Linking Health Outcomes with Environmental Exposures: Asthma and Air Quality

by
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A MASTER'S THESIS

Presented to the Department of Medical Informatics and Clinical Epidemiology
and the Oregon Health & Science University
School of Medicine
in partial fulfillment of
the requirements for the degree of
Master of Science
March 2008

School of Medicine
Oregon Health & Science University

CERTIFICATE OF APPROVAL

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ACKNOWLEDGEMENTS

I would like to thank my thesis committee for all there help with this project. Dr. Joan Rothlein, from the Center for Research on Occupational and Environmental Toxicology (CROET) has been extremely instrumental in helping me frame and analyze the questions and data for this project. Joan helped me secure a workstation with GIS software in CROET where I could complete the project and gave me so much encouragement and helped motivate me to complete this research. Dr. Judy Logan and Dr. Christopher Dubay gave me the extra push I needed to finish this thesis. I am grateful for the advice and encouragement given to me by my PI, Dr. Thomas Yackel. I would especially like to thank Phil Allen of the Oregon Department of Environmental Quality. He was instrumental in providing the air quality data and answering any question I had about the data. I would like to thank the OHSU Emergency Department, especially Christopher Bangs, for providing the health care data. Christopher Bangs really helped me learn GIS and gave me several ideas on data analysis. Lastly, I would like to thank my parents and my wife Christina for supporting me and encouraging me through this process.

ABSTRACT

The objective of this research was to analyze the correlation between the proportion of asthma visits to all health care visits at the OHSU Emergency Department and the air pollution levels for the time period between July 18, 1999 and July 17, 2000. The analysis was accomplished using a robust air pollution model from the Oregon Department of Environmental Quality (DEQ) called the Portland Air Toxics Assessment Program (PATA). Similar studies have compared health data to modeled air pollution from single sources. This study utilized model data derived from multiple sources for the Portland metropolitan area. Air pollution concentration levels for diesel particulate matter (PM), benzene and chromium were extracted from the model for 938 geographic points or virtual receptors. The concentration results were averaged for the study year for each receptor. The virtual receptors corresponded to census block groups within the geographic domain of the study. OHSU ED patient residence locations were mapped out within the study domain for the study year. Air pollutant concentration levels computed for each virtual receptor (census centroid) were divided into quartiles from low to high pollution levels. The proportion of asthma visits per all OHSU ED visits for each quartile was calculated. A risk ratio was calculated for each concentration quartile to determine trends in proportion of asthma visits with concentrations of air pollution. The results showed a statistically significant trend in rising risk ratio with increased air pollution concentrations for benzene and chromium in the study domain. The results did not show statistically significant risk ratio trends for diesel PM. The results do not take into account several confounding factors such as work history and is limited to exposure at the given patient residency. However, the research indicates surprising trends in the correlation of asthma visits and benzene and chromium exposure which warrants further study.

INTRODUCTION

Asthma is a disease of rising prevalence in the United States, increasing from 3.1 % in 1980 to 7.3 % in 2001. In 2004, it is estimated that over 20 million people in the United States reported an asthma attack over a 12 month period [1] and in 2005,asthma was the twelfth most common diagnosis for emergency department (ED) visits [2]. In 1998, the annual health care cost for asthma in the United States was estimated at $12.7 billion. Due to the increasing burden of asthma on public health and health care costs, there is great interest in determining preventable causes of asthma exacerbation.

One of the major preventable causes of asthma exacerbation is poor air quality. The three primary characteristics of asthma: airway inflammation, altered epithelial function, and recurrent airflow obstruction [3] make the asthmatic more susceptible to airborne irritants than a non-asthmatic. Several studies have linked exposure to Hazardous Air Pollutants (HAPs) and asthma exacerbation in adults and children [3, 4, 5, 6]. Because of the HAPs' burden on health and well being, the Environmental Protection Agency (EPA) started the National Air Toxics Assessments (NATA) in 1996 with the goal of identifying HAPs for large geographic regions in the United States.

The NATA is a comprehensive evaluation of air toxics in the United States for 1996. The goals of NATA were to compile a national emissions inventory of air toxics emissions from outdoor sources, estimate ambient air toxics concentrations, evaluate population air toxics exposure, and estimate the risk of that exposure level. Thirty-three air pollutants were the focus of NATA. The 33 pollutants include a subset of 32 listed in the Clean Air Act plus Diesel Particulate Matter (PM). An air dispersion modeling system was used to produce ambient air pollutant levels over the entire United States based on actual air monitoring data, topography and meteorological factors [7]. Once NATA data became available, local municipalities took advantage of the data to perform their own, more detailed analyses.

The Portland Air Toxics Assessment Program, PATA, is a local extension of NATA. PATA utilized the NATA modeling data to identify a subset of 12 HAPs (1,3-butadiene, primary acetaldehyde, primary acrolein, arsenic, benzene, chloroform, diesel PM, primary formaldehyde, nickel, polycyclic organic matter, perchloroethylene and chromium) that were at relatively high levels in the Portland metro area. Emissions inventories were compiled from July 18, 1999 to July 17, 2000 and were combined with monitoring data in an air dispersion model. The model output the ambient concentrations of each of the 12 air toxics for the Portland metro area.

In addition to air toxics concentrations, PATA included an evaluation of population exposure and a risk assessment for the air toxics [6], including 3 which have been identified as triggering asthma exacerbations: - diesel particulate matter, chromium and benzene [3].

Diesel PM is a very significant pollutant within urban areas and can affect the health of individuals exposed to high concentrations. When diesel fuel is combusted, the exhaust is made up of mainly carbon and adsorbed organic compounds. Smaller amounts of particulate sulfate, nitrate, metals and other trace elements are present in diesel exhaust. These particles range in sizes from $< 0.1 \mu m$ to $10\ \mu m$ and greater. Because of the ultra-fine qualities of diesel particulates, the particulates can easily become airborne, enter and reach deep lung regions [9].

The EPA Health assessment document for diesel engine exhaust report cites health effects from both short and long-term exposure to diesel PM [9]. Diesel PM exposure has been shown to exacerbate asthma by causing inflammation of the lungs and acting as a courier of allergens into the deeper parts of the lungs [10, 11].

Chromium is a metal primarily used for making steel and is also used in chrome plating, making dyes and pigments, leather tanning, and wood preservation [12]. Chromium particulates can be found near lumber mills and metal working factories. These small aerosolized chromium particles can be inhaled deep into the lungs. There is little data to indicate that links asthma exacerbation and high open air concentrations. However, it has been demonstrated that workplace exposure to aerosolized chromium may cause occupational asthma [13, 14].

Benzene is an air toxic that, in urban areas, primarily eminates from cigarette smoke and is expelled through the exhaust of automobiles from unburned fuel [15], [16]. It is a volatile organic compound (VOC) and a known carcinogen. Wood burning is another common source of VOCs, although less common in urban areas [17]. Benzene is another pollutant which exacerbates asthma. A study following the air pollutant exposures of asthmatic Hispanic youth in Los Angeles found a correlation between increased exposure to benzene and exacerbation of asthma [18]. In a more recent study, Arif and Shah examined a cross section of 550 adults in the United States and found that aromatic compounds, such as benzene, increased the rate of adverse respiratory effects [19].

While there are several studies linking diesel PM, chromium, and benzene to asthma, there is releatively little known about whether modeled air polution data can be used to evaluate health condition prevelance. For instance, in 2002, Levy et al evaluated the health benefits of adding pollution control systems to five local power plants in the Washington DC area [20]. Levy modeled possible dispersion of pollution from the power plants with and without pollution controls. Oyana, in 2004, evaluated the rates of asthma in proximity to known pollution sources in the Buffalo, NY area [21]. In both these cases the pollution dispersion was modeled from one or two types of sources.

RESEARCH QUESTIONS:

For this study, modeled air pollution levels for diesel PM, chromium, and benzene (as determined by the PATA study) will be evaluated against asthma visits at the OHSU Emergency Department (ED) to attempt to answer the questions:

1. Can asthma emergency department data be spatially and temporally linked with air quality dispersion model data?

2. Does this linkage demonstrate an association between asthma and air quality measures?

The main hypothesis for this study is that there will be an increased proportion of asthma visits per all OHSU emergency department visits with exposure to increased concentrations of benzene, diesel PM or chromium.

MATERIALS:

Programs and Databases Used:

Geographic Information System (GIS)
A geographic information system is a program or set of programs used to capture, store, analyze and display data on maps [22]. A GIS System can take non geographic data and link it to a geographic or spatially based data. It can calculate a spatial component for non-spatial data by analyzing geographic components of the data, like a street address. Most GIS applications allow a user to select data visually, by highlighting areas on a map. In this study, the GIS application used is ARC GIS Version 9.1.

Perl 5.0 is a scripting language used in this study for text and data manipulation.
MySQL version 5.0 was used to store GIS and pollutant modeling data.
MS Access 2003 was used to store Emergency Department data.

Modeled Pollution Data:

The dispersion model program chosen for PATA is CALPUFF. CALPUFF is a meteorological and air quality modeling system. Sponsored by the California Air Resources Board (CARB), CALPUFF was developed by scientists at Sigma Research Corporation and is maintained and supported by the Atmospheric Studies Group ASG. CALPUFF is available for free download and is distributed by the TRC Company, an engineering consultant firm. The CALPUFF dispersion model system has been peer reviewed by the EPA in 1999 and has been certified for regulatory level modeling work. It has been used to estimate population exposure to power plant emissions in Beijing and Illinois and more recently to model transport of small particles from the World Trade Center following September 11, 2001. CALPUFF is the tool used for PATA to accurately model the concentrations of an air pollutant to hundreds of geographic points within the Portland Metro Area.

CALPUFF utilizes a Gaussian puff model that disperses puffs of pollutants. Point sources and plume heights of pollution emitters, temperature and wind fields can be taken into account by the modeling system. Additionally, CALPUFF is able to take into account the pollutant transport, transformation and removal from the atmosphere over the course of the modeling period. According to the CALPUFF users guide, CALPUFF contains algorithms for near-source effects. Examples of near-source effects would be building downwash (buildings will cause pollutants emitted from elevated sources to be mixed rapidly towards the ground due to aerodynamic turbulence) and plume rise effects. In essence, CALPUFF excels in modeling what happens to an emitted pollutant near its source. CALPUFF contains algorithms that take into account long-range dispersion effects such as wet deposition (settling of pollutants due to rain fall) and dry deposition (natural settling of pollutants as they slowly settle towards the ground) [23].

