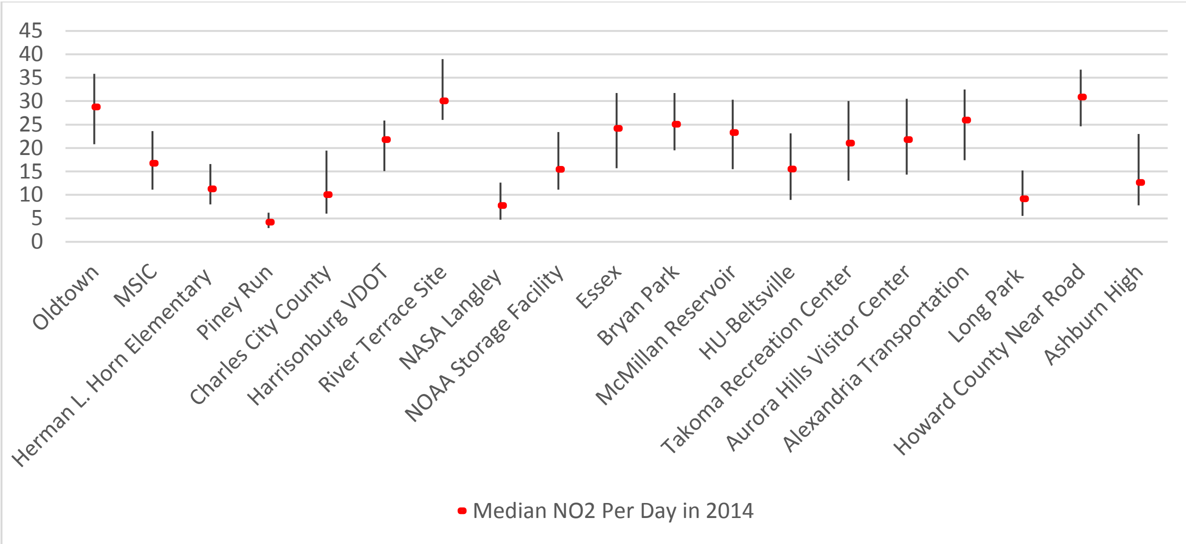


Figure 33. Median and Interquartile Range for NO_2 Monitors Ordered by Lowest to Highest Median Household Income in Census Tracts Nearest to Monitors, DC, Maryland, and Virginia, 2014.

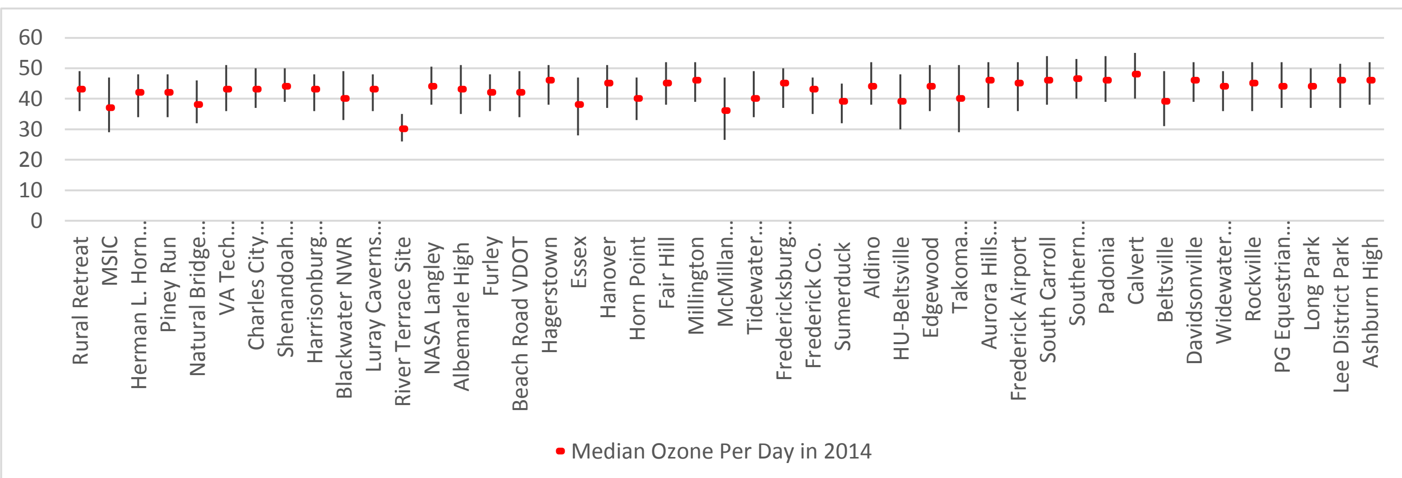


Figure 34. Median and Interquartile Range for Ozone Monitors Ordered by Lowest to Highest Median Household Income in Census Tracts Nearest to Monitors, DC, Maryland, and Virginia, 2014.

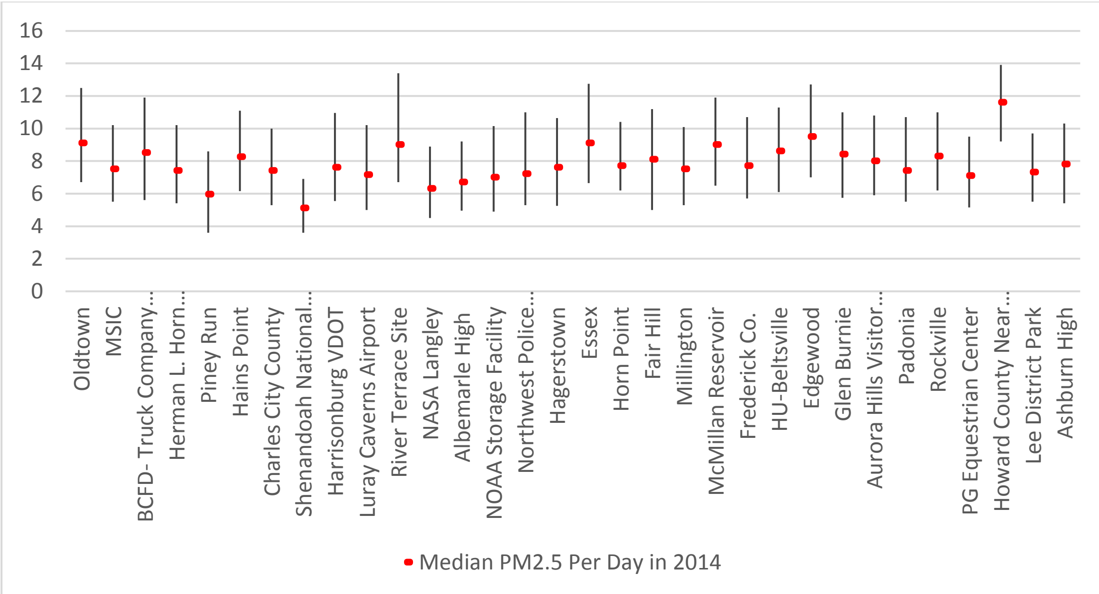


Figure 35. Median and Interquartile Range for $PM_{2.5}$ Monitors Ordered by Lowest to Highest Median Household Income in Census Tracts Nearest to Monitors, DC, Maryland, and Virginia, 2014.

Chapter V

DISCUSSION

5.1 Environmental Exposures

All environmental exposures of interest are monitored due in part to their potential to adversely affect human health. Overall, air pollution monitors are strategically so that they cover a variety of pollutions and types of areas. They are sensibly concentrated in densely-populated urban areas allowing for more accuracy in level of exposure among different places within a metropolitan area. The design of monitoring systems, the publically available data hub for daily data, and the uniformity of resources across regions make them a valuable source to consider for syndromic surveillance purposes. Air pollution data was the most straightforward to find and download. Data are complete for different levels of geography including state, MSA, and county. The time lengths of monitor measurements different among pollutants. Time of measurements are 24-hour $PM_{2.5}$, 8-hour ozone, and 1-hour NO_2.

Both ozone and $PM_{2.5}$ are described as regional pollutants, because they vary on a large spatial scale. The correlations between air pollutants were similar to the findings of other research in that $PM_{2.5}$-ozone and $PM_{2.5}$-NO_2 are positively correlated, whereas ozone-NO_2 is a negative correlation[17]. The inverse relationship between in NO_2 and ozone is due to NO_2 being a precursor to ozone production. All three air pollutants showed clear peaks that were generally in the same time frame over a 3-year period. $PM_{2.5}$ and ozone concentrations are highest in the summer, whereas NO_2 displays wintertime peaks. Other studies have contemplated the actual exposure estimate of individuals using based on their residence. It has been considered that there may be potential measurement error due to lack of specificity in exposure estimates[17]. Using residential address does not represent time spent in other locations or time spent indoor versus outdoors. Overall, it is important to consider spatial gradients within a large area when attempting to identify associations between air pollution and health outcomes, and understand that air pollution concentrations consist of both local particles and particles transported over a larger area[88]. Upon literature review for this study, no research was found that considered residence compared to work or school locations to estimate individual exposure.

Pollen monitoring should be considered based on the proximity to a monitor. Since there is typically only one in a major area, and there is large variation in deposits of pollen, daily data may only be useful for a small number of clinics. With the burden pollen places on those with allergies and chronic conditions, accessible data should definitely be added to syndromic surveillance. Pollen has a well-established connection to respiratory health particularly among those with allergies or chronic respiratory conditions. Tree and grass pollen have distinct peaks in the spring. Air pollutant concentrations may still be high around March and April, which appears to be the time frame for the most overall between these exposures, because these types of pollen are normally not a problem before March and after June. Tree pollen in particular is virtually nonexistent during these time periods. Pollen and other allergens like mold directly affect hospital admissions for costly respiratory conditions such as asthma. In a study conducted in King County, WA, tree pollen was found to have a strong link to admissions for respiratory conditions and other health outcomes[89]. With its known seasonality, pollen would make an excellent addition to syndromic surveillance. Currently, NAB is the best source of pollen data, however based on our experience in requesting data from three different NAB pollen stations obtaining their data is not guaranteed. Only the US Army Centralized Allergen Extract Lab in DC complied with our request, and did so in a timely matter and free of charge.

A reliable source of data for water contaminants was not uncovered during this investigation. While there are federal agencies (e.g. EPA, USGS) that monitor water quality, it was unclear what parameters would be most suitable for syndromic surveillance. Furthermore, most available monitor data is for ambient and chemical parameters such as dissolved oxygen, temperature, pH, and turbidity. Microbiological contaminants, which includes pathogens, would logically be most likely to elicit, however reliable continuous monitoring could not for microorganisms could not be found. Likewise EPA STORET publically available microbiological data ended on 1/24/2014. Although turbidity can be used as a rough estimate of microbial contaminants, like E. coli, drinking water is largely filtered, which decreases turbidity. Likewise, water systems may serve many different populations and these populations can easily be located outside of the watershed, or at least the general proximity, of the source water.

There is limited ability to track important localized water contaminant exposures, particularly water main breaks and boil water advisories. When using water quality indicators for water contamination, temporality is difficult to assess between when water leaves a treatment plant after turbidity is measured and the time until it reaches an individual’s residence. Also involved in this relationship is the incubation period of a particular pathogen. The study of water turbidity and GI-related ED visits identified individual differences in water consumption aside from tap water as a limiting factor to estimating the impact of using turbidity as a proxy. A strength of this study is that it performed a sensitivity analysis comparing using zip codes with a treatment plant's service area in which only 20% of residences receive water from that plant compared to zip codes in which all residences are served, and found the results to be similar. Measures of raw water turbidity among plants were found to be heterogeneous, but all positively associated with GI ED visits [24].

