MODELLING PM2.5 CONCENTRATIONS AND SPATIAL CORRELATION WITH WEATHER CONDITIONS AND ADULT ASTHMA IN NORTH TEXAS IN 2014

by

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Abstract

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The questions to be answered by this study are whether weather conditions correlate with $PM_{2.5}$ concentrations, and whether there is a correlation between asthma-related hospital admissions and $PM_{2.5}$ concentrations. The focus is on the Dallas-Fort Worth area of Texas—comprised of Collin, Dallas, Denton, Ellis, Erath, Hood, Hunt, Johnson, Kaufman, Navarro, Palo Pinto, Parker, Rockwall, Somervell, Tarrant, and Wise Counties—during the year 2014. A radial basis function neural network, via the Matlab Neural Network toolbox, is used to create a model to estimate the $PM_{2.5}$ concentrations in the DFW area. Spatial statistical techniques are used to analyze the spatial autocorrelations among asthma-related hospital admissions. Spatial statistical analysis reveals that asthma-related hospital visits are concentrated in urban centers. Further statistical analysis results indicate that daily average $PM_{2.5}$ concentration is positively correlated with daily maximum temperature, daily average station pressure, daily average wind speed, and daily sustained wind speed. Research indicates that the results *concerning wind speed may be related to drought. The results also indicate that daily average $PM_{2.5}$ concentration is negatively correlated with daily precipitation and daily average relative humidity when precipitation days are considered alone; however, when both precipitation and non-precipitation days combined are considered, there is no correlation between precipitation and $PM_{2.5}$ concentration. Daily asthma-related hospital visits are weakly positively correlated with daily average $PM_{2.5}$ concentrations when days with precipitation are considered, but weakly negatively correlated when non-precipitation days are considered alone.*

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Chapter 1

Introduction

The Dallas-Fort Worth metropolitan area (DFW), located in north Texas, has a long history of surpassing safe levels of air pollutants and unsafe air quality. Air quality is a concern for human health in that it affects people with cardiovascular and respiratory diseases (U.S. EPA, 2015). When it comes to respiratory diseases, asthma is of particular concern due to air pollutants exacerbating asthma in known asthma patients and even causing the onset of asthma in others (Guarnieri & Balmes, 2014). There is plenty of evidence suggesting that ground level ozone plays a key role in aggravating asthma (Goodman et al., 2017; Guarnieri & Balmes, 2014; Khamutian et al., 2015; Lu & Fang, 2015; U.S. EPA, 2015), and there has been recent research which examines whether particulate matter, specifically $PM_{2.5}$ (particulate matter with a diameter under 2.5 µm), may play a role in the same (Baldacci et al., 2015; Guarnieri & Balmes, 2014; Mirabelli et al., 2016). As Jacquemin et al. (2012) point out, research on the effect of chronic exposure to air pollution on asthma is quite limited. Even more limited, based on the literature review for this study, is research combining those elements with the added layer of various weather patterns. Out of 84 literary sources cited for this research dated from 2012 through 2018, only 14 combined weather, air pollution, and asthma for their research focus. Further research remains to be executed on the effects that meteorological variables may have on air pollution and asthma (DeSario, Katsouyanni, & Michelozzi, 2013), though there is evidence that certain meteorological factors are correlated with both.

As far as DFW is concerned, there is limited research that has been conducted on the possible correlations between asthma exacerbation and air pollution concentrations in general, let alone research which focuses on $PM_{2.5}$ and adult asthma, and includes weather patterns as a factor. Out of the 84 literary sources which were cited in this study, 5 of them focus on north Texas or DFW. It is important to focus on the DFW area for research concerning the effect of air quality on human health, as DFW is considered the fourth largest metropolitan area in the United States and is still growing in population and urbanization (Hu & Xue, 2016). Increased populations and urbanization typically lead to decreased air quality (more air pollution). For example, Dallas and Harris Counties, which contain the cities of Dallas and Houston, reported the highest number of asthma-related hospital admissions in Texas between 2007 and 2010 (Goodman et al., 2017). Due to the changing climate, it is also important to find out if there is a link between air quality and extreme weather conditions in a changing climate.

By modeling the ambient $PM_{2.5}$ concentrations, it should become clearer whether the $PM_{2.5}$ concentrations are correlated with the reported weather variables. The completion of this study could be useful in prediction of asthma prevalence related to $PM_{2.5}$ concentrations in the atmosphere for areas with similar populations or population growth rates. It could provide a guideline for determining the air quality and human health fate of such areas, including DFW, and assess whether weather conditions can act to predict cases of asthma aggravation.