The parameters used in CALPUFF are the key to acquiring accurate and reliable pollutant concentration results. For PATA, the geographic domain selected for the study was the Portland Metro Area, focusing on Multnomah County, Washington County, Columbia County, Clackamas County and parts of Clark County in Southwest Washington State. Specifically, the domain is contained by a 60 x 50 km region with its Southwest corner at UTM (Universal TransMercator) coordinates 495000 meters east and 5015000 meters north. Figure 1 shows a map with two domains displayed. The outer rectangle is the monitoring domain described above. The inner rectangle is the inner domain where real life air pollutant monitoring and inventories were processed by PATA.

Meteorological data for CALPUFF was retrieved from the National Weather Service (NWS), the Portland Airport and DEQ's own weather monitoring data. The topography and terrain data were obtained from the United States Geological Survey (USGS) Digital Elevation Model (DEM). Land cover data was obtained from USGS and Oregon state agencies.

The CALPUFF dispersion model requires input from real world pollution sources in the Portland Metro Area. The DEQ evaluated what types and amounts of emissions were present in the area. In 1999, as part of the Statewide Emission Inventory project, DEQ evaluated the types of emissions and emission sources for Washington, Multnomah and Clackamas County. Additionally, raw emissions data and emission point source locations were determined. For each stationary point source, parameters such as stack height and velocity of the emissions were collected. Emission sources were broken down into five distinct categories to be modeled separately in CALPUFF:

1. Industrial point sources
2. Area sources*
3. On-road mobile sources
4. Non-road mobile sources
5. Special non-road sources

*Area sources were not calculated for Diesel PM.

Industrial point sources include manufacturing plants, power plants and other major air pollutant emitters. Industrial sources are considered major point sources. For these sources, emission release height, velocity and temperature were collected.

Area sources are sources of pollution that have smaller emissions than major point sources and can arise from varied forms of emission production. As defined by the Clean Air Act, an area source includes facilities or practices that emit less than 10 tons of a single air pollutant or less than 25 tons of toxic air pollutants in one year. This would include facilities like dry cleaners, wildfires and prescribed burns. Estimates of area emissions are based on land use data and burning permit information. In the case of dry cleaners, Oregon law requires the exact location of all dry cleaners to be registered with the state. This source data was combined to provide total area source data for the CALPUFF model.

On-road mobile sources mainly include motor vehicle traffic along the major highways and arterials of Portland. DEQ used traffic patterns from Portland Metro for input into CALPUFF. The traffic pattern data came from Metro's EMME/2 program. EMME/2 is sophisticated traffic modeling software that models how traffic flows in a particular road network.

Non-road sources include commercial/recreational marine vessels and railway traffic.

Special non-road sources include aircraft and construction vehicles. Construction vehicle location was based on construction permit data which showed the type of vehicles and durations the vehicles were at a particular location.

As a part of the emissions inventory, data from DEQ's monitoring stations were used as input and validation points for the CALPUFF model. The DEQ has seven air monitor stations strategically placed throughout the Portland Metro area. Air monitoring stations are located in Northeast, Northwest, Southeast, Southwest (downtown) Portland and Beaverton. These monitors measure levels of 12 target pollutants on a 24 hour basis and are generally used to calculate air pollution concentrations for their respective region.

Each emission data point is entered in with a spatial location value and a temporal value. With this data, the dispersion model can accurately calculate air pollutant concentration levels spatially and output those levels over the period of a year with a resolution of one hour. CALPUFF needs output virtual monitors to be entered into the model. These points are where CALPUFF will calculate concentration values. In the case of PATA, 938 points were determined for the output. Because PATA is to be used for estimating population exposure levels, the points chosen were the centroids of census blocks and census block groups.

A *census block* is the smallest geographical unit of measure for the United States Census. Census blocks are bounded on all sides by visible features such as streets, streams and railroad tracks. They can be bound by invisible features such as city and county borders. Census blocks are usually fairly small in size in urban areas, comprised of 5 to 10 city blocks. In rural areas, as the population become sparser, the census block area increases in size. *Census block groups* are census geographic categories that contain several census blocks. . The centroid is a point used to represent the center of a census block or block group. In some cases, the cenroid may not actually exist within the block group, for instance, a block group may have a crescent shape. In this case the centroid would be located at the center of the crescent rather than lie within the crescent area.

The output of the CALPUFF data was a flat file for each pollutant in each of the 5 sources calculated. For instance, benzene would have 5 flat files associated with it. These flat files contain the UTM coordinates for the 938 output receptors and concentrations at each receptor point at every hour for one year.

There was an earlier run on 1999 data in order to compare the model pollutant concentrations with that of the monitor reading for the same period. The CALPUFF model was adjusted following those comparisons. For instance, airline traffic originally was modeling only for exhaust fumes on the ground. For the final model run, the model took into account ground traffic and exhaust just after take-off. It was found that the model met the specifications for accurately matching the monitor data.

OHSU ED Data:

The ED visit data in 1999 – 2000 at OHSU was recorded on the EmSTAT Emergency Department information system. EmSTAT is a product of AllScripts™. Before the patient discharge, clinicians entered their primary and secondary diagnosis (if applicable) into EmSTAT. The diagnoses are selected from a pick-list linked to ICD-9 CM codes.

For this study, OHSU ED patient data (asthma and non-asthma visits) from July 18, 1999 – July 17, 2000 were used for analysis. Patient names were removed from the data set to protect patient confidentiality. The following data fields from the OHSU ED were obtained:

- Admittance date/time
- Diagnosis
- Age
- Gender
- Race/Ethnicity
- Street/Residential address

METHODS:

In order to analyze the correlation of asthma visits at the OHSU ED with the PATA modeling data, the two data sets were linked temporally and spatially using ARC GIS. For each pollutant concentration, the proportion of asthma visits to the ED to all ED visits were determined for a given location and time between July 18, 1999 and July 17, 2000. Average concentrations for benzene, diesel PM and chromium were calculated for the year and at monthly increments at each census block centroid.

Processing PATA model data:

The PATA project averaged the modeled concentrations for the entire year's worth of data. My study required concentration data at a more finite temporal level. In order to average the PATA concentrations for smaller time periods, the raw output from the CALPUFF model was required. As described above, the PATA data was output by CALPUFF in large flat files. In order to use the data with GIS, the data had to be entered into a database. MySQL was chosen as the database because it is free for use in a research setting and it's capable of handling large amounts of data. The flat files represented a source type for a particular pollutant. For example, one flat file would only contain the non-road concentrations for benzene for the entire year at every hour. In order to process these files into a form useable by GIS, a relational database was created as seen below. For ease of use with GIS, three tables were created to hold this data. One table was created to hold the XY coordinates, in UTM, for the locations of the 938 virtual receptors created by CALPUFF. Another table was created to hold the flat file names and their corresponding air pollutant and source. This table was then tied to the very large table of hourly concentration data corresponding to each source and each XY coordinate. A Perl script was coded to parse the flat files and load them into the database given the directory location of all the flat files.

For this study, the PATA data is stored in a MySQL Database version 5.0. The tables used to store the PATA data are as follows. tblCoord stores the coordinate data for each virtual receptor form the CALPUFF output. The following table lists the fields for tblcoord.

tblCoord	
Field	**Function**
cid	Primary Key
Receptor	Receptor ID
SourceID	Source of Coordinates
XCoord	UTM X Coordinate
YCoord	UTM Y Coordinate

Table 1

The numerous source files for the pollutant data were stored in the table tblSourcePoint_final. The ID for each pollutant model source would later be tied to the main concentration data. The location of the source filename was stored in this table as well along with a description of the file and a receptor count for quality control of the perl loader. The description indicates the pollutant for each source. The following table lists the fields for tblSourcePoint_final.

tblSourcePoint_final	
Field	**Function**
sID	Primary Key – Source Point ID
Description	Text description of source data
Filename	File name and path of source file
ReceptorCount	Number of virtual receptors reported in source file

Table 2

The table, tblPataout, stores the bulk of the modeling data. All the concentration data from each source, receptor and concentration for every hour of the PATA study year. TblPataout stores the source id and receptor id in order to tie the concentration data back to a pollutant source and for mapping a concentration value to a specific geographic location. The day value from the source files was stored as the number of days since January first of the record's year. In other words, day 199 for the year 2000 would be correspond to July 18, 2000. These dates were converted to the more traditional mm/dd/yyyy format and stored in the field pDate. The mm/dd/yyyy format allowed for more standard querying of the data using SQL script. The following table lists the fields for tblPataout.

tblPataout	
Field	**Function**
SourcePoint	Primary Key – individual record ID
SourceID	Links table to tblSourcePoint_final and source files
Year	Year of modeled concentration
Day	Date of modeled concentration
Hour	Hour of modeled concentration
Value	Modeled Concentration result
pDate	Date formatted as mm/dd/yyyy
pDay	Day of the month
pMonth	Two digit month

Table 3

An initial projection, or map, was needed to map the OHSU ED and PATA data to. The locations of the virtual receptors served as the basis for the maps in this study. Of the 938 virtual receptors generated by the PATA model, 932 corresponded to census centroids. The PATA project mapped virtual receptors to census block group centroids within its geographic domain. In rural regions within the domain, PATA mapped the virtual receptors to 1990 cenus tract centroids. Within the Portland metro area portion of the PATA domain, 5 receptors mapped to census tract centroids. All virtual receptors within Washington state mapped to census tract centroids as well. All other receptors, save the 7 monitor locations, mapped to census block group centroids. This receptor geographic layer was projected on the 1983 NAD geographic projection. For each receptor, the boundaries of the corresponding block group or tract were mapped onto the projection. This projection was to be used for all the subsequent layers in order to map all the receptor points and pollution concentrations corresponding to block groups or census tract regions accurately.