5.2 SES

Heterogeneity of SES distribution is evident in both study areas. The metropolitan Atlanta area possessed distinct gradients among census tracts nearest air pollution monitors in regards to proportions of Blacks, individuals with a high school education or less, and median household income. These gradients were also evident in the DC, Maryland, and Virginia region. DC, like Atlanta, contained significantly large proportions of Blacks. The DC, Maryland, and Virginia study area also appeared to display trends between medians for the SES factors of Blacks, high school education or less, and median household income. The range of medians of households with individuals age 65 and older was smaller than the other SES variables. Throughout Maryland and Virginia, rural areas consistently possessed large proportions of this vulnerable population. In Atlanta, areas of wealth were typically in northern parts of the metropolitan area, while in the other study locations, census tracts with a very high median household income ($105,000 to $150,000 and $150,000 and greater) were largely concentrated in DC and northern Virginia. Although SES does not seem correlated with air pollution (or other) exposure in this dataset, this still does not rule out the potential moderating effect of SES on an exposure response.

Despite the significant differences in SES characteristics of residents in the catchment areas of each monitor, the exposures to air pollutants were generally consistent, on average. Since ozone and $PM_{2.5}$ only vary at a much larger spatial scale, it should not be surprising that, across multiple monitors in a specific metropolitan area, the variation in these pollutants is relatively homogeneous compared to the variation in SES in the monitor catchment areas. The discrepancies in the SES-NO_2 relationships observed in both study areas, could have been due to the significant influence of motor vehicle traffic on NO_2 exposure as some monitors were situated near major roads that many motor vehicles travel on. The EPA has recently been focused on monitoring NO_2 exposure near high trafficked roadways as this accounts for the majority of ambient NO_2 maximum concentrations. Residents around highly traveled roads area are generally more likely to be exposed to higher NO_2 concentrations. In the Atlanta area, for example, the Georgia-Tech Near-Road monitor the median daily NO_2 concentration was 4 times greater than the median daily NO_2 concentration of the Monastery monitor because it was set up to target I-85, which has an average annual daily traffic count of approximately 285,000 making it one of the most highly trafficked roadways in the nation. Conversely, the Monastery monitor is located towards the outskirts of the metropolitan area where the volume of traffic is not nearly as great. However, as a result of NO_2 exposure being primarily linked to traffic there was no trend in higher median of SES characteristic with increasing mean NO_2 concentration. Thus, the geographic disparities do not necessarily translate into exposure disparities.

At the time of this study, only a small sample of NO_2 monitors met the criteria for the near-road NO_2 network, which is currently still in development. The plan to create this near-road NO_2 network, which consists of both new and already established monitors, has three phases set from 2014 to 2017: Phase 1 was due January 1, 2014, Phase 2 was due January 1, 2015, and Phase 3 is due January 1, 2017. As of May 2015, only one monitor (Georgia Tech Near-Road) in the Atlanta area, one monitor (Howard County Near-Road) in Maryland, and one monitor (Bryan Park) in Virginia that were used in this study met the criteria of the near-road NO_2 network; however, the Virginia monitor, located in Richmond, is not in northern Virginia where most of the state's KPMAS clinics are. The DMRC monitor in Dekalb County, Atlanta began monitoring NO_2 at the end of 2014. Maryland will have a monitor in Baltimore County in September 2015. Virginia will have a monitor in Fairfax County set to start collecting NO_2 data in August 2015. Finally, DC established a new monitor to measure near-road NO_2 concentration in April 2015. Future research should largely take into account the influence of motor vehicle traffic, the need to target major roads, and the change in NO_2 NAAQS as they apply to near-road NO_2 monitors when collecting historical data of daily NO_2 concentrations for syndromic surveillance purposes.

5.3 Limitations

This study is limited by the lack of spatial analysis for environmental exposures. The monitor data was not linked to healthcare data, which would be necessary to evaluate the magnitude by which air pollutants or pollen actually generate respiratory symptoms in a population. Another limitation is that the KP clinics were used as a proxy for the membership population of each clinic when calculating the distance from the nearest monitor. Although KP members typically use the clinic closest to them, members could live closer to another monitor. Also, due to the spatial variation of exposures due to meteorological parameters like temperature and wind speed, the measurements from the nearest monitor to a clinic may not enable an accurate approximation of members' level of exposure. Finally, it was recently discovered that near-road NO_2 monitors provide a better assessment of peak NO_2 exposure than monitors that are not within the near-road network. The majority NO_2 monitors used in this study are not near-road monitors.

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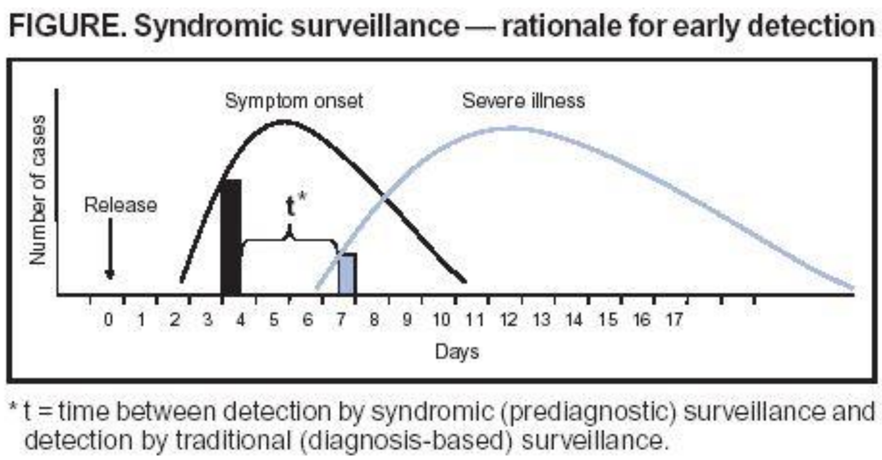
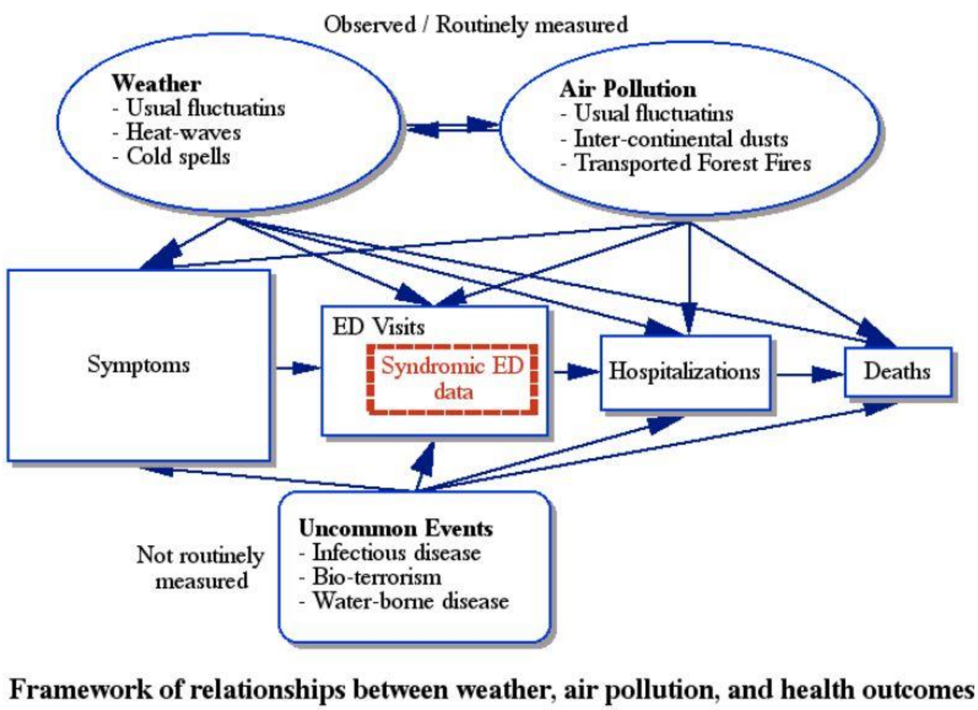
APPENDIX



(Source: **http://www.cdc.gov/Mmwr/preview/mmwrhtml/su5301a3.htm**)

Figure A1. Timeliness of syndromic surveillance detection of an event from exposure to the onset of severe illness.



(Source: http://epa.gov/ncer/events/calendar/2008/jan22/ito.pdf)

Figure A2. Framework for incorporating environmental exposure data and meteorological data with healthcare data in a syndromic surveillance system.

Pollutant [final rule cite]	Primary/ Secondary	Averaging Time	Level	Form
Carbon Monoxide [76 FR 54294, Aug 31, 2011]	primary	8-hour	9 ppm	Not to be exceeded more than once per year
		1-hour	35 ppm	
Lead [73 FR 66964, Nov 12, 2008]	primary and secondary	Rolling 3 month average	0.15 μg/m^3 (1)	Not to be exceeded
Nitrogen Dioxide [75 FR 6474, Feb 9, 2010] [61 FR 52852, Oct 8, 1996]	primary	1-hour	100 ppb	98th percentile of 1-hour daily maximum concentrations, averaged over 3 years
	primary and secondary	Annual	53 ppb (2)	Annual Mean
Ozone [73 FR 16436, Mar 27, 2008]	primary and secondary	8-hour	0.075 ppm (3)	Annual fourth-highest daily maximum 8-hr concentration, averaged over 3 years
Particle Pollution Dec 14, 2012 — $PM_{2.5}$	primary	Annual	12 μg/m^3	annual mean, averaged over 3 years
	secondary	Annual	15 μg/m^3	annual mean, averaged over 3 years
	primary and secondary	24-hour	35 μg/m^3	98th percentile, averaged over 3 years
PM_{10}	primary and secondary	24-hour	150 μg/m^3	Not to be exceeded more than once per year on average over 3 years
Sulfur Dioxide [75 FR 35520, Jun 22, 2010] [38 FR 25678, Sept 14, 1973]	primary	1-hour	75 ppb (4)	99th percentile of 1-hour daily maximum concentrations, averaged over 3 years
	secondary	3-hour	0.5 ppm	Not to be exceeded more than once per year

(Source: http://www.epa.gov/air/criteria.html)

Figure A3. The EPA six criteria air pollutants with primary and secondary standards.

NAB SCALE							
* MOLD		GRASS		TREE		WEED	
0	Absent	0	Absent	0	Absent	0	Absent
1 - 6499	Low	1 - 4	Low	1 - 14	Low	1 - 9	Low
6500 - 12999	Moderate	5 - 19	Moderate	15 - 89	Moderate	10 - 49	Moderate
13000 - 49999	High	20 - 199	High	90 - 1499	High	50 - 499	High
>50000	Very High	>200	Very High	>1500	Very High	>500	Very High

(Source: http://www.aaaai.org/global/nab-pollen-counts/reading-the-charts.aspx)

Figure A4. The National Allergy Bureau (NAB) pollen and mold scale.