There is scientific evidence showing a relationship between asthma and air pollution, including $PM_{2.5}$. Existing research focuses on ozone, particulate matter (which includes $PM_{2.5}$), general air pollution (not always specified) or a combination of different pollutants. Studies which examine the relationship between weather variables and air pollution do not always attempt to show how specific meteorological factors or events affect $PM_{2.5}$ concentrations, but research to date suggests it is likely that higher daily average maximum temperatures and higher daily average station pressure are indicative of higher $PM_{2.5}$ concentrations and higher counts of asthma-related hospital visits. It is also likely that slower daily average and sustained wind speeds, lower or higher daily average relative humidity, and less daily total precipitation are indicative of higher $PM_{2.5}$ concentrations. High temperatures are often found to be associated with high concentrations of air pollutants, including ozone and PM (L. Li et al., 2014; Veremchuk et al., 2016; Kalbarczyk et al., 2015; Lai, 2012). This is due to chemical reactions that form ozone and fine PM occurring faster with increasing temperature, according to basic chemical theory. High pressure areas are associated with inversions—sinking air which traps pollutants near the ground—so higher levels of $PM_{2.5}$ would be expected (L. Li et al., 2014; Lai, 2012). Wind typically removes pollutants from an area via dispersion, hence lower $PM_{2.5}$ concentrations are expected when the wind speed is higher (Pesic, Blagojevic, & Zivkovic, 2014; Ahmadi & John, 2015; Bella et al., 2016; Zhang et al., 2015). Relative Humidity has been found in some studies to be associated with lower PM concentrations as it increases (Cai et al., 2014; Li et al., 2014; Lai, 2012). This could be due to the increase of humidity before the onset of precipitation events. In other cases, higher relative humidity leads to higher PM concentrations because more water vapor condenses onto the particles, increasing their weight. Precipitation causes removal of pollutants due to wet deposition, which would lead to lower concentrations of $PM_{2.5}$ (Brunner et al., 2015; Zhang et al., 2015; Zhen et al., 2013; Lai, 2013; Jacobson, 2012, p. 294).

In order to estimate the likelihood of the weather effects on $PM_{2.5}$ concentrations, an extensive review of the available literature on similar concepts has been conducted. The available literature has covered a wide array of geographical study areas, and each research article related to weather has a specific focus on certain weather conditions. The literature representing the most recent research conducted on the relationship between weather and $PM_{2.5}$ concentration, $PM_{2.5}$ concentration and asthma-related hospitalization, and weather conditions and asthma-related hospitalization were compiled to assess the relevance of the proposed research.

One aim of this research is to determine the potential spatial correlations of weather variables (including daily maximum dry-bulb temperature, daily average wind speed, daily sustained wind speed, daily average station pressure, daily average relative humidity, and daily total precipitation) with ambient $PM_{2.5}$ concentration. The other aim of this research is to determine the potential correlation between $PM_{2.5}$ concentration and adult asthma-related hospital admissions. The focus will be on the Dallas-Fort Worth area of Texas comprised of Collin, Dallas, Denton, Ellis, Erath, Hood, Hunt, Johnson, Kaufman, Navarro, Palo Pinto, Parker, Rockwall, Somervell, Tarrant, and Wise Counties. These counties were chosen based on their having asthma data available for the analysis. In addition, 10 of the counties - Collin, Dallas, Denton, Ellis, Johnson, Kaufman, Parker, Rockwall, Tarrant, Wise – are classified as serious nonattainment for ozone based on the 2008 0.075 ppm 8-hour standard. Nine of them—Collin, Dallas, Denton, Ellis, Johnson, Kaufman, Parker, Tarrant, and Wise Counties—are classified as marginal nonattainment for ozone based on the 2015 0.070 ppm 8-hour standard (Texas Commission on Environmental Quality, 2020).

The questions to be answered by this research are 1) does ambient $PM_{2.5}$ concentration correlate with weather conditions (the maximum dry-bulb temperature, average wind speed, average station pressure, sustained wind speed, average relative humidity, and total precipitation), and 2) what is the correlation between asthma-related hospital visits and $PM_{2.5}$ concentrations? These questions were answered by modelling the ambient $PM_{2.5}$ concentrations in the DFW area for the year 2014 by using the variables of daily meteorological factors (specifically daily maximum dry-bulb temperature, daily average wind speed, daily sustained wind speed, daily station pressure, daily average relative humidity, and daily total precipitation), road type, average daily traffic counts, dominant land use, and the $PM_{2.5}$ concentrations which were measured by the pre-existing stationary monitors in the DFW metropolitan area, and seeing if the modeled $PM_{2.5}$ concentrations showed any significant correlation with the mentioned weather variables and with asthma cases. The 2014 reported asthma cases were assessed as well in the spatial analyses.