All virtual receptors represented a point for the modeled concentrations for benzene, chromium and diesel PM. For the purpose of this study, the modeled concentration at a given virtual receptor was used to represent the ambient concentration for the virtual receptors' corresponding census block group or tract. . ArcGIS shape files for the 1990 block groups and tracts for Oregon and Washington were obtained from the US Census website (http://www.census.gov). Utilizing ArcGIS' ability to link tables with geographic data, census tracts and block groups corresponding to the PATA domain were filtered out of the census shape file data. Three distinct data layers were created. Oregon PATA domain census tracts and block groups and Washington PATA domain census tracts. These distinct layers were then merged into a PATA domain layer which was used to assign a virtual receptor concentration to an area within the PATA domain. The PATA domain layer is shown in Figure 1 below:

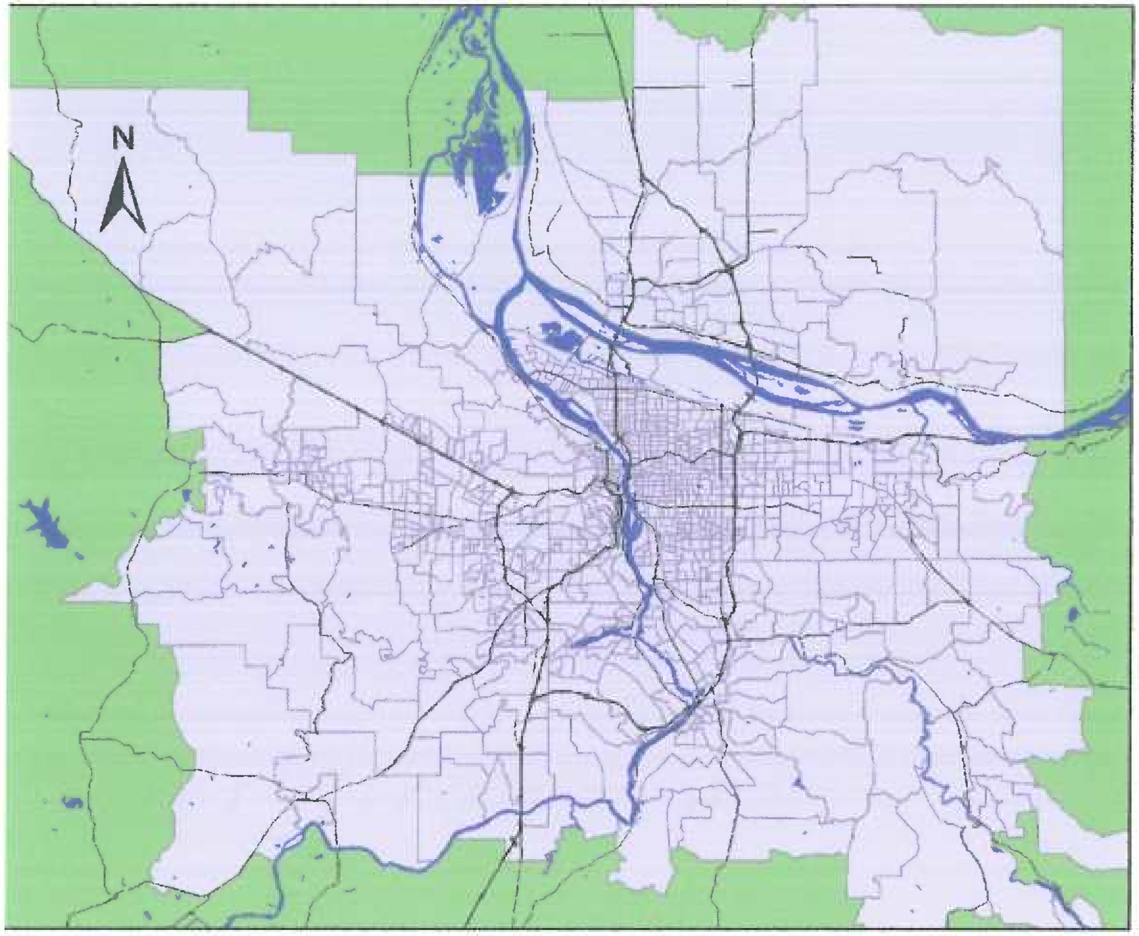

Figure 1 - PATA domain map

The PATA domain is the lavender colored area on the map above. The darker black lines indicate the major highways in Oregon and Washington and the blue areas indicate the major waterways within the domain. The grey lines are the boundaries for the census block group and tracts. The large blue river in the north eastern part of the map is the Columbia River. The major river traversing north and south through the map is the Willamette River.

Each census block group and census tract in the PATA domain was linked to a concentration value of benzene, diesel PM and chromium. For the PATA study, the DEQ summed the concentration values from each source for their final output. For this study, the concentrations for each source at each virtual receptor were summed for each pollutant at each hour. The summed concentrations were then averaged for each virtual receptor and each pollutant for the year from tblpataout and loaded into three separate tables:

- tblDiesel_avg_year
- tblBenzene avg_year
- tblChromium_avg_year

The fields included in these tables are as follows:

- SourcePoint (corresponding to the virtual receptor IDs)
- Avg_val (the average concentration for the given pollutant)

DEQ provided a table listing the background concentration levels for each pollutant by virtual receptor ID. The background concentrations were added to the calculated average concentrations. Because the PATA study covers the time period between July 18, 1999 and July 17, 2000, 12 date divisions were created, dividing the dates at the 18th of the following month. A date range ID was created for each of these date ranges for use in the mySQL database. A date range ID of 1 corresponded to the time period between July 18th 1999 and August 17th 1999. A date range ID of 2 corresponded to the time period between August 18th and September 17th, 1999 and so on.

Summed pollutant concentrations were averaged for the time periods corresponding to the date ranges calculated above. These data were loaded into three new tables:

- tblDiesel_avg_dateranges
- tblBenzene_avg_dateranges
- tblChromium_avg_dateranges

The tables above contained the following fields:

- SourcePoint (corresponding to the virtual receptor IDs)
- Avg_val (the average concentration for the given pollutant)
- dRange (the date range ID for the averaged concentration data)

With the pollutant concentration data set up in a consolidated format, average concentrations could be compared with the proportion of asthma visits per all OHSU ED visits.

In the 1996 NATA study, the EPA estimated nationwide background air pollutant concentrations. These background concentrations needed to be added to the monthly and yearly aggregated results for the pollution concentrations. Diesel PM had census block group/tract specific background concentrations values. The background concentrations for benzene affected the entire domain. There were no background concentration values to add for chromium. Listed below are the background concentrations for benzene and diesel PM:

Pollutant	Annual Average Background Concentration ($\mu g/m^3$)
Benzene	0.48 (all census block group/tracts effected)
Diesel PM	0.24 – 0.42 (census block group/tract specific)
Chromium	No background reported

Table 4 – Background Pollutant Concentrations Added to PATA Results

These concentration corrections were taken into account when calculating the exposure concentrations from the raw CALPUFF data.

Geocoding addresses:

In order to link the PATA concentration data with ED data, the home address for each hospital case was used to attach spatial coordinates and geographically position the ED visits within the PATA layer. Each address was geocoded using Tiger/Line files available through the US Census Bureau. Tiger files are Topologically Integrated Geographic Encoding and Referencing system files. Tiger files for 2006 Oregon and Washington Street and zip codes were used for the geocoding process. Geocoding is a process for assigning geographic coordinates to a street address. ArcGIS has an automatic geocoding process. Automatic geocoding mapped 46% of all patient locations. In order to improve the geocoding capability, addresses were manually edited, primarily correcting spelling mistakes. For example, 1234 NE 10th St #1 would not geocode properly because of the apartment number (#1) at the end of the address. Once the "#1" was removed, the address was properly mapped. There were recurring spelling errors in the addresses recorded, such as "Beaverton Hillsdale Highway" was spelled "Bvtn Hdale Hwy". For ARCMAP to recognize the address, the full spelling of the highway was required. Several of the addresses not automatically geocoded did not have the correct zip code corresponding to the given home address. Once the zip code was corrected, ArcGIS could assign geographic coordinates to the given address. To facilitate the zip code correction, a utility was written in Perl which looped through all the non-geocoded addresses and sent the street address, via SOAP (Single Object Access Protocol), to the server http://www.geocoder.us. Geocoder.us uses the Tiger/Line files to generate the proper zip code and latitude and longitude for a given street address, city and state within the United States. The street address, city and zip codes for the OHSU ED visits were sent to the Geocoder.us web service and the correct zip code for the given address was stripped out of the returning SOAP message. The correct zip code was then updated in the patient database. The data with the corrected zip codes were then geocoded automatically by ArcMap. Approximately 34% of the visits were not geocoded.

Visits that were not geocoded did not contain a street address, contained an address that did not correspond to a real address, or the address was not in the states of Oregon or Washington.

Asthma Case Definition:

A case-definition of asthma was required to identify which OHSU ED cases were asthma cases. An asthma diagnosis was chosen based on the masters thesis work of Leslie Davidoff at the OHSU School of Public Medicine in 2003. Davidoff determined the ICD-9 CM codes and diagnoses for asthma in the OHSU ER using EmSTAT data [25]. Davidoff compared the primary and secondary diagnoses with the OHSU Lifetime Cinical Record to verify that the patient does in fact have asthma. The following are the four diagnoses for asthma in EmSTAT:

- Asthma, acute
- Asthma, status asthmaticus/status asthmaticus
- Bronchospasm
- Reactive airway disease

For this chosen set of diagnoses, the Davidoff study reported a 90.2% sensitivity, 69.4% specificity and a 86.8% positive predictive value for diagnosing a true asthma case.

For this study, a case was considered an asthma case if any of the above diagnoses were found in the primary or secondary diagnosis in the EmSTAT record. Newborn EmSTAT records were removed from the total OHSU ED visit population of the study. The newborn record was the result of a birth and the record for the birth mother was retained. For the purpose of this study, a newborn would not have the potential to be an asthma visit.

Using GIS, the residences for all OHSU ED cases that were accurately geocoded were layered onto the PATA domain. Using the ArcMAP intersect utility, which combines the data of two distinct layers where they intersect geographically, each OHSU ED case was assigned a census block group or tract ID and a virtual receptor ID based on their geographical intersection with the PATA domain. From this a new table was created and exported from ArcMAP. The fields for the new table, Patient_total are listed in the table below:

Patients_Total	
Field	**Function**
Primdiag	Primary Diagnosis coded in ICD-9
Secndiag	Secondary Diagnosis coded in ICD-9
Gender	
Ethnicity	
DOB	Date of birth
Arrvdate	Arrival date into the OHSU ED
SourcePoint	Ties the case to a census block/tract and pollutant concentration value

Table 5

Individual tables for each pollutant were created by aggregating the concentration values for each over the one year study period. The format of the tables is as follows:

[Pollutant name]_year	
Field	**Function**
SourcePoint	Virtual Receptor ID
Avg_val	Average concentration for the Receptor

Table 6

The table described above was then linked to the Patients_Total table by the SourcePoint field. The use of two tables for the final analysis allowed for great flexibility on the queries that could be run.

In order to analyze the concentration data with the OHSU ED case data in a manageable way, the annual or monthly average concentration data at each virtual receptor was assigned to a concentration quartile. Quartile cutoffs were created by calculating the nested means to create four divisions. The nested means were calculated from the average concentrations for the year. The mean for the year was calculated and used as the division between quartiles two and three. The mean concentration for values found below the quartile two and three division was calculated and used as the division between quartiles one and two. Finally, the mean concentrations found above the quartile two and three divisions was calculated and used as the division between quartiles three and four. A table showing the quartile concentration cutoffs is listed below in Table 7.