Table A1. Levels of contaminants to avoid filtration as identified by EPA surface water treatment rules.*

Contaminant	**Rule**
Cryptosporidium	Unfiltered systems are required to include Cryptosporidium in their existing watershed control provisions
Giardia lamblia	99.9% removal/inactivation.
Viruses	99.99% removal/inactivation.
Legionella	No limit, but EPA believes that if Giardia and viruses are removed/inactivated, according to the treatment techniques in the Surface Water Treatment Rule,
Turbidity	For systems that use conventional or direct filtration, at no time can turbidity (cloudiness of water) go higher than 1 Nephelometric Turbidity Unit (NTU), and samples for turbidity must be less than or equal to 0.3 NTUs in at least 95 percent of the samples in any month. Systems that use filtration other than the conventional or direct filtration must follow state limits, which must include turbidity at no time exceeding 5 NTUs.
Heterotrophic Plate Count (HPC)	No more than 500 bacterial colonies per milliliter.
Long Term 1 Enhanced Surface Water Treatment	Surface water systems or groundwater under the direct influence (GWUDI) systems serving fewer than 10,000 people must comply with the applicable Long Term 1 Enhanced Surface Water Treatment Rule provisions (such as turbidity standards, individual filter monitoring, Cryptosporidium removal requirements, updated watershed control requirements for unfiltered systems).
Long Term 2 Enhanced Surface Water Treatment Rule	This rule applies to all surface water systems or ground water systems under the direct influence of surface water. The rule targets additional Cryptosporidium treatment requirements for higher risk systems and includes provisions to reduce risks from uncovered finished water storage facilities and to ensure that the systems maintain microbial protection as they take steps to reduce the formation of disinfection byproducts.
Filter Backwash Recycling	The Filter Backwash Recycling Rule requires systems that recycle to return specific recycle flows through all processes of the system's existing conventional or direct filtration system or at an alternate location approved by the state.

* Rules also apply to ground water under the direct influence of surface water.

(Source: http://water.epa.gov/drink/contaminants/)

Table A2. Mean monthly air pollution concentrations, Atlanta, GA, 2012-2014.

	$PM_{2.5}$ (μg/m^3)	**Ozone (ppb)**	**NO_2 (ppb)**
2012			
Jan	8.49	30.06	16.11
Feb	9.34	34.41	14.37
Mar	10.14	42.56	13.85
Apr	11.01	47.81	12.74
May	11.24	50.16	13.64
Jun	11.08	53.28	13.35
Jul	12.23	46.4	12.6
Aug	10.76	45.06	11.71
Sep	10.06	41.66	12.62
Oct	9.24	37.28	12.85
Nov	11.85	35.33	16.14
Dec	9.04	30.34	13.09
2013			
Jan	8.77	29.75	15.03
Feb	6.99	37.57	15.04
Mar	8.44	44.94	13.36
Apr	8.98	45.58	11.91
May	8.58	43.15	10.61
Jun	10.96	39.19	8.07
Jul	8.48	33.8	6.82
Aug	10.9	36.34	8.47
Sep	12.2	44.12	11.12
Oct	10.65	35.26	12.1
Nov	9.15	29.45	13.52
Dec	8.25	24.95	14.02
2014			
Jan	**7.62**	**31.46**	**17.32**

Feb	**8.89**	**35.28**	**16.43**
	$PM_{2.5}$ (µg/m^3)	**Ozone (ppb)**	**NO_2 (ppb)**
2014 (continued)			
Mar	10.58	43.82	16.62
Apr	9.33	47.19	13.65
May	10.47	46.45	12.36
Jun	10.69	41.56	13.15
Jul	12.19	43.27	15.3
Aug	11.73	45.82	16.09
Sep	8.06	34.94	12.8
Oct	9.52	37.34	15.45
Nov	10.09	33.03	18.33
Dec	8.89	23.97	16.56

Table A3. Mean monthly air pollution concentrations, DC, Maryland, Virginia, 2012-2014.

	DC			Maryland			Virginia		
	$PM_{2.5}$ (μg/m^3)	**Ozone (ppb)**	**NO_2 (ppb)**	**$PM_{2.5}$ (μg/m^3)**	**Ozone (ppb)**	**NO_2 (ppb)**	**$PM_{2.5}$ (μg/m^3)**	**Ozone (ppb)**	**NO_2 (ppb)**
2012									
Jan	9.83	22.98	30.47	9.39	27.42	26.98	7.5	32.85	21.13
Feb	11.08	28.82	34.93	10.65	33.18	32.72	8.46	39.04	23.89
Mar	9.43	38.26	28.88	9.48	41.84	27.94	7.28	47.47	19.91
Apr	6.86	48.8	32.28	7.12	48.83	24.97	6.7	47.7	19.16
May	7.8	48.69	26.1	8.82	49.11	22.26	7.18	46.55	14.83
Jun	11.73	56.03	24.27	10.86	56.94	22.77	9.55	51.38	14.6
Jul	13.81	58.32	20.17	12.21	58.75	20.79	11.58	52.94	13.34
Aug	13.42	57.08	25.92	11.73	55.15	22.65	10.02	49.58	14.33
Sep	8.17	43.97	29.04	7.97	43.85	22.44	7.17	40.31	16.3
Oct	7.8	30.16	26.94	8.39	33.25	21.7	6.76	33.98	17.53
Nov	11.93	24.63	33.87	11.3	29.98	27.74	9.49	34.98	24.42
Dec	12.61	19.08	30.06	11.21	26.5	25.26	9.31	30.68	21.51
2013									
Jan	11.61	22.02	32.23	11.07	28.82	27.53	8.83	31.93	22.26
Feb	9.91	27.02	29.51	9.06	34.74	24.6	7.29	38.61	21.21
Mar	7.43	40.7	23.24	7.04	43.0	23.01	6.7	44.54	20.33
Apr	8.63	48.77	26.24	7.9	51.28	21.6	7.22	49.87	17.29
May	8.8	44.82	20.19	8.23	48.44	19.01	7.03	45.13	13.32
Jun	10.2	45.77	22.94	9.03	48.28	19.36	8.25	42.08	12.93
Jul	10.88	43.97	14.27	9.94	43.47	16.64	8.79	36.84	11.33
Aug	10.44	45.27	16.64	9.57	44.89	17.95	8.64	39.21	11.82
Sep	8.69	42.8	25.64	7.71	44.21	21.19	8.01	41.51	15.03
Oct	9.25	30.54	26.33	9.1	34.71	23.49	7.8	33.56	17.9
Nov	7.92	25.15	25.98	7.55	30.45	25.32	6.25	33.26	20.91
Dec	11.41	21.01	27.15	11.19	27.34	28.5	8.22	32.11	23.53
2014									

Jan	9.94	26.05	27.72	10.02	30.65	23.44	7.95	34.41	25.06
	DC			**Maryland**			**Virginia**		
	$PM_{2.5}$ (µg/m^3)	**Ozone (ppb)**	**NO_2 (ppb)**	**$PM_{2.5}$ (µg/m^3)**	**Ozone (ppb)**	**NO_2 (ppb)**	**$PM_{2.5}$ (µg/m^3)**	**Ozone (ppb)**	**NO_2 (ppb)**
2014 (continued)									
Feb	12.17	29.8	30.0	12.71	30.65	25.86	9.31	40.33	23.96
Mar	10.24	35.8	29.61	9.83	36.96	24.91	8.01	45.75	22.1
Apr	7.8	45.52	26.48	7.84	41.12	22.68	6.37	49.24	16.79
May	8.84	48.64	19.07	8.79	48.96	19.57	7.83	47.29	15.87
Jun	9.85	51.36	15.34	9.27	48.98	18.03	8.66	45.44	13.52
Jul	11.02	51.24	15.57	9.71	48.73	17.58	8.93	43.63	12.24
Aug	9.97	48.46	20.19	9.0	46.26	18.56	9.04	42.96	12.89
Sep	7.6	39.35	20.76	6.91	38.34	17.95	6.52	35.96	13.32
Oct	6.73	31.62	21.95	6.15	33.56	18.74	5.75	34.21	15.76
Nov	9.19	26.27	29.51	9.19	30.59	22.96	7.32	35.47	20.76
Dec	11.2	19.85	25.57	10.52	23.99	21.58	8.43	28.48	19.63

Table A4. Percent (%) of Black individuals as indicated by American Fact Finder data among census tracts nearest to air pollution monitor, Atlanta metropolitan area, 2010.*

Monitor	Census Tracts (n=783)	Median	Interquartile Range	
South DeKalb	69	72.8	89.1	93.5
Confederate Ave	50	44.8	77.1	88.4
Georgia DOT	88	37	67.3	82
Monastery	21	30.6	42.9	58.6
W Strickland St	26	27.4	41.2	50.6
County Extension	22	20.3	36.5	48.2
Fire Station 8	99	11.2	26.1	47.1
Georgia Tech Near-Road	97	9.3	17.45	57.95
Gwinnett Tech	197	5.9	13.2	23.4
National Guard	114	4.6	8.8	19.8

*Based on 2010 SF1 census data.

Table A5. Percent (%) of households with individuals age 65 and over as indicated by American Fact Finder data among census tracts nearest to air pollution monitor, Atlanta metropolitan area, 2009-2013.*

Monitor	Census Tracts (n=783)	Median	Interquartile Range	
Monastery	21	21.8	20	24.1
W Strickland St	26	18.65	15.3	20.7
County Extension	22	18.55	15.6	19.8
Fire Station 8	99	18.5	10.2	27.6
National Guard	114	18.35	15.7	22.4
Confederate Ave	50	17.3	13	24
South Dekalb	69	17.1	13.6	21.8
Georgia DOT	88	16.2	12.4	22.8
Gwinnett Tech	197	11.4	15.6	19.8
Georgia Tech Near-Road	97	7.2	13.55	20.35

*Based on 5-yr American Community Survey estimates 2009-2013.

Table A6. Percent (%) of individuals with a high school education or less as indicated by American Fact Finder data among census tracts nearest to air pollution monitor, Atlanta metropolitan area, 2009-2013.*

Monitor	**Census Tracts (n=783)**	**Median**	**Interquartile Range**	
Confederate Ave	50	34.13	25.47	46.51
Georgia DOT	88	33	26.96	41.47
W Strickland St	26	32.925	29.29	37.17
Monastery	21	32.7	24.75	35.98
County Extension	22	31.81	24.2	34.78
South Dekalb	69	31.42	25.55	37.81
Gwinnett Tech	197	25.11	16.6	31.37
National Guard	114	21.18	14.89	30.14
Fire Station 8	99	20.5	10.45	33.84
Georgia Tech Near-Road	97	17.615	10.495	33.78

*Based on 5-yr American Community Survey estimates 2009-2013.

Table A7. Median Household Income (adjusted for 2013 inflation) as indicated by American Fact Finder data among census tracts nearest to air pollution monitor, Atlanta metropolitan area, 2009-2013.*

Monitor	**Census Tracts (n=783)**	**Median**	**Interquartile Range**	
National Guard	114	$ 73,490	$ 53,906	$ 97,778
Gwinnett Tech	197	$ 70,261	$ 51,467	$ 91,206
County Extension	22	$ 61,226	$ 43,145	$ 72,361
Fire Station 8	99	$ 57,784	$ 37,857	$ 88,477
W Strickland St	26	$ 56,120	$ 45,830	$ 64,917
Monastery	21	$ 54,146	$ 43,438	$ 67,588
Georgia Tech Near-Road	97	$ 53,589	$ 32,265	$ 72,279
South Dekalb	69	$ 45,877	$ 38,259	$ 56,056
Georgia DOT	88	$ 42,665	$ 33,030	$ 60,798
Confederate Ave	50	$ 34,925	$ 20,047	$ 48,466

*Based on 5-yr American Community Survey estimates 2009-2013.