A Radial Basis Function (RBF) neural network via the Matlab Neural Network Toolbox was used in order to create an estimate of the $PM_{2.5}$ concentrations in the DFW area which were not reported by $PM_{2.5}$ monitors. In the DFW area, there are very few air pollution monitors in the area (seven monitors which were available for the study area and dates) which actually reported $PM_{2.5}$ concentrations, and 19 monitors in the area which reported all-inclusive and persistent weather data. The RBF network model estimates what the $PM_{2.5}$ concentrations would be in the surrounding areas, even where there are not $PM_{2.5}$ monitors. The RBF network was defined and run based on input of known daily maximum dry-bulb temperature, daily average wind speed, daily sustained wind speed, daily average station pressure, daily average relative humidity, daily total precipitation, road type, average daily traffic count (ADT), dominant land use type, and known $PM_{2.5}$ concentrations from monitors.

Definitions

Particulate matter (PM) describes particles in the atmosphere, and it can be described as PM_{10} or $PM_{2.5}$. PM_{10} is particulate matter that is less than 10 μm in diameter, while $PM_{2.5}$ is particulate matter that is less than 2.5 μm in diameter. $PM_{2.5}$ is often called fine PM or aerosols.

Ordinary kriging is a spatial tool that was used in this study. Gorai et al. (2014) describe that “in kriging, a smooth surface is estimated from irregularly spaced data points based on the assumptions that the spatial variation in the feature (O_3, $PM_{2.5}$, and SO_2) is homogeneous over the domain and depends only on the distance between sites” (p. 4854).

An artificial neural network (ANN) consists of an input layer, a hidden layer, and an output layer. The input layer acts as a set of “neurons” and are fed into the hidden layer (Mishra, Goyal, & Upadhyay, 2015). The hidden layer functions as a “feature detector,” and the output is determined once it collects the detected features from the hidden layer (Mishra et al., 2015). A radial basis function (RBF) network also has the input, hidden, and output layers. Furthermore, the “radial basis version of the Gaussian function is employed to represent the distribution of variable values in the input layer” (Zou et al., 2015, p. 10398).

Oxidative stress is the result of an “imbalance between the production of reactive oxygen species and reactive nitrogen species and the capacity of antioxidant defense mechanisms” (Jesenak, Zelieskova, & Babusikova, 2017). In asthma, oxidative stress is more evident in acute exacerbation situations or when induced by allergens (Jesenak et al., 2017).

Wet deposition is the process of rain or snow particles forming on top of particulate matter in the atmosphere, and those rain or snow particles are deposited to the earth’s surface (Jacobson, 2012, p. 294). Wet deposition also refers to the process of particulate matter being scavenged by rain or snow particles as they are falling, also resulting in the deposition of the particulate matter to the earth’s surface (Jacobson, 2012, p. 294). Dry deposition refers to the process of particulate matter falling to the surface due to either their own weight or the wind (Jacobson, 2012, p. 294).

A temperature inversion is the increase in temperature with the increase in atmospheric height (Jacobson, 2012, p. 50). Air pollutants are typically trapped within or beneath an inversion, so if an inversion occurs closer to the ground, pollutant concentrations increase (Jacobson, 2012, p. 50).

Photochemical smog refers to a mixture of pollutants (mainly ground-level ozone) which are the result of chemical reactions in the atmosphere (Friis, 2012, p. 254). The chemical reactions include reactions among fossil fuel combustion products, i.e. VOCs (volatile organic compounds) (Friis, 2012, p. 254).

A cyclone is the large-scale circulation of wind around a low-pressure center on the earth's surface (Jacobson, 2012, p. 130). An anticyclone is the large-scale circulation of wind around a high-pressure center on the earth's surface (Jacobson, 2012, p. 130). Anticyclones are distinguished by "gently subsiding vertical motion in the troposphere" and typically favor clear skies (which is associated with high-pressure systems), which promotes strong nighttime radiative cooling on the surface of the earth (Colucci, 2015). Sinking air warms while radiative cooling takes place on the earth's surface, which often results in an inversion in the vertical temperature profile (Colucci, 2015).

A street canyon is an urban street lined with buildings on both sides, and these areas typically have high traffic density (Pesic et al., 2014). Air pollutants (i.e. $PM_{2.5}$) may not be diluted or dispersed by wind in this setting due to winds being inhibited by the presence of those buildings on both sides of the street (Pesic et al., 2014). The Urban heat island effect describes the phenomenon of urban areas being generally warmer than rural areas (Winguth & Kelp, 2013). In the daytime, heat is stored in urban structures (i.e. buildings), and at night, that stored heat is released. Thus, the intensity is generally increased at night (Hu & Xue, 2016).