Benzene		
Quartile	Lower Concentration Cut Off (ug/m^3)	Upper Concentration Cut Off (ug/m^3)
1	0.00000	2.70791
2	2.70791	3.81946
3	3.81946	4.98938
4	4.98938	10.319518

Diesel PM		
Quartile	Lower Concentration Cut Off (ug/m^3)	Upper Concentration Cut Off (ug/m^3)
1	0.00000	1.59799
2	1.59799	2.41135
3	2.41135	4.05906
4	4.05906	30.63688

Chromium		
Quartile	Lower Concentration Cut Off (ug/m^3)	Upper Concentration Cut Off (ug/m^3)
1	0.0000	0.0014
2	0.0014	0.0025
3	0.0025	0.0045
4	0.0045	.01410

Table 7 – Air Pollutant Concentration Quartile Divisions

These quartiles were used for both the average monthly and annual aggregated data as the cut-offs for benzene, chromium and diesel PM concentrations.

The EPA maintains the Integrated Risk Information System (IRIS), a database of human health effects that may result from exposure to various pollutants [26]. The Reference Concentration for Chronic Inhalation Exposure (RfC) for benzene [27], chromium [28] and diesel PM [29] were recorded from the IRIS database. In this study diesel PM was the only pollutant that exceeded its RfC of 5 $\mu g/m^3$. An additional analysis was done using the diesel PM's EPA RfC to divide the monthly and annual aggregated concentration data for analyzing asthma visit proportions above and below the RfC.

Total asthma visits in each of the census block groups/tracts within the PATA domain were counted. Total OHSU ED visits within each of the corresponding census block groups/tracts within the PATA domain were counted. By dividing the number of asthma visits by the total number of OHSU ED case visits, the proportion of asthma visits was calculated for each census block group and quartile pollutant level. For each month, the proportion of asthma visits were calculated within each quartile of benzene, chromium and diesel PM concentrations. A proportion of asthma visits per all OHSU ED visits was used for this study to reduce the amount of confounders introduced.

For the study year, the proportion of all asthma visits was calculated. A chi-square was calculated to determine the statistical significance of the difference between the observed and calculated proportions. The overall annual proportion of asthma visits was used as the expected proportion for the chi-square calculation. The observed proportion of asthma visits within each pollutant concentrations quartile were compared to the expected proportion to determine its chi-square value. Additionally, the risk ratio was calculated with asthma case proportions within the lowest quartile set as the baseline. The risk ratio was calculated by dividing the observed asthma visits by the expected asthma visits for each quartile. The value calculated for the lowest concentration quartile was divided by itself to give a risk ratio of 1 as the baseline. Risk ratios for quartiles 2, 3 and 4 were calculated by dividing the observed by the expected asthma visits for quartiles 2, 3 and 4 by the observed/expected calculated for quartile 1.

RESULTS:

Geocoding

Utilizing the geocoding methods described above, 67% of all OHSU ED visits within the study time frame were geocoded to a latitude and longitude. Of these geocoded addresses, 99% were located within the PATA geographic domain as seen in Table 8 below.

Geocoding Results

Total OHSU ED visits (not geocoded)	65127	Percentage of Total
Automatically geocoded visits	31025	48%
Additional visits geocoded with manual corrections and zipcode corrections using the Perl utility	12842	20%
ED visits without any address information (unuseable for geocoding)	10666	16.4%
ED visits with addresses outside the PATA range or incorrect or unuseable addresses	10594	16.3%
Total geocoded visits	43867	67%
Total geocoded visits within the PATA domain	43341	66.55%
Total geocoded visits within the PATA domain minus births	42984	66.00%

Table 8

Asthma Visit Totals:

The following table reports the total asthma case proportion before and after geocoding. The table provides a national estimate for the proportion of asthma ED visits for the year 1999. The percentage of asthma visits for the geocoded results was the value used for calculating the risk ratio for an increase in the number of asthma visits. The calculation will be explained later.

	Total OHSU ED Visits	Total Asthma Visits	Percentage of Asthma Visits
Raw OHSU ED Data	1014	60971	1.66%
Geocoded without newborn visits	704	42984	1.64%
United States national estimatade percentage of asthma ED visits for 1999 [30]			1.90%

Table 9 – Percentage of Asthma Visits for the Study Year

The following map (Figure 2) displays the PATA domain together with the distribution of OHSU ED visits per census group for the one year period of the study. The light purple areas on the map are census block groups that contained no visits. The borders of these areas are indicated by a light gray line. The color gradient indicates an increase in counts for all OHSU ED visits for the census group with yellow indicating low number of visits and red indicating the highest number of visits.

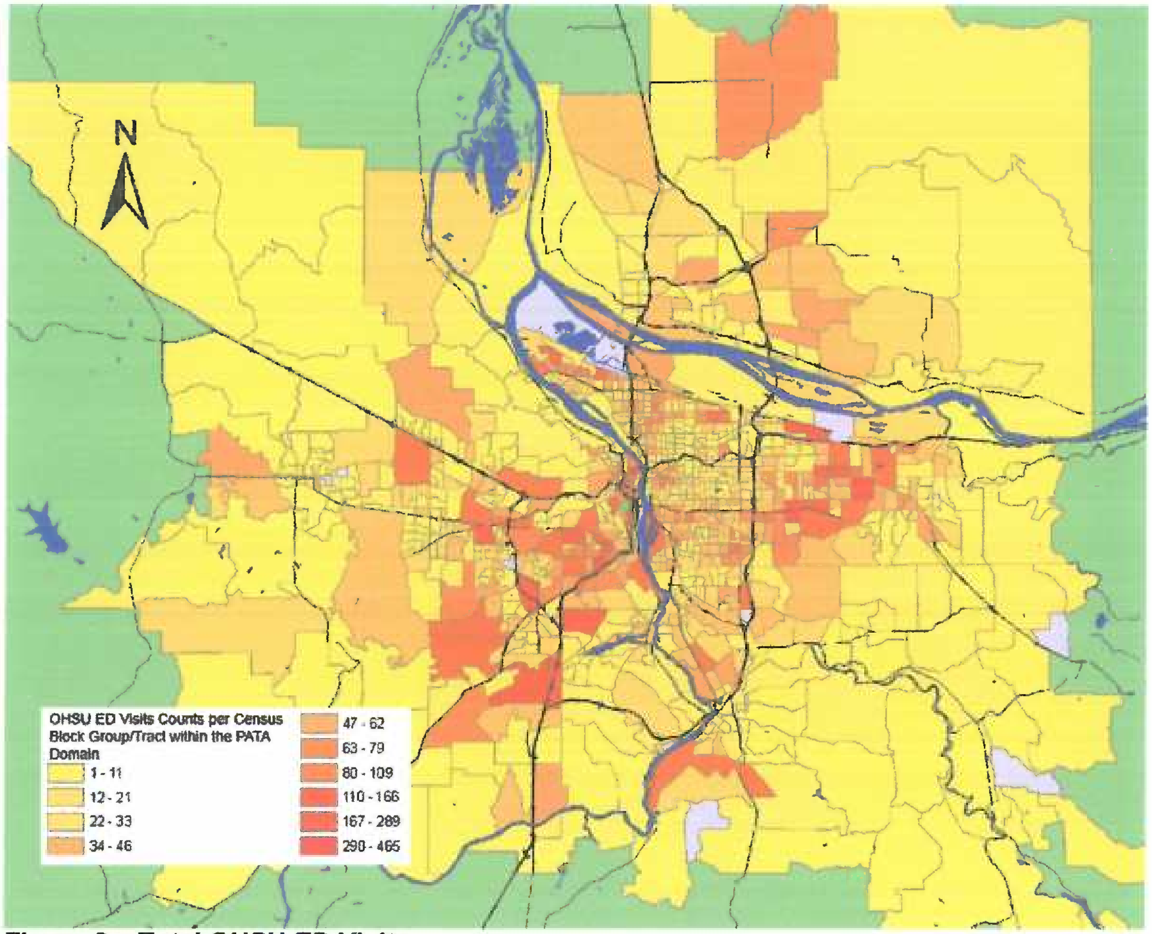

Figure 2 – Total OHSU ED Visits

Note: Green dot on map indicates the location of the OHSU ED

Figure 3, below, displays the number of asthma visits for the study year (purple dots) over the number of total OHSU ED visits. The size of the purple dot represents the number of asthma visits per census group. The larger the purple dot indicates a larger number of asthma visits and a smaller dot indicates a smaller number of visits. No dot indicates no asthma visits.