Table A8. Percent (%) of Black individuals as indicated by American Fact Finder data among census tracts nearest to air pollution monitor, DC, Maryland, and Virginia, 2010.*

Monitor	Census Tracts (n=3,492)	Median	Interquartile Range	
River Terrace Site	124	89.15	77.75	93.6
Hains Point	20	80.9	28.7	95.45
PG Equestrian Center	33	80.3	70.7	86.9
Oldtown	108	74.3	22.9	95.2
MSIC	55	69.1	33	87.8
Northwest Police Station	119	64.6	14.9	87.3
Beltsville	30	55.4	21.5	67.7
McMillan Reservoir	52	53.6	38.35	70.55
Furley	68	50.05	15.8	83.25
HU-Beltsville	37	49.4	26.9	56.9
Tidewater Community College	32	43.4	21.85	66.15
VA Tech Agricultural Research Center	30	40.45	22.8	58.4
Charles City County	50	39.7	19.1	67.2
Southern Maryland	29	30.1	14.4	51.4
NASA Langley Research Center	127	27	11.5	45.9
Beach Road VDOT	92	26.7	13.1	39.3
NOAA Storage Facility	245	23.35	13.8	40.7
Widewater Elem. School - Widewater	62	22.05	16.85	30.9
Takoma Recreation Center	115	21.1	6	41.1
Hanover	25	20.4	13.2	31.2
Howard County Near Road	56	20	8.95	30.6
Lee District Park - Fairfax County	64	19.45	13.45	34.75
Blackwater NWR	61	17.1	6.5	27.3
Alexandria Transportation	38	16.25	5.7	53.9
Fredericksburg Geomagnetic Observatory	52	15.3	13.05	21.7
Bryan Park	111	13	6.3	32.4
Natural Bridge Station	68	12.75	6.05	20.85
Calvert	27	12.4	9.3	23.2
Edgewood	27	12.3	4	20.7
Davidsonville	46	11.8	5.1	24.3
Rockville	128	11.55	6.8	20.45
Albemarle High School	61	11.2	5.8	18.6
Horn Point	26	10.6	8.3	19.4
Aurora Hills Visitor Center	57	10.4	4.4	23.8
Sumerduck - C. Phelps Wildlife Mgmt Area	25	9.8	8.4	14.6
Herman L. Horn Elementary School	163	8.9	3.6	26.3

Essex	45	8.85	3.95	16.35
Long Park - Haymarket	74	8.45	5.2	11.4
Glen Burnie	68	8.1	5.1	22.6
BCFD- Truck Company 20	28	7.8	4.3	16.4
Millington	13	7.8	4.7	11.3
Ashburn - Broad Run High School	109	6.4	4.6	9.1
Hagerstown	35	6.1	2	9.5
Fair Hill	11	5.7	1.3	13
Stevenson Park	158	5.7	3.2	9.9
Frederick Airport	61	5.4	2.1	12.9
Frederick Co. Public School Maint. Dept.	26	4.45	1.7	6.3
Shenandoah National Park - Big Meadows	9	4.2	1.3	8.6
Aldino	38	4.05	2.2	11.2
Verizon Telephone	61	4	2.2	5.9
Harrisonburg VDOT	43	3.1	1.1	6.2
Padonia	48	2.65	1.6	5.6
South Carroll	41	2.6	1.7	4
Piney Run	30	2.1	0.5	4.7
Luray Caverns Airport	18	1.55	1	4.4
Rural Retreat	113	1	0.4	3.2

*Based on 2010 SF1 census data.

Table A9. Percent (%) of households with individuals age 65 and over as indicated by American Fact Finder data among census tracts nearest to air pollution monitor, DC, Maryland, and Virginia, 2009-2013.*

Monitor	Census tracts (n=3,492)	Median	Interquartile Range	
Piney Run	30	32	30.4	35.4
Luray Caverns Airport	18	31.9	28.6	35.2
Horn Point	26	31.3	27.9	39.2
Natural Bridge Station	68	30.65	24.45	33
Rural Retreat	113	30.6	28.5	32.8
Padonia	48	30.3	24.55	35.55
Shenandoah National Park - Big Meadows	9	30.2	27.3	31.4
Blackwater NWR	61	29.9	25	35.4
Herman L. Horn Elementary School	163	29.65	25	33.8
Essex	45	29.6	21.95	35.05
Millington	13	28.6	24	31.7
Hanover	25	28.4	23.4	31.8
VA Tech Agricultural Research Center	30	28.15	26.1	30.9
Harrisonburg VDOT	43	27.4	24.1	31.5
Charles City County	50	26.95	22.4	31.1
Hagerstown	35	26.6	21.9	28.4
Albemarle High School	61	26.4	21.1	30.4
BCFD- Truck Company 20	28	26.3	16.5	29.5
Northwest Police Station	119	26.1	19	32.7
Aldino	38	25.45	22.3	30.6
Frederick Co. Public School Maint. Dept.	26	25.45	22.3	28.8
South Carroll	41	25.4	22.6	27.3
Beach Road VDOT	92	25	18.8	32.1
Sumerduck - C. Phelps Wildlife Mgmt Area	25	24.7	21.3	26.8
Bryan Park	111	24.4	16.9	30.6
NASA Langley Research Center	127	24.3	17.7	31.1
Takoma Recreation Center	115	24.3	17.8	32
Davidsonville	46	23.8	21.4	29.4
Frederick Airport	61	23.5	17.1	27.7
Tidewater Community College	32	23.25	17.2	27.35
Edgewood	27	22.9	16.2	32.1
Glen Burnie	68	22.7	19.4	30
Calvert	27	22.5	17.6	25.7
Rockville	128	22.05	15.2	29.65
Fair Hill	11	21.9	19.7	24.6

Furley	68	21.55	18.3	26.55
MSIC	55	21.45	16.1	27
Southern Maryland	29	21.4	15.1	26.2
Stevenson Park	158	21.35	15.7	28.4
Fredericksburg Geomagnetic Observatory	52	21.1	17.15	27.95
Beltsville	30	21.05	13.7	27.5
Oldtown	108	20.95	13.9	28.3
River Terrace Site	124	20.75	15.8	25.5
NOAA Storage Facility	245	20.5	14.2	27
HU-Beltsville	37	20	10.6	23.1
Lee District Park - Fairfax County	64	20	12.55	29.25
Verizon Telephone	61	19.4	10.4	31.2
PG Equestrian Center	33	19.2	16.2	26.7
Alexandria Transportation	38	17.95	12.1	26.2
McMillan Reservoir	52	17.7	13.3	25.8
Howard County Near Road	56	17.5	11.1	24
Hains Point	20	15.95	12.95	20.2
Aurora Hills Visitor Center	57	13.7	10.4	17.9
Ashburn - Broad Run High School	109	13.65	9.2	18.35
Widewater Elem. School - Widewater	62	13.5	9.3	17.65
Long Park - Haymarket	74	13.3	9	23.7

*Based on 5-yr American Community Survey estimates 2009-2013.

Table A10. Percent (%) of individuals with a high school education or less as indicated by American Fact Finder data among census tracts nearest to air pollution monitor, DC, Maryland, and Virginia, 2009-2013.*

Monitor	Census tracts (n=3,485) †	Median	Interquartile Range	
Shenandoah National Park - Big Meadows	9	47.7	44.7	51.28
BCFD- Truck Company 20	28	47	38.67	54.05
Rural Retreat	113	46.16	39.72	50.82
Piney Run	30	44.41	36.45	48.96
Luray Caverns Airport	18	44.4	41.51	46.7
Essex	45	42.53	31.85	49.33
Charles City County	50	42.29	34.41	48.8
VA Tech Agricultural Research Center	30	41.825	34.47	46.99
MSIC	55	41.55	32.43	48.9
Millington	13	41.35	33.26	44.35
Oldtown	108	40.76	29.78	50.12
Herman L. Horn Elementary School	163	40.59	32.24	45.27
Hagerstown	35	39.85	34.28	45.98
Natural Bridge Station	68	39.715	29.925	45.665
Blackwater NWR	60	39.6	31.34	45.11
Horn Point	26	39.2	30.88	43.94
River Terrace Site	124	39.05	33.775	43.645
Hanover	25	38.61	35.66	42.59
Harrisonburg VDOT	42	37.91	32.61	48.53
Beach Road VDOT	91	37.155	25.4	46.48
Sumerduck - C. Phelps Wildlife Mgmt Area	25	35.48	30.14	43.12
Frederick Co. Public School Maint. Dept.	26	35.01	30.85	40.27
Fair Hill	11	34.07	30.27	43.36
Fredericksburg Geomagnetic Observatory	52	33.98	26.99	40.4
Furley	68	33.76	28.305	40
Southern Maryland	29	33.12	26.16	40.47
Hains Point	20	33.08	13.3	45
Glen Burnie	68	31.71	23.16	42.18
Albemarle High School	61	31.65	21.39	41.9
Northwest Police Station	119	30.58	18.27	39.8
NASA Langley Research Center	127	29.75	21.8	34.95
NOAA Storage Facility	244	29.74	21.4	37.32
McMillan Reservoir	52	29.675	22.97	38.01
Edgewood	27	29.35	23.96	36.35
South Carroll	41	29.16	22.7	33.48

Calvert	27	29.11	27.27	36.68
Tidewater Community College	32	28.73	24.76	37.9
Aldino	38	28.71	24.06	40.73
Frederick Airport	61	26.33	19.31	33.26
Widewater Elem. School - Widewater	62	25.815	20.235	32.45
HU-Beltsville	37	25.63	20.93	30.51
PG Equestrian Center	33	25.27	21.92	31.71
Bryan Park	110	24.15	14.18	32.05
Beltsville	30	22.14	17.72	29.19
Davidsonville	46	21.645	15.7	28.59
Lee District Park - Fairfax County	64	21.35	16.72	27.52
Takoma Recreation Center	115	20.8	8.14	32.68
Padonia	48	20.515	15.745	25.83
Long Park - Haymarket	74	19.805	13.99	27.85
Aurora Hills Visitor Center	56	17.66	7.78	34.38
Stevenson Park	158	17.48	11.25	24.75
Rockville	128	17.3	11.68	26.44
Alexandria Transportation	38	14.995	9.4	29.72
Howard County Near Road	56	14.5	12.05	22.715
Ashburn - Broad Run High School	109	12.86	8.91	18.755
Verizon Telephone	60	7.615	5.485	9.775

*Based on 5-yr American Community Survey estimates 2009-2013.

† Discrepancies in census data led to a calculated percent greater than 100% for 7 census tracts. These census tracts were removed.

Table A11. Median Household Income (adjusted for 2013 inflation) as indicated by American Fact Finder data among census tracts nearest to air pollution monitor, DC, Maryland, and Virginia, 2009-2013.*

Monitor	Census tracts (n=3,492)	Median	Interquartile Range	
Ashburn - Broad Run High School	109	$120,096	$93,235	$151,827
Verizon Telephone	61	$113,614	$87,233	$156,786
Lee District Park - Fairfax County	64	$108,502	$79,780	$120,716
Stevenson Park	158	$107,065	$84,547	$138,355
Howard County Near Road	56	$105,964	$82,563	$135,423
Long Park - Haymarket	74	$104,437	$78,285	$135,227
PG Equestrian Center	33	$100,539	$90,156	$111,935
Rockville	128	$99,539	$76,282	$130,114
Widewater Elem. School - Widewater	62	$99,312	$78,035	$119,264
Davidsonville	46	$98,685	$87,250	$111,438
Alexandria Transportation	38	$97,639	$84,568	$116,685
Beltsville	30	$94,818	$77,905	$110,859
Calvert	27	$92,195	$85,169	$107,585
Padonia	48	$91,568	$76,573	$105,319
Southern Maryland	29	$90,128	$73,621	$102,321
South Carroll	41	$89,728	$78,958	$107,857
Frederick Airport	61	$87,436	$68,274	$102,763
Aurora Hills Visitor Center	57	$87,227	$62,414	$114,559
Glen Burnie	68	$82,678	$65,524	$101,414
Takoma Recreation Center	115	$80,565	$59,840	$124,464
Edgewood	27	$80,380	$68,679	$93,160
HU-Beltsville	37	$75,525	$55,664	$85,203
Aldino	38	$74,488	$66,434	$94,544
Sumerduck - C. Phelps Wildlife Mgmt Area	25	$74,427	$69,408	$97,750
Frederick Co. Public School Maint. Dept.	26	$70,598	$51,287	$76,882
Fredericksburg Geomagnetic Observatory	52	$69,171	$57,005	$87,873
Tidewater Community College	32	$68,483	$41,215	$83,614
McMillan Reservoir	52	$64,489	$53,421	$84,375
Bryan Park	111	$63,177	$46,859	$83,594
Millington	13	$63,054	$54,792	$70,102
Fair Hill	11	$62,733	$53,941	$73,561
Horn Point	26	$61,996	$46,786	$71,458
Hanover	25	$60,298	$48,929	$72,079
Essex	45	$59,963	$50,753	$70,169
Hagerstown	35	$58,968	$42,467	$70,189

Northwest Police Station	119	$58,404	$44,838	$77,976
Beach Road VDOT	92	$58,300	$37,866	$77,086
Furley	68	$55,488	$46,170	$66,259
NOAA Storage Facility	245	$54,850	$43,670	$72,757
Albemarle High School	61	$54,482	$42,396	$67,917
NASA Langley Research Center	127	$54,304	$44,082	$72,445
River Terrace Site	124	$53,888	$42,099	$69,196
Luray Caverns Airport	18	$50,276	$43,951	$56,346
Blackwater NWR	61	$50,266	$38,281	$60,104
Harrisonburg VDOT	43	$49,625	$39,740	$54,840
Shenandoah National Park - Big Meadows	9	$49,579	$43,469	$57,328
Charles City County	50	$48,852	$33,513	$64,680
VA Tech Agricultural Research Center	30	$48,510	$36,307	$62,904
Hains Point	20	$44,356	$28,347	$91,458
Natural Bridge Station	68	$43,127	$36,122	$52,291
Piney Run	30	$43,055	$36,019	$47,604
Herman L. Horn Elementary School	163	$42,857	$34,025	$51,129
BCFD- Truck Company 20	28	$41,855	$35,219	$53,117
MSIC	55	$36,486	$27,214	$45,561
Rural Retreat	113	$36,152	$32,388	$41,178
Oldtown	108	$33,240	$23,843	$50,263

*Based on 5-yr American Community Survey estimates 2009-2013.

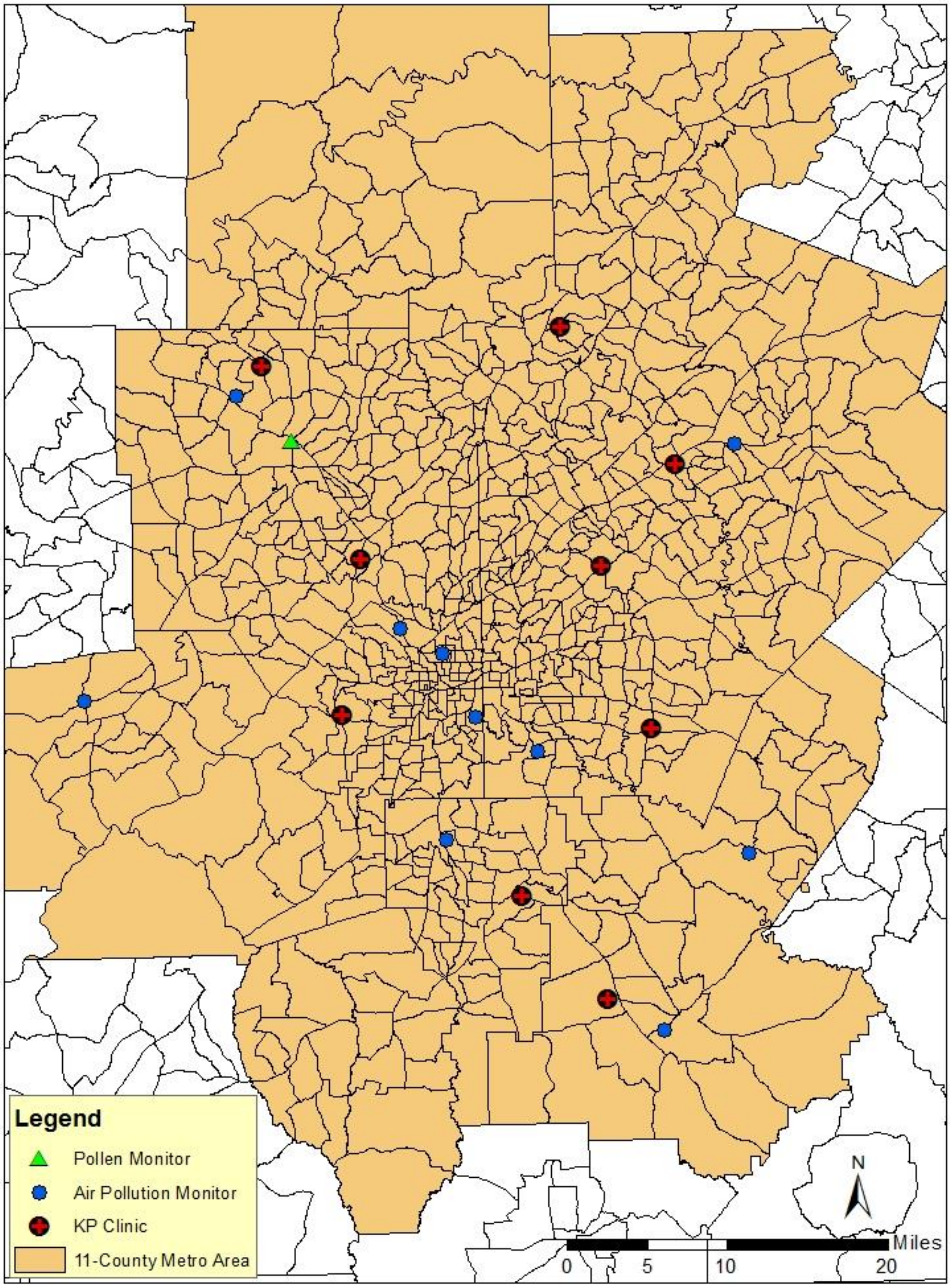


Figure A5. Kaiser Permanente (KP) clinics offering primary care services, air pollution monitors for $PM_{2.5}$, ozone, and NO_2, and a pollen monitor, metropolitan area of Atlanta, GA.

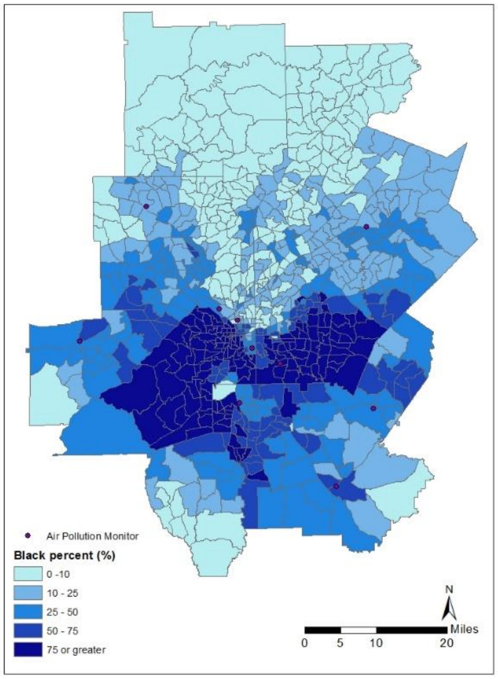


Figure A6. Median Percent of Blacks in Census Tracts Nearest to Air Pollution Monitors, Atlanta, GA.

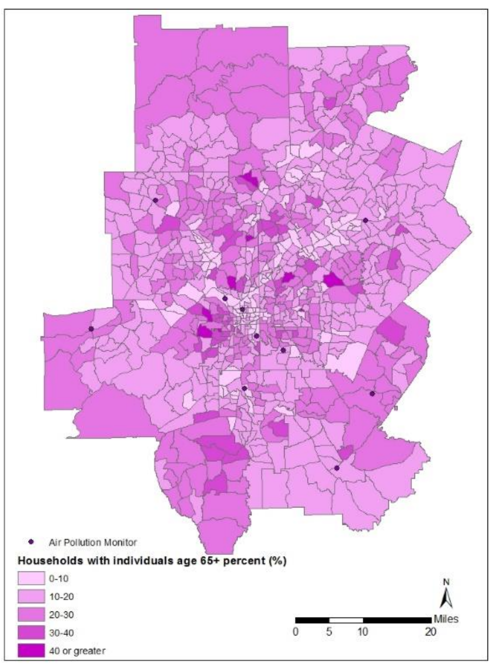


Figure A7. Median Percent of Households with Individuals Age 65 and Older in Census Tracts Nearest to Air Pollution Monitors, Atlanta, GA.

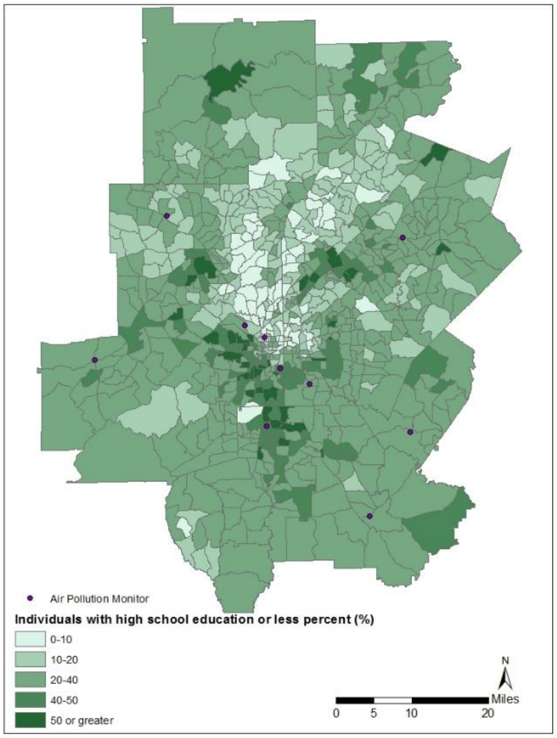


Figure A8. Median Percent of Individuals with High School Education or Less in Census Tracts Nearest to Air Pollution Monitors, Atlanta, GA.