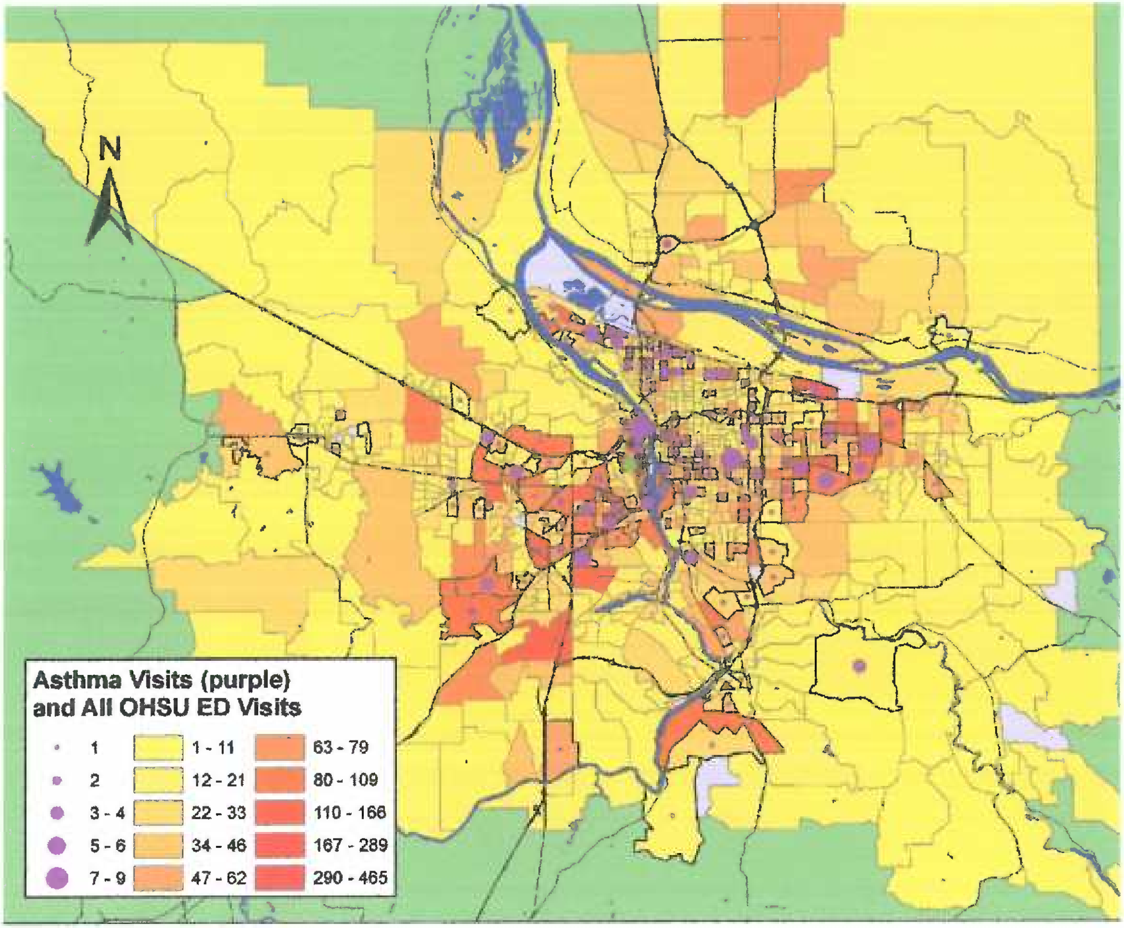

Figure 3 - OHSU ED visits and ED asthma visits

Note: Green dot on map indicates the location of the OHSU ED

Air Pollutant Concentration Data

Figure 4 below displays the average monthly concentration of benzene, diesel PM and chromium for the study period over the entire PATA domain. The y-scale is logarithmic to allow the trend in chromium concentrations to be noticeable as the average concentrations of chromium were much smaller than those of benzene and diesel PM.

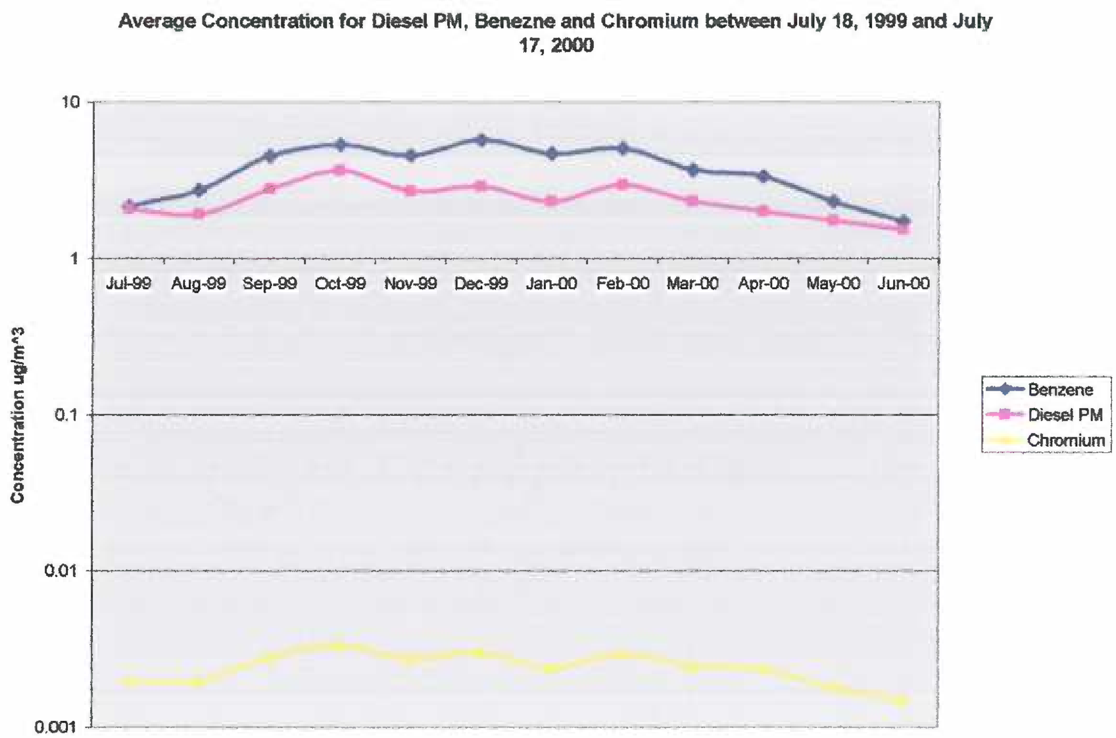

Figure 4

Figures 5 – 8 display average annual concentrations of the three pollutants in the study in each census block group/tract for the PATA domain for the one year study period.