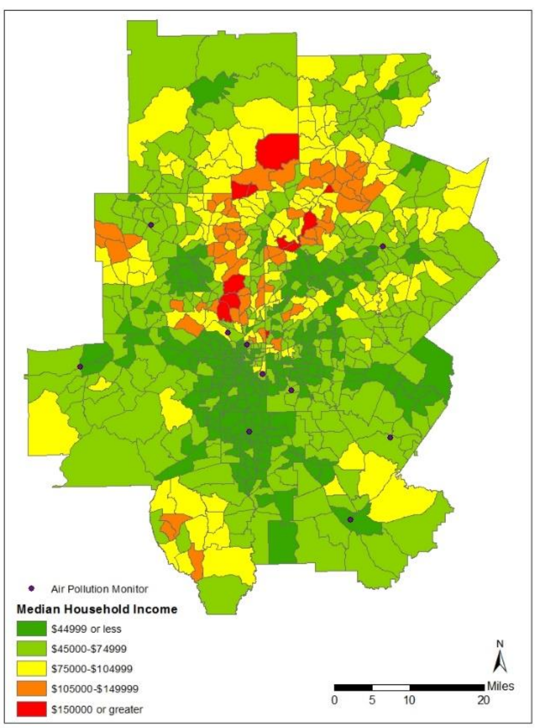


Figure A9. Median Household Income in Census Tracts Nearest to Air Pollution Monitors, Atlanta, GA.

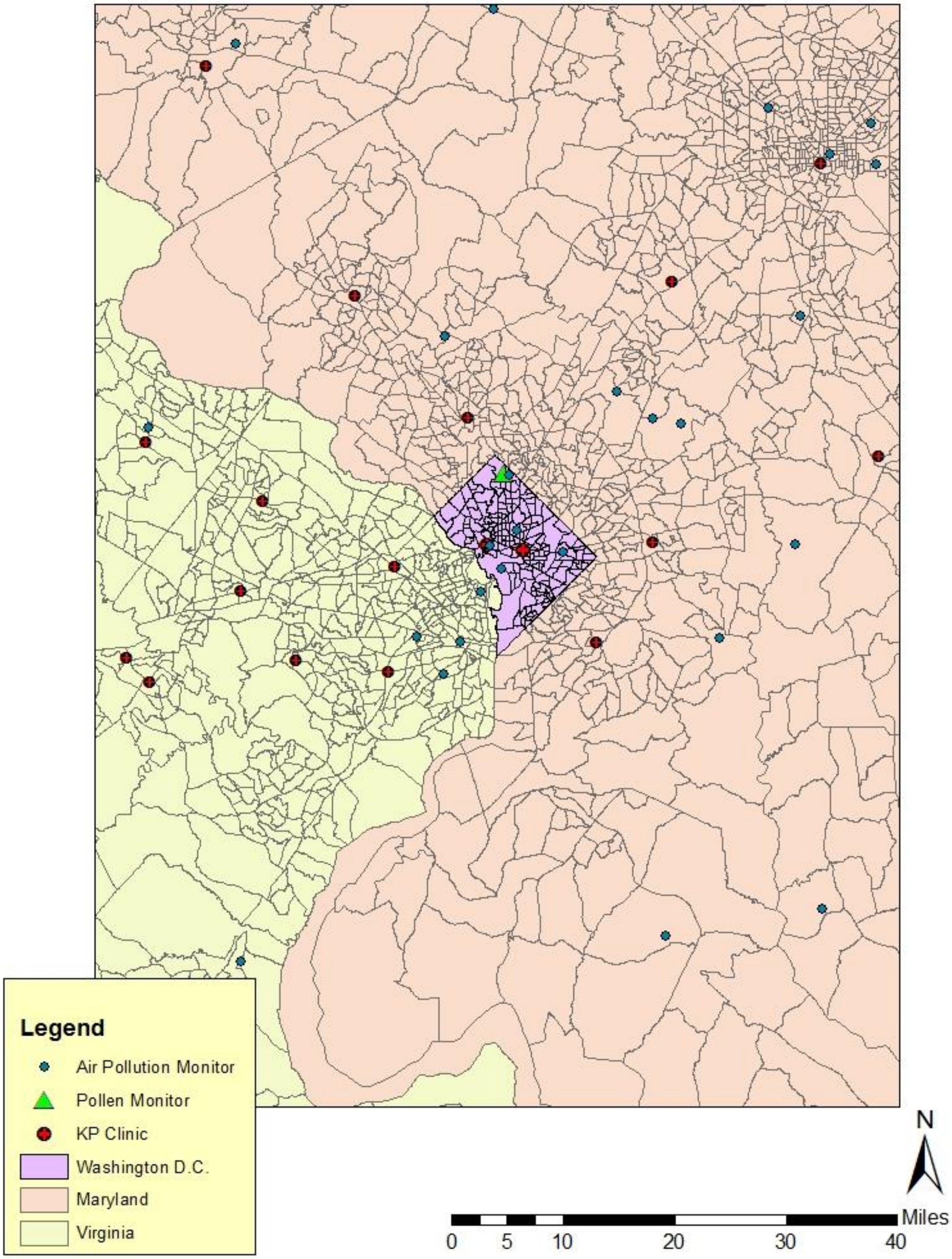


Figure A10. Kaiser Permanente (KP) clinics offering primary care services, air pollution monitors for $PM_{2.5}$, ozone, and NO_2, and a pollen monitor, DC, Maryland, and Virginia.

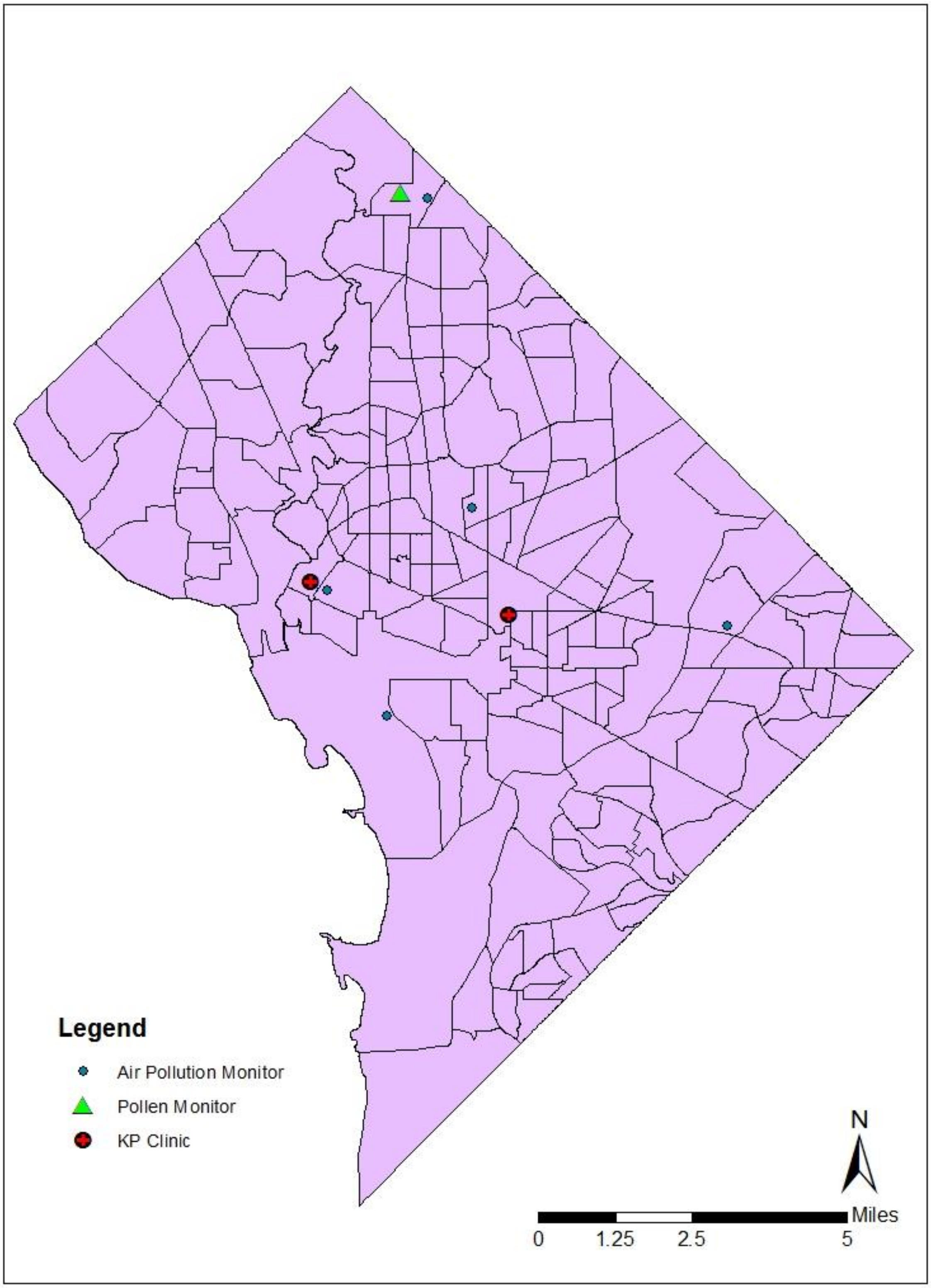


Figure A11. Kaiser Permanente (KP) clinics offering primary care services, air pollution monitors for $PM_{2.5}$, ozone, and NO_2, and a pollen monitor, DC.

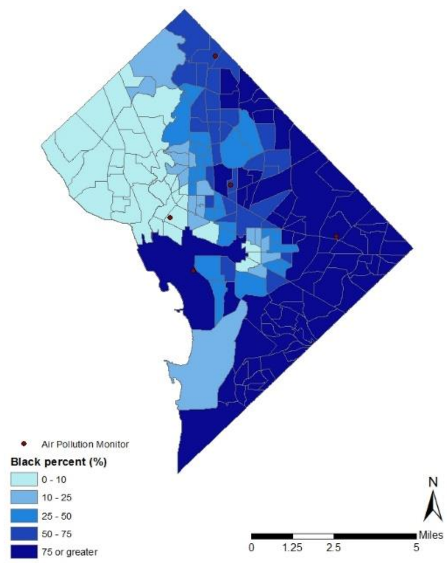


Figure A12. Median Percent of Blacks in Census Tracts Nearest to Air Pollution Monitors, DC.

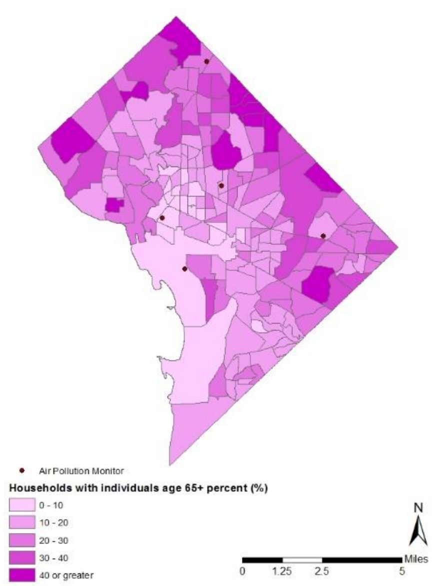


Figure A13. Median Percent of Households with Individuals Age 65 and Older in Census Tracts Nearest to Air Pollution Monitors, DC.

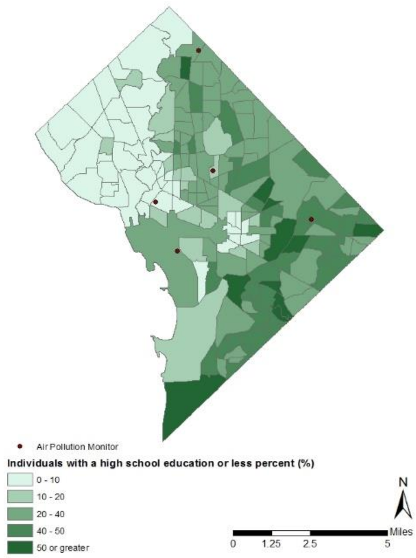


Figure A14. Median Percent of Individuals with High School Education or Less in Census Tracts Nearest to Air Pollution Monitors, DC.

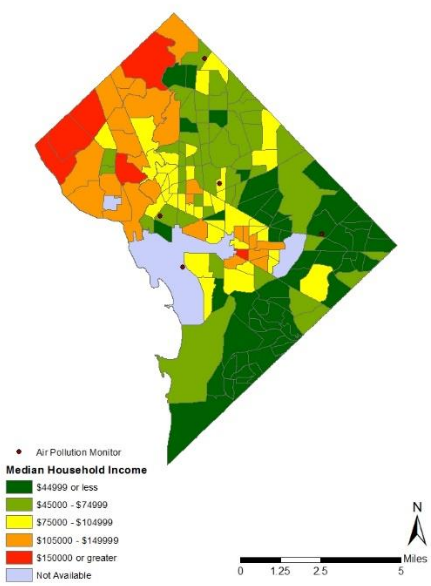


Figure A15. Median Household Income in Census Tracts Nearest to Air Pollution Monitors, DC.

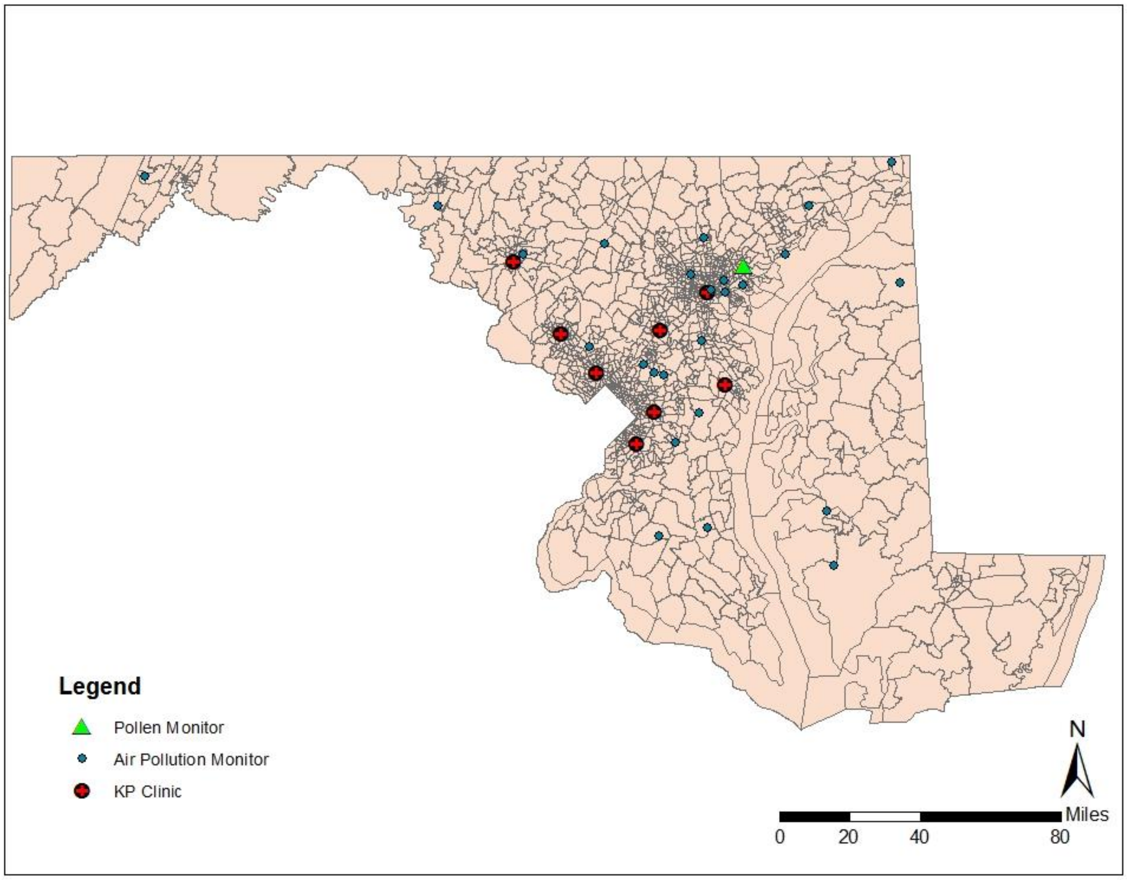


Figure A16. Kaiser Permanente (KP) clinics offering primary care services, air pollution monitors for $PM_{2.5}$, ozone, and NO_2, and a pollen monitor, Maryland.

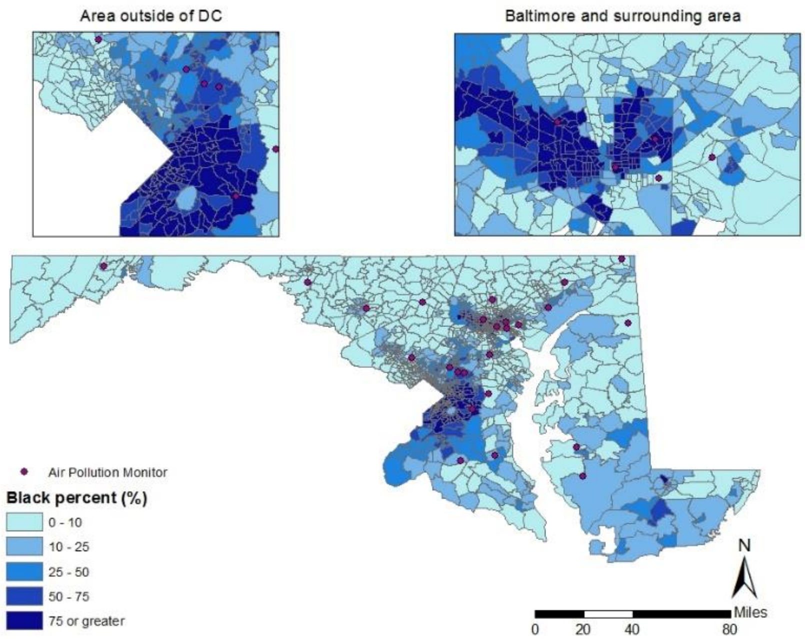


Figure A17. Median Percent of Blacks in Census Tracts Nearest to Air Pollution Monitors, Maryland.

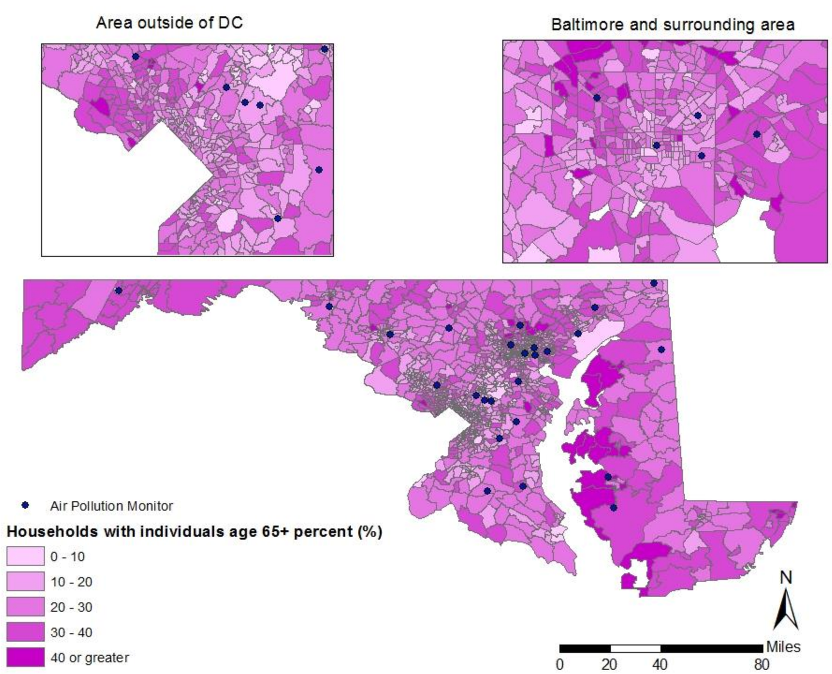


Figure A18. Median Percent of Households with Individuals Age 65 and Older in Census Tracts Nearest to Air Pollution Monitors, Maryland.

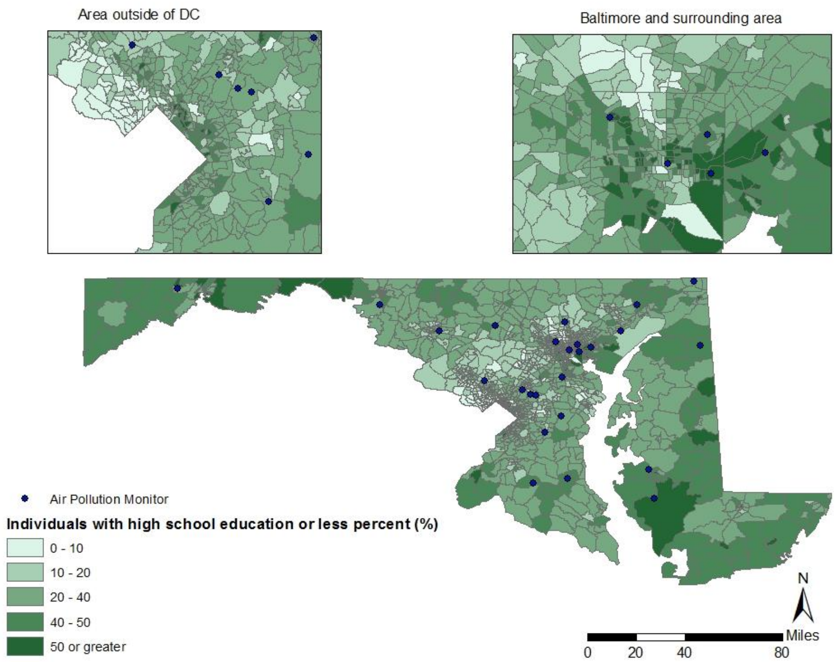


Figure A19. Median Percent of Individuals with High School Education or Less in Census Tracts Nearest to Air Pollution Monitors, Maryland.

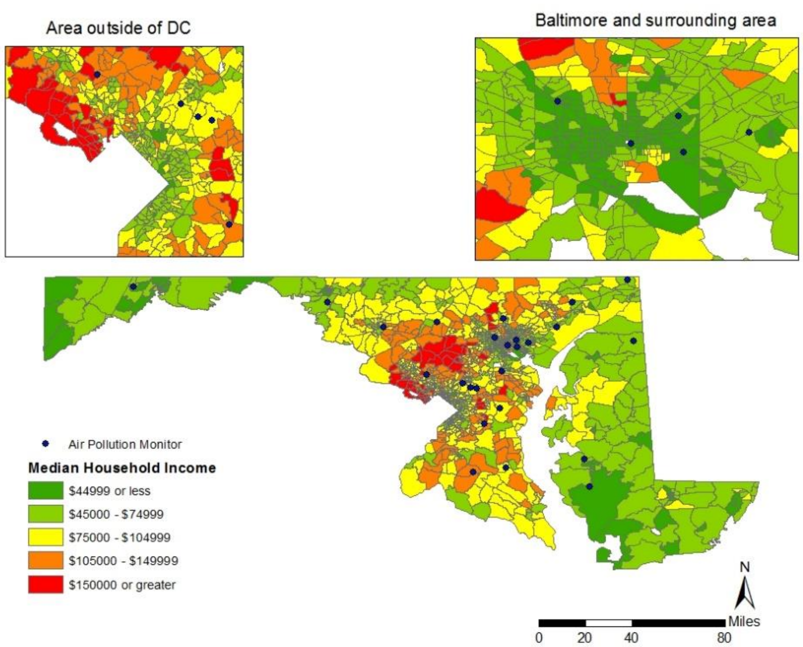


Figure A20. Median Household Income in Census Tracts Nearest to Air Pollution Monitors, Maryland.