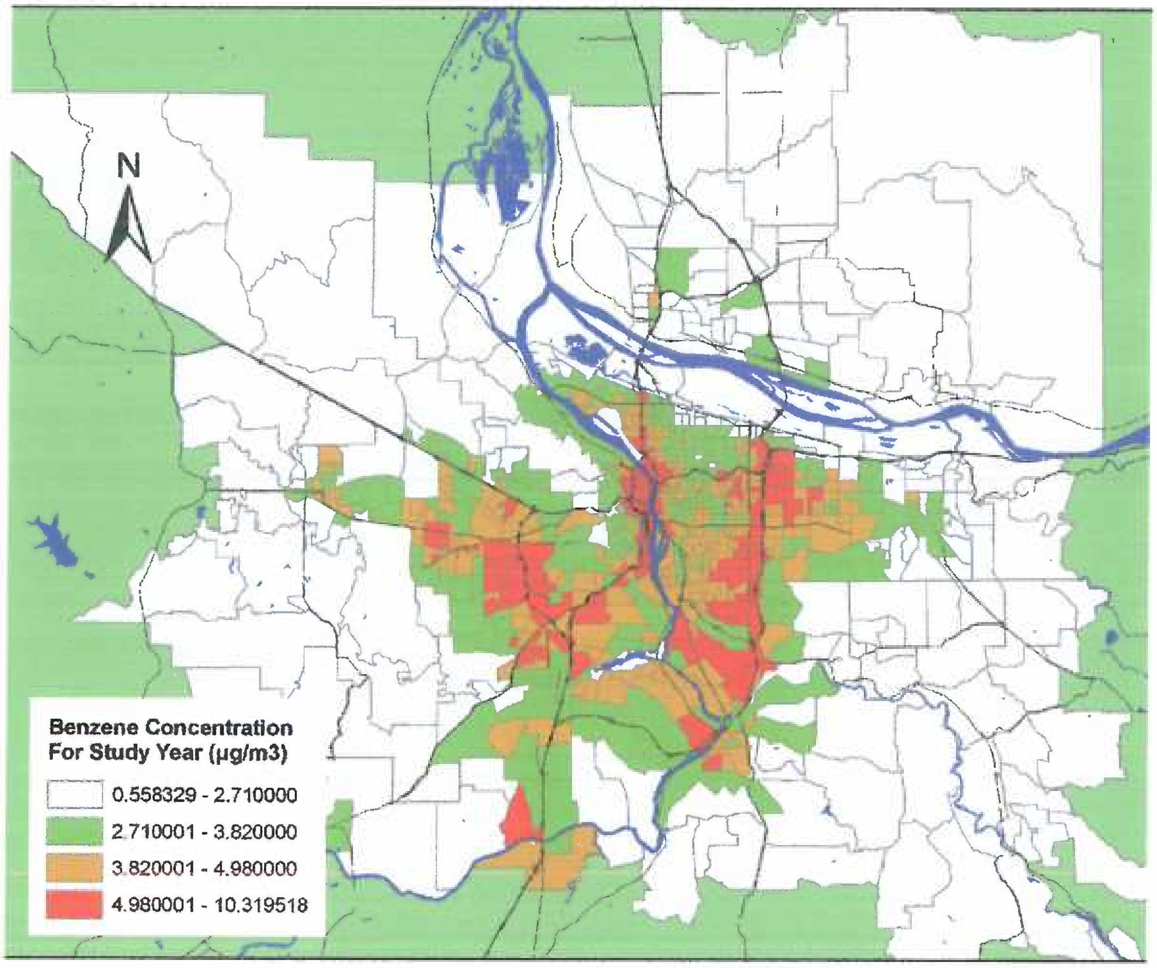

Figure 5 – Average Concentrations of Benzene for the Year

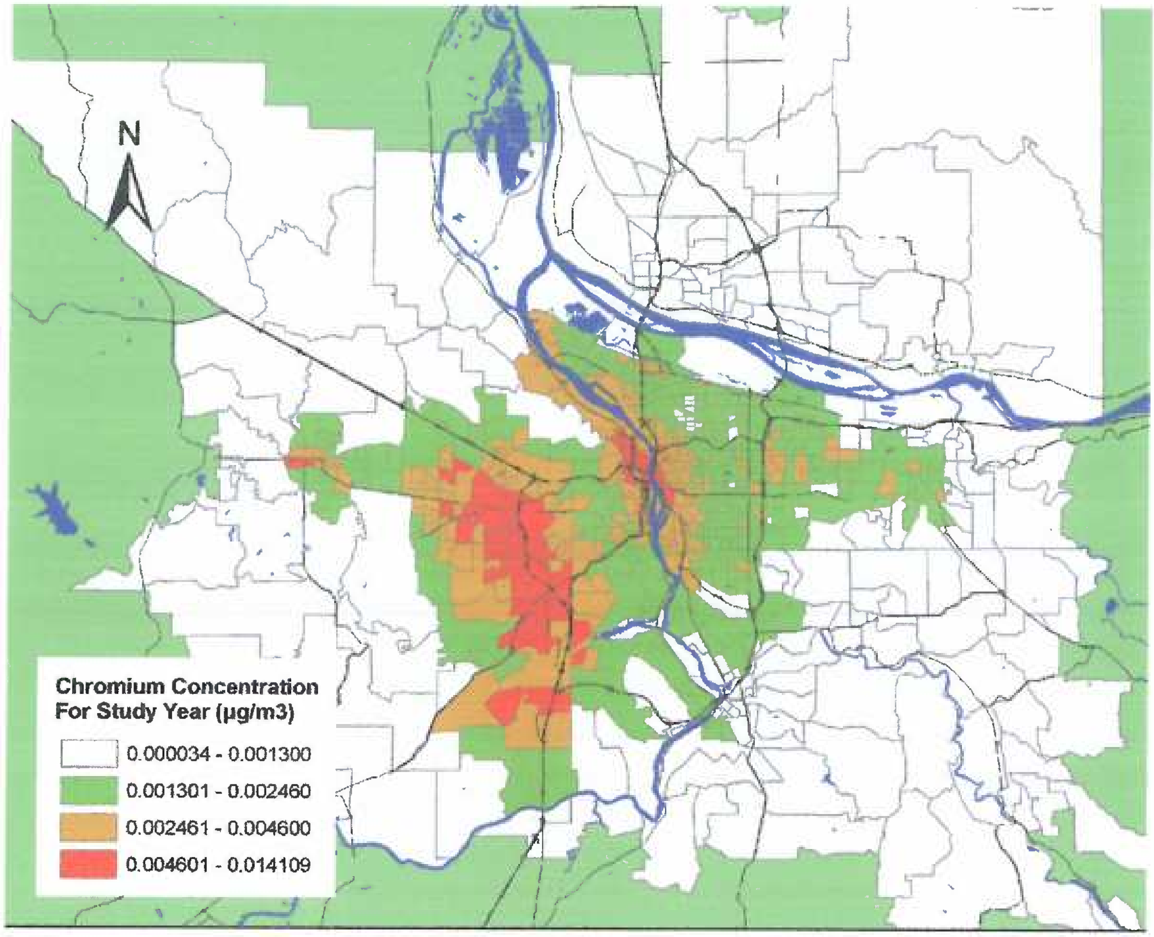

Figure 6 – Average Concentrations of Chromium for the Year

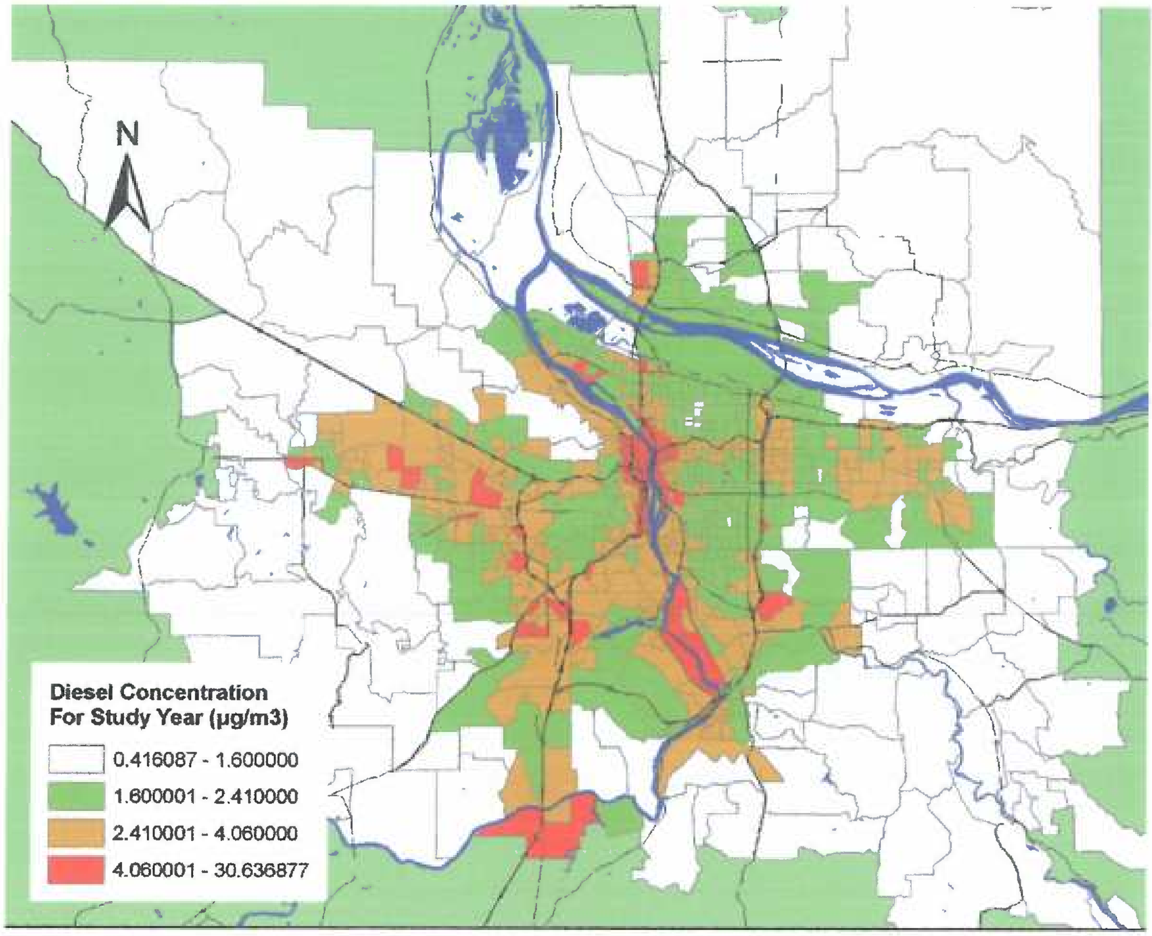

Figure 7 – Average Concentrations of Diesel PM for the Year

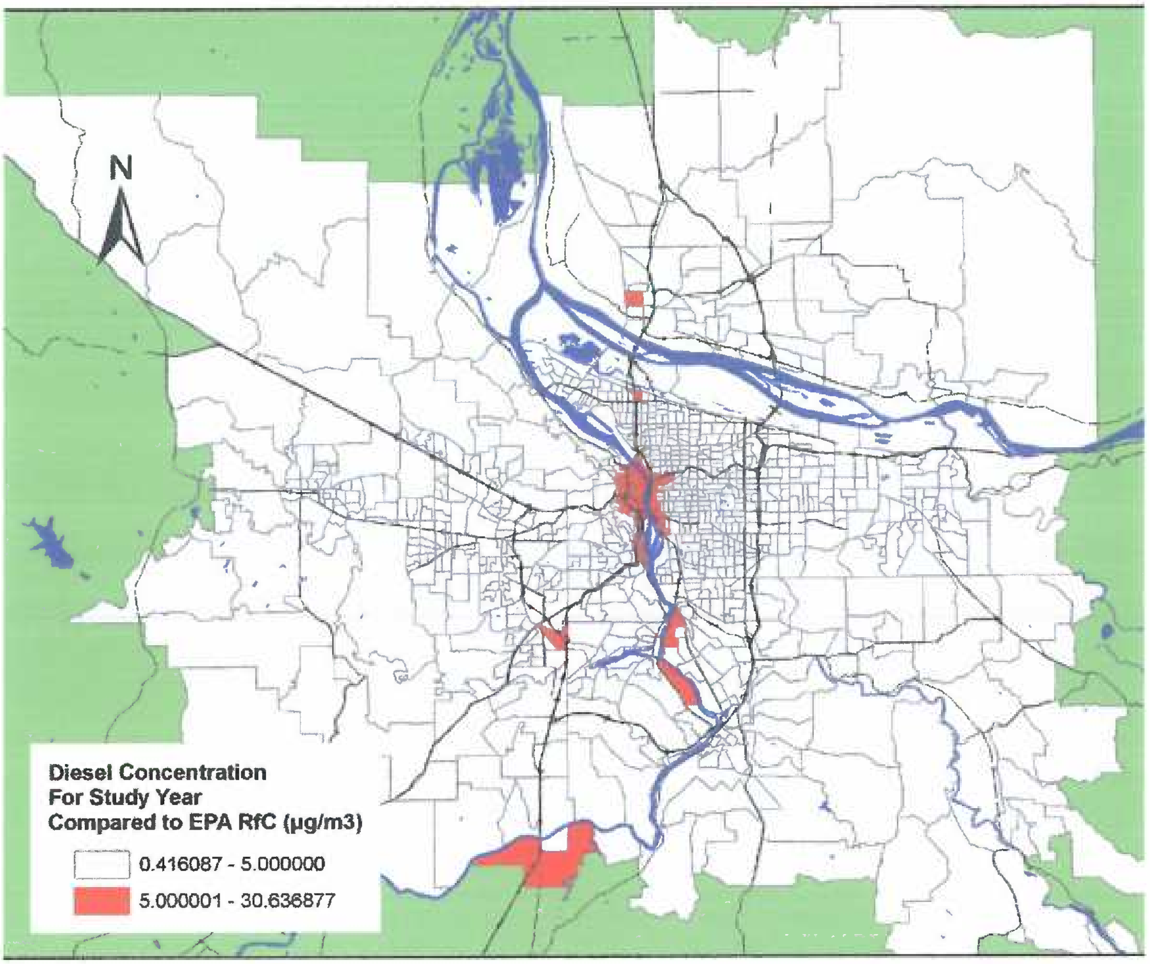

Figure 8 – Average Concentrations of Diesel PM for the Year using EPA RfC to divide the concentration data

Analysis

Table 10 below reports the annual number of all OHSU ED visits and the number of OHSU ED asthma visits found in each concentration quartile of benzene, chromium and diesel PM in this study. The resulting expected asthma case ratio was used to calculate the chi-square value for each proportion calculated for each of the concentration quartiles per pollutant. More specifically, the chi-square was calculated by multiplying the expected asthma case ratio by the observed total case count in each of the concentration quartiles. This calculation provided a value for the expected number of asthma visits for each quartile. The final chi-square value was calculated by subtracting the expected asthma case count (E) from the observed asthma case count (O) and squaring this result. The squared result was then divided by the expected number of asthma visits. The formula for the chi-square calculation is listed below:

$\chi^2 = (O-E)^2/E$

The chi-square values were summed and a p-value was determined by comparing the number to a standard chi-square distribution table. In order to calculate the risk ratio at each quartile, the ratio of observed asthma proportion of visits to expected proportion of asthma visits (O/E) was calculated. The O:E ratio for the lowest concentration quartile was divided by itself to create the baseline asthma case ratio. The O:E ratios for the increasing concentration quartiles were divided by the O:E for the lowest concentration quartile. By doing this, a trend in increase or decrease asthma visits with exposure to higher levels of pollutants could be observed.

Year Asthma Case Proportion, Chi-Square and Risk Ratio calculations

Diesel PM					
Concentration Quartile	All ED Cases	Asthma Observed	Asthma Expected	erved Asthma / Expected Ast	Risk Ratio
1	6207	105	101.659	1.033	1
2	25600	404	419.282	0.964	0.933
3	7342	135	120.249	1.123	1.087
4	3835	60	62.810	0.955	0.925
Degrees of freedom:	**3**				
Chi-Square:	**2.602**	**p > 0.1**			

Benzene					
Concentration Quartile	All ED Cases	Asthma Observed	Asthma Expected	erved Asthma / Expected Ast	Risk Ratio
1	18889	264	309.368	0.853	1
2	8149	156	133.466	1.169	1.370
3	8484	152	138.953	1.094	1.282
4	7462	132	122.214	1.080	1.266
Degrees of freedom:	**3**				
Chi-Square:	**12.466**	**p < 0.01**			

Chromium					
Concentration Quartile	All ED Cases	Asthma Observed	Asthma Expected	Observed / Expected Asthma	Risk Ratio
1	19863	280	325.320	0.861	1
2	7291	131	119.413	1.097	1.275
3	9697	183	158.819	1.152	1.339
4	6133	110	100.447	1.095	1.272
Degrees of freedom:	**3**				
Chi-Square:	**12.028**	**p < 0.01**			

Diesel PM - Compared to EPA RfC of 5 ug/m^3					
Concentration Quartile	All ED Cases	Asthma Observed	Asthma Expected	erved Asthma / Expected Ast	Risk Ratio
1	40081	659	656.454	1.004	1
2	2903	45	47.546	0.946	0.943
Degrees of freedom:	**1**				
Chi-Square:	**0.146**	**p > 0.1**			

Expected Asthma Case Ratio:	**0.016378187**

Table 10

Figures 9 – 11 are a further visualization of the calculated risk ratios for the quartiled data reported in table 10.

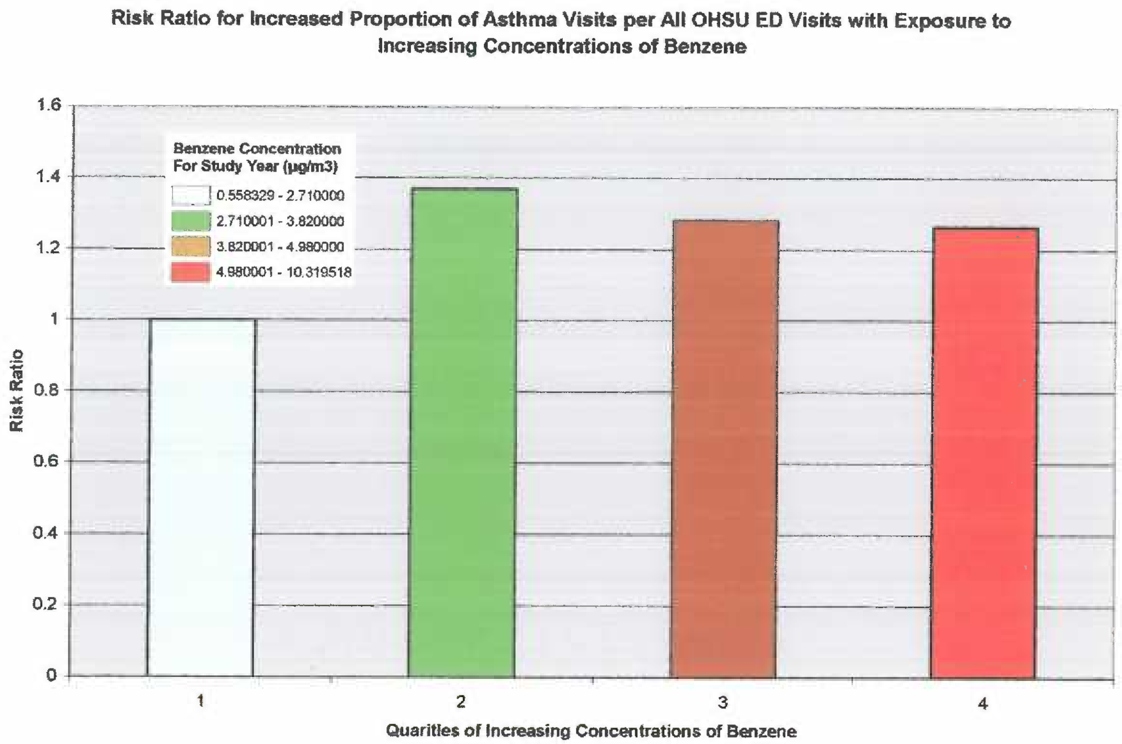

Figure 9

Risk Ratio for Increased Proportion of Asthma Cases per All OHSU ED Cases with Exposure to Increasing Concentrations of Diesel PM

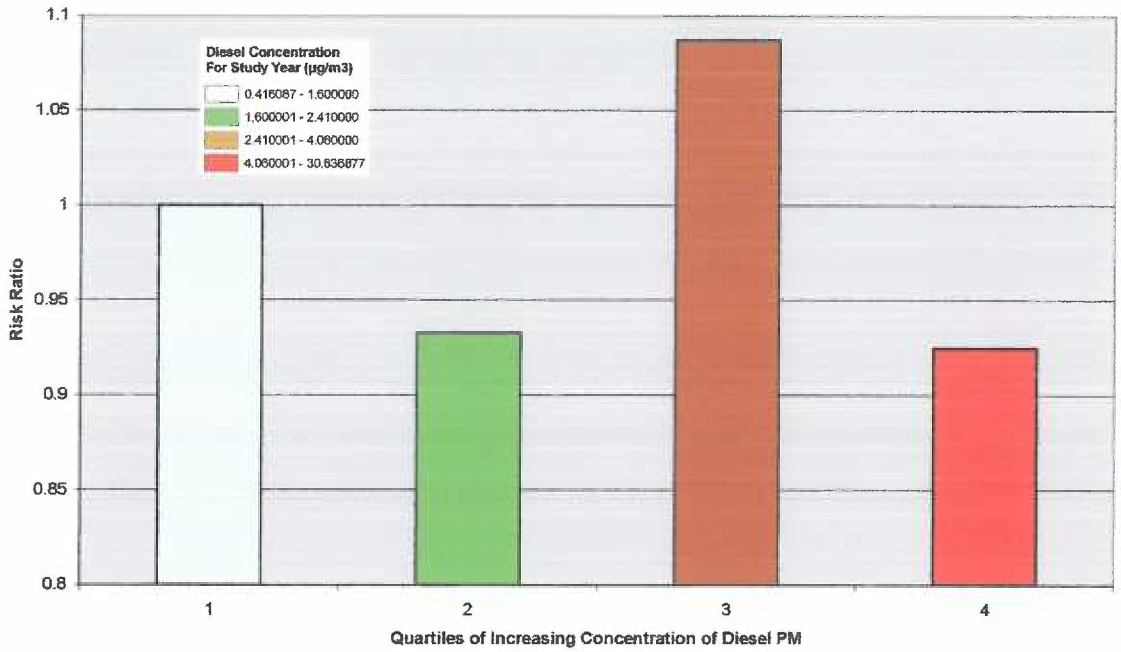

Figure 10

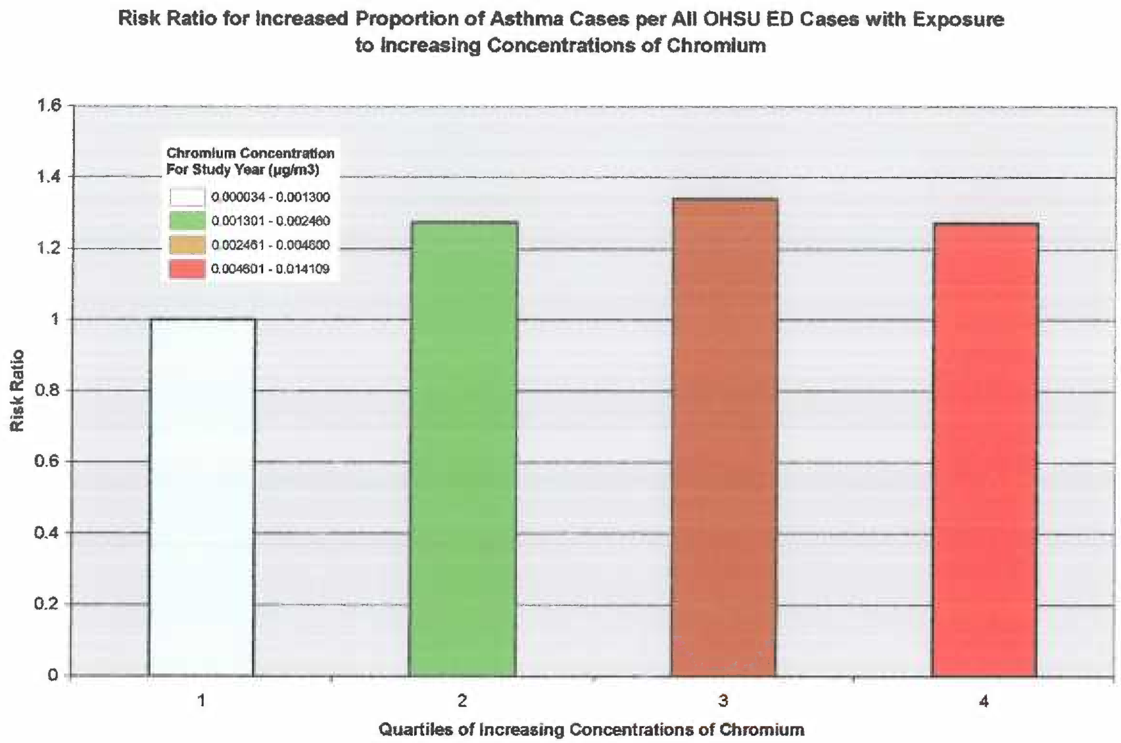

Figure 11

DISCUSSION:

The methods for geocoding OHSU ED visits were successful in assigning locations for residences for 67 % of all the OHSU ED visits. The visits that were successfully geocoded contained enough pertinent address information in the case file for mapping purposes. Of all the visits, as seen in Table 9, 16.4 %, did not contain any address information. 16.3 % contained incorrect or non useable address information. The final tally for geocoded asthma visits were slightly less than the demographics of the CDC's national estimates for asthma visits in the ED. As seen in table 9, the CDC estimated the percentage of asthma ED visits, nationally, was 1.9 % and of the studies case population, 1.64 % were asthma visits.

In Figure 2, the population density map of OHSU ED visits within the PATA domain, the most densest number of ED visits can be found near the location of the OHSU ED as indicated by the areas highlighted in red. The higher to mid level case density appear to be conglomerated around the east side of the PATA domain, west of the Willamette River and south of the Columbia River that divides Washington and Oregon. Within the central part of the city, east of the

Willamette River, there is less population density. This is most likely due to the routing of emergency visits and the proximity to 2 major emergency room hospitals in the region. A relatively higher density of asthma visits can bee seen east of the major highway, Interstate 205. It is speculated that individuals in this part of the Portland Metro Area choose to travel to OHSU for care as opposed to their local emergency room. The records received for the study did not indicate whether the patients were brought in via ambulance or via other means. Thus, ambulance routing cannot solely be responsible for the distribution of visits on the PATA domain map.