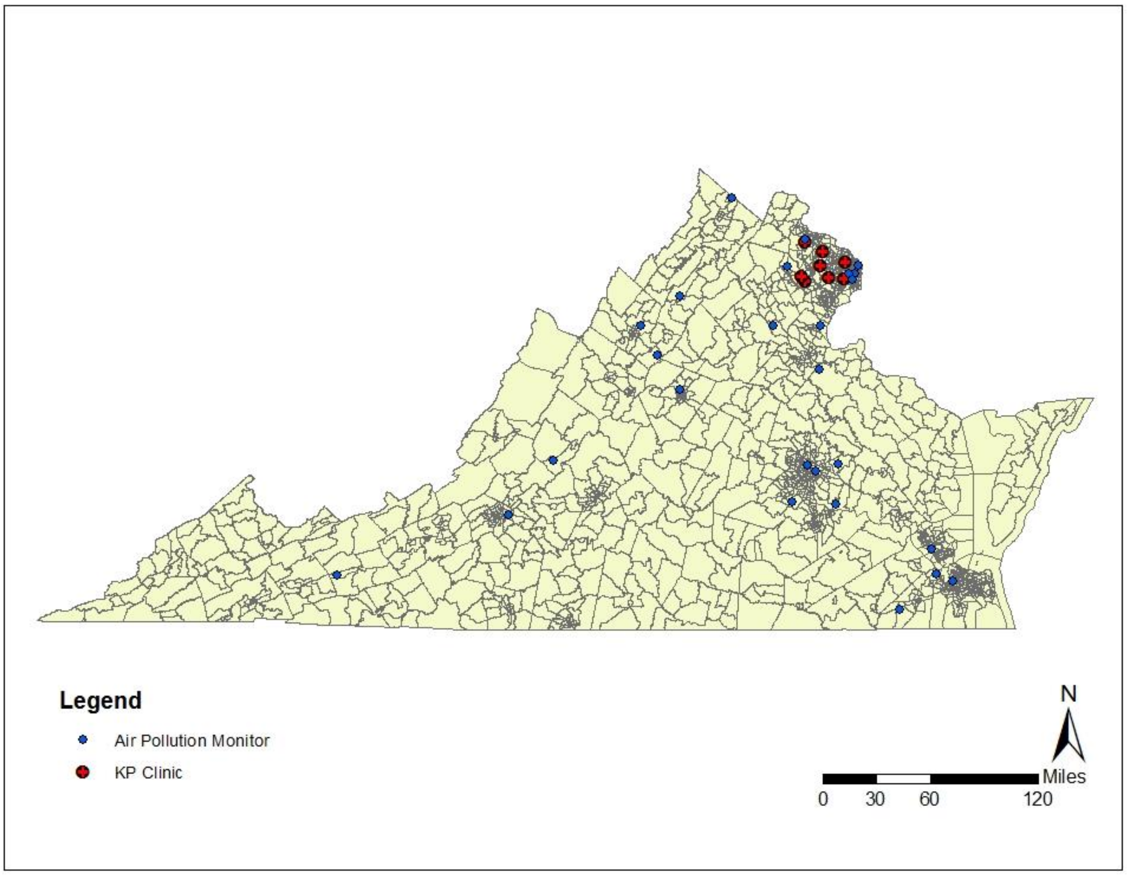


Figure A21. Kaiser Permanente (KP) clinics offering primary care services and air pollution monitors for $PM_{2.5}$, ozone, and NO_2, Virginia

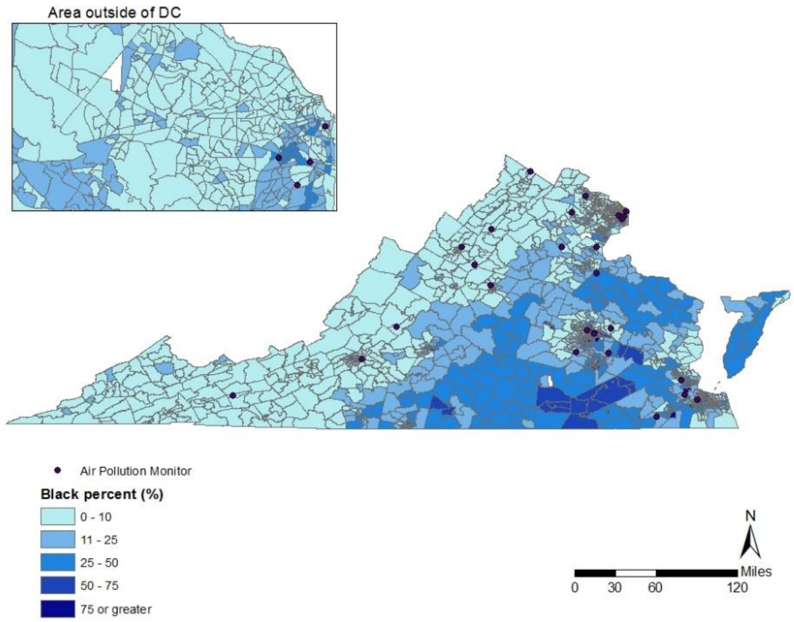


Figure A22. Median Percent of Blacks in Census Tracts Nearest to Air Pollution Monitors, Virginia.

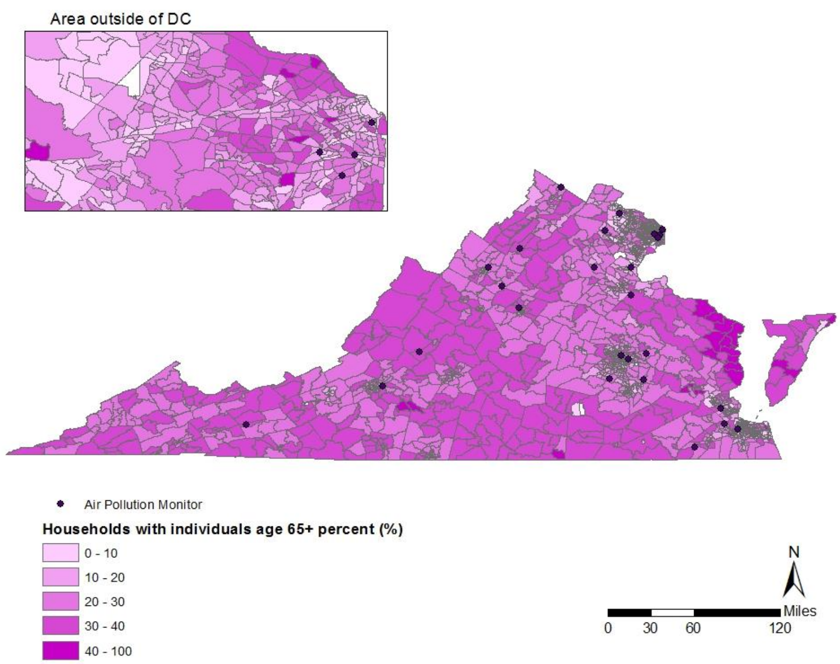


Figure A23. Median Percent of Households with Individuals Age 65 and Older in Census Tracts Nearest to Air Pollution Monitors, Virginia.

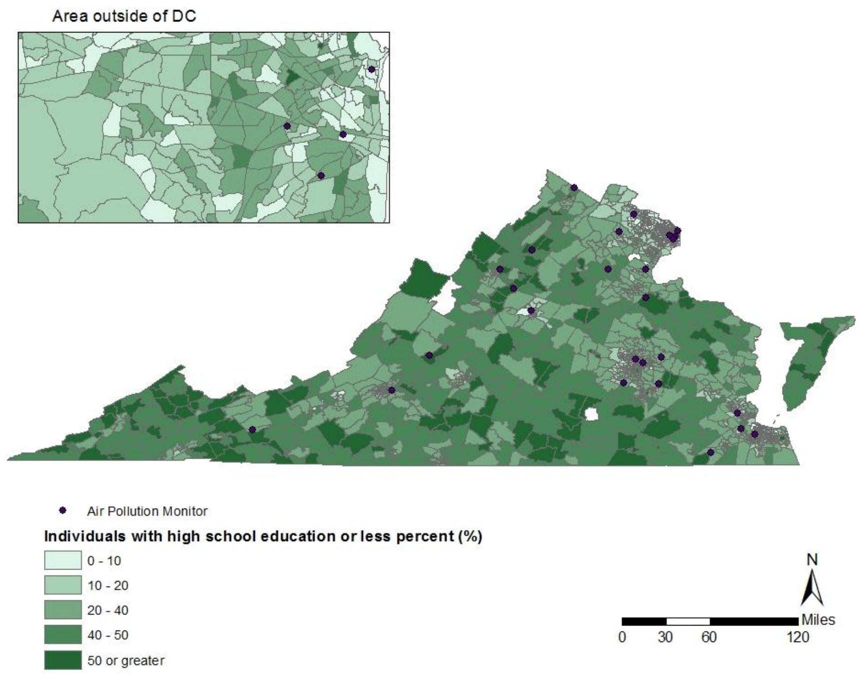


Figure A24. Median Percent of Individuals with High School Education or Less in Census Tracts Nearest to Air Pollution Monitors, Virginia.

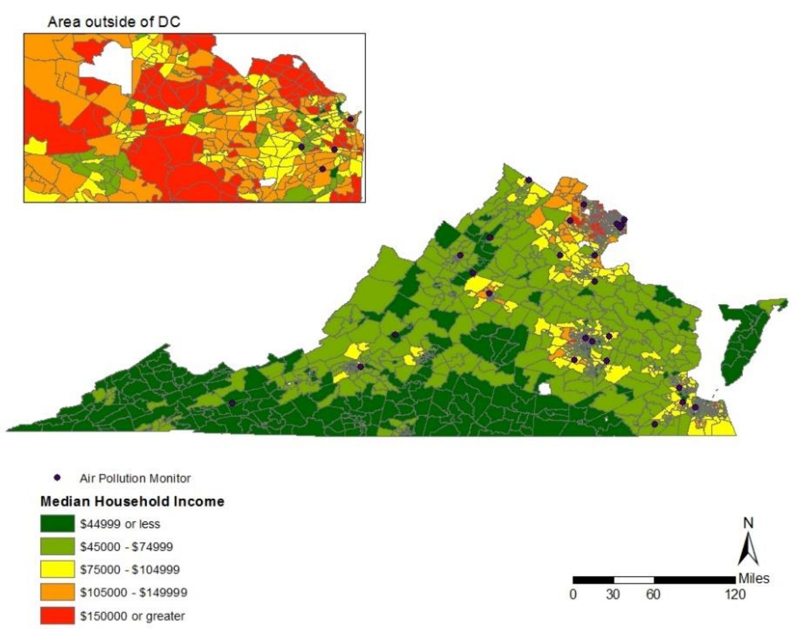


Figure A25. Median Household Income in Census Tracts Nearest to Air Pollution Monitors, Virginia.