Figure 3 shows the OHSU visit population density for the PATA domain with an overlay of white points representing asthma visits. These points are not the actual physical location of the patient's home address, but are randomly placed within its respective census block group/tract. The distribution does not appear to follow any particular pattern. There seems to be more asthma visits near the center of the Portland Metro Area, where the general population density is the highest. The locations of asthma visits do not seem to cluster in close proximity to major highways. The asthma location comparison to modeled concentrations data will allow for more specific trend analysis.

Figure 4, above, shows the monthly average concentration of the three pollutants for the study year. As seen in the graph, there is a trend for higher concentrations of chromium, benzene and diesel PM during the fall and winter months, September through March. The colder ambient temperatures and cloud cover probably dampen the dispersion of the pollutants. Thus, the higher concentrations of pollutants are seen during this period. In the case of diesel PM concentrations, this upward trend is additionally facilitated by the use of more wood burning stoves during the winter month.

Figures 5 - 8 show the geographical locations of higher and lower concentrations of the study pollutants within the PATA domain. Figure 5 shows the concentration distribution of Benzene for the study year within the PATA domain. The map shows that the highest concentrations of benzene aggregate around the major highways. This is as expected because benzene is a bi-product of automobile exhaust. The concentration levels decrease as the distance from the highways and major city centers increase.

Figure 7 shows the average yearly concentrations of diesel PM for the study year within the PATA domain. Similar to the pattern of benzene concentrations, the diesel PM aggregates near the major highways, but to a lesser degree. The highest concentrations of diesel PM aggregates near downtown Portland and the major highway, Interstate 5. Because a major component of diesel PM is construction vehicles, the results in figure eight are somewhat expected because there are constantly construction projects in progress at or near downtown Portland. The second quartile of diesel concentration levels mirrors the benzene high concentration levels as it aggregates near the major highways. Figure 8 displays the average concentrations for Diesel PM for the year using the EPA RfC to divide the concentration data. Diesel PM, on average, exceeds the EPA RfC within downtown Portland and in parts of the southern regions of the PATA domain.

Figure 6 shows the average yearly concentration of chromium for the study year within the PATA domain. The concentration pattern of chromium differs from benzene and diesel PM as the higher concentrations of chromium do not aggregate near the major highways. There is a high concentration region within downtown Portland and along the Willamette River. Along the western part of the Willamette River lies several industrial factories which may account for the high concentration of chromium. On the southwest part of the PATA domain, high levels of chromium are indicated in the figure. There are several micro chip manufacturing plants and metal processing plants within this region which are a probable source for the high levels of chromium.

Table 10 describes the combination of the results described above. All OHSU ED visits were mapped to a census block group/tract. The average concentrations for each pollutant were mapped to a census block group/tract as well. The data were layered upon each other using GIS and counts of asthma visits versus all ED visits for each concentration region were determined. The combined spatial data was used to calculate the increase (or decreased) risk of an asthma visit at the OHSU ED with exposure to increasing concentrations of chromium, benzene or diesel PM.

Based on the literature, it was expected that diesel PM would show the most significant effect on asthma exacerbation. However, based on the results summarized in Table 10, The risk ratio for increased proportion of asthma visits decreased between the first and second quartile of diesel PM concentrations. Quartile three showed a slight increase in risk with a risk ratio of approximately 1.09. Within block groups/tracts exposed to the highest concentration of diesel PM, the risk was less than the lowest concentration risk with a risk ratio of approximately 0.92. In addition, the chi square calculation yielded a chi-square value of 2.6. Using a standard chi-square distribution table, the chi-square result yields a p-value > 0.1. Thus, there is no statistically significant difference between the risk ratio values for exposure to diesel PM in all four concentration quartiles.

The results for four quartiles of diesel PM concentrations is mirrored in the diesel PM concentrations compared to the EPA RfC of 5ug/m^3. The risk ratio for asthma visits is less than that of the baseline risk ratio of 1. The risk ratio values between the lower concentration quartile and the quartile above the EPA RfC are not statistically significantly different as the chi-square value yielded a p-value greater than 0.1. It was anticipated that diesel PM would show a significant difference and increase risk ratio for each increasing pollution concentration quartile due to the amount of literature showing increased asthma exacerbation with exposure to increase ambient levels. The sources for diesel PM for the PATA model were primarily from construction sites, non-road traffic such as airlines and barges. The sparseness of the sources may contribute to the lack of statistical significance and a rising trend in risk ratio

The results for Benzene show a trend of rising risk ratio with exposure to higher benzene concentrations. The risk ratio increased by 37% between the lowest concentration quartile and the 2nd highest quartile and remained elevated at higher concentrations. The p-value for these calculations ($p < 0.01$) indicates that the calculated risk ratios are statistically significant. Thus, with exposure to higher levels of benzene, specifically concentrations greater than 2.7 ug/m3, the risk ratio of increased proportion of asthma visits for the OHSU ED increases by 26 to 37%. Figure 9 illustrates the increase in risk ratio between the lowest concentration quartile and the 2nd, 3rd and 4th quartiles.

The results for chromium exposure levels show a trend of rising risk ratio for asthma visits with exposure to increasing concentrations of chromium. The risk ratio increases by 27% between the first concentration quartile and the second. The risk ratio for quartile three is 33 % higher than quartile one and quartile four shows a risk ratio 27% higher than quartile one. This upward trend in risk ratio indicates that with exposure to chromium concentrations greater than 0.0014 ug/m3 there is a 27 to 33 % higher risk of increased proportions of asthma visits at the OHSU ED. Figure 11, above, further demonstrates the disparity between the risk ratio at the first quartile and the 3rd concentration quartile. As shown in figures 9 and 11, the expected rise in risk for each increasing pollution concentration level relationship was not found. However, the lack of a dose-response relationship could be explained by a saturation of risk. The areas with higher pollution levels may contain more industrial buildings rather than housing and residences.

Limitations:

There are many limitations to this study and difficulties with interpreting the significance of the results. The results only pertain to the OHSU ED population for the study year. By only using OHSU ED visits and not including all hospitals within the PATA domain as the base population of the study, the effects of confounders such as ambulance routing and proximity to the ED are present. Because of the uneven population distribution of the OHSU ED visits within the PATA domain, it does not reflect the actual population distribution within the Portland metro area. However, the results do show a trend that indicates a more general population based study similar to this one could be warranted.

Additionally, asthma visits in this study would most likely be the result of acute asthma exacerbations. In most cases, an asthma attack would not warrant a visit to the ER. A more accurate measure of asthma prevalence could be accomplished by measuring inhaler purchase patterns or study a cohort of known asthmatics within the Portland metro area. In this study, there was no way to determine whether there were any repeat patient ED visits. The data provided by the ED did not contain individual identifiers like a social security number or first and last name.

The use of modeled concentration data allowed for a more precise measure of exposure levels at a particular geographic location. The address information for this study has several limitations. The address may or may not be the home address of the patient. It may have been the address of the patient's workplace or of another family member. The study assumes that this is the home address and that the patient was exposed to the modeled level of pollution at this address. The actual location of the patient throughout each hour of the year is not known and it is very likely that the patient spent time at a job or school for many hours of the day. By using the concentration data for the year, this confounding factor may have been partially accounted for. Yet, a study which tracked the location of asthmatics would give a more accurate picture of pollution exposure.

FUTURE DIRECTIONS:

Daily analysis of the data could yield more statistically significant results. Comparing seasonal asthma visits with seasonal fluctuations in the environmental data may show what parts of the year create higher risk of increased asthma visit proportions. An additional temporal analysis would be the division of the data into day and night time air quality and case data. Because the addresses in this study are presumed to be home addresses, a comparison between nighttime exposure and day time asthma visit proportions could be demonstrated. Additionally, stratifying the data by age, sex, race, income and other demographic factors may show a greater or lesser effect of air pollution on asthma for different study groups. Unfortunately, in this study, when any demographic stratification was attempted, the total asthma cases dropped so low that any difference in risk ratio was statistically insignificant.

A comparison of these results with results from a future air pollutant modeling study could show trends in air pollutant levels and asthma visit proportions. However, another PATA is not planned for the near future. There is an air pollution model currently running for the northwestern United States called AIRPACT-3. AIRPACT-3 is a modeling system used for predicting the air quality for Washington, Oregon and Idaho [31]. The system models the chemistry and physics air pollutants and predicts the current air quality and the air quality for up to three days into the future. Chromium and benzene levels are currently not predicted by AIRPACT-3. $PM_{2.5}$ and PM_{10} are predicted, however. Ozone, carbon monoxide, and nitrous oxides are predicted. Diesel PM would make up some of the $PM_{2.5}$ and PM_{10} component. Ozone has been shown to exacerbate asthma as well [5]. The modeled data does not have the geographical precision that the PATA model does. AIRPACT-3 models data for 21km grids [31]. Using the data model in this study, asthma surveillance data, such as the data generated by NEDSS (National Electronic Disease Surveillance System) [32], could be compared with the AIRPACT-3 data retrospectively to view regional pollutant effects and asthma exacerbation.

More robust statistical methods could be used to determine a more causal relationship between pollution levels and asthma exacerbation. Time lag studies and other multivariate statistical methods could be employed in future studies. A time lag study could demonstrate a statistical relationship between the cumulative effect of pollution exposure and the onset of an asthma attack. The best time lag study would include geographically specific pollution data, as that of PATA, and possibly a cohort of asthma and non asthma visits.

CONCLUSIONS:

This study demonstrated that asthma emergency department data could be spatially and temporally linked with air quality dispersion data. By utilizing GIS to combine the data, risk ratios were calculated for asthma visit proportions of total ED visits. The spatial analysis of the health data and air quality data was performed at the census block/tract level. This fine level of spatial analysis allowed for a more precise link between the health and air quality data.

The study also demonstrated an association between asthma and air quality measures. Increased ambient levels of chromium and benzene yielded higher asthma visit proportions for the OHSU ED.

As more pollutant model data and real time monitoring data become for frequently available, there will be more potential for more frequent or real-time analysis, as demonstrated by this study. This real time or frequent reporting of environmental effects on health will be an invaluable tool for public health agencies in predicting, observing and even containing a serious disease outbreak due to environmental pollution.

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