The rapid population growth and urbanization of the Dallas-Fort Worth region of north Texas will presumably lead to increasing $PM_{2.5}$ concentrations. Due to that and the relative lack of information on the correlations, more research on the effects of $PM_{2.5}$ on human health—specifically asthma—is needed. In the following chapter, a review of recent literature will assess what is known about the effects of weather elements on $PM_{2.5}$ concentrations, and the effects of $PM_{2.5}$ concentration on asthma.

Chapter 2

Literature Review

This chapter will focus on the recent literature pertaining to air pollutants, weather conditions, and asthma. The purpose of the chapter is to assess what is currently known about $PM_{2.5}$, weather, their effects on each other and their effects on the presence or exacerbation of asthma symptoms. There will also be a focus on the methodology used for modelling those variables in recent literature.

EPA Air Quality Standards

The U.S. Environmental Protection Agency specifies National Ambient Air Quality Standards (NAAQS) for six criteria pollutants: particulate matter, ground-level ozone (O_3), carbon monoxide (CO), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), and lead (Pb) (Lu & Fang, 2015). If the NAAQS is exceeded for any one or more of these criteria pollutants, the air quality is considered "bad" on varying levels (Lu & Fang, 2015). The air quality index is used to assess the severity of air pollutant concentrations in a given area:

> *Air quality index (AQI) indicates the degree of air pollution and the potential health effects from air pollution. It is a tool designed to help the public understand the local air quality and the adverse health effects of ambient air…The U.S. EPA calculates AQI based the concentration of major air pollutants, i.e., ground-level O_3, $PM_{2.5}$, PM_{10}, carbon monoxide (CO), nitrogen dioxide (NO_2), and nitrogen oxide (NOx). AQI is reported following a six-color scheme from green to maroon, corresponding to good air quality to hazardous air quality, respectively.* (Lu & Fang, 2015, p. 33)

Figure 2-2 shows the color scheme of the U.S. EPA's AQI. AQI is calculated for each pollutant using the formula, $I = \frac{I_h - I_l}{B_h - B_l}(C - B_l) + I_l$, "where *I* is the AQI value for a pollutant of concern, *C* is the air pollutant concentration, B_h is the high break point ($\geq C$) for the concentration of the pollutant, B_l is the low break point (≤C) for the concentration of the same pollutant, I_h is the high AQI limit corresponding to B_h, I_l is the low AQI limit corresponding to B_l" (Lu & Fang, 2015, p. 33). The EPA has defined for each pollutant the threshold concentration values of B_h, B_l, I_h and I_l based on the health impacts of each pollutant (Lu and Fang, 2015). The AQI of a given day is the highest AQI value recorded during that day (Lu and Fang, 2015). The fact that $PM_{2.5}$ is one of the criteria pollutants listed by the U.S. EPA indicates the significance of $PM_{2.5}$ in relation to human health in general. It is important to understand the way the AQI system works when studying the effects of $PM_{2.5}$, or any air pollutant, on asthma. Lu and Fang (2015) are exemplary at clarifying how the AQI is calculated, and their figure (Figure 2-1) is helpful in showing which levels are considered to be unhealthy for those with asthma (sensitive groups) and for those without. Figure 2-2 shows how the AQI index translates specifically to $PM_{2.5}$ concentration.

AQI	Health Concern	Color	Explanation
0–50	Good	Green	Clean air, no health risk
51–100	Moderate	Yellow	Light air pollution, little health risk
101–150	Unhealthy for sensitive groups (USG)	Orange	Only sensitive groups are affected
151–200	Unhealthy	Red	Unhealthy air for everyone
201–300	Very Unhealthy	Purple	Serious health effects for everyone
301–500	Hazardous	Maroon	Severe adverse health effects, even death

Figure 2-1. The AQI standard for the U.S. EPA (Lu and Fang, 2015).

AQI Category	Index Values	Revised Breakpoints (ug/m^3, 24-hour average)
Good	0 - 50	0.0 – 12.0
Moderate	51 - 100	12.1 – 35.4
Unhealthy for Sensitive Groups	101 – 150	35.5 – 55.4
Unhealthy	151 – 200	55.5 – 150.4
Very Unhealthy	201 – 300	150.5 – 250.4
Hazardous	301 – 400	250.5 – 350.4
	401 – 500	350.5 – 500

Figure 2-2. $PM_{2.5}$ AQI levels in terms of health effects (Du & Varde, 2016).

DFW Air Quality

It is helpful to look again at the air quality index for ozone and $PM_{2.5}$ for DFW in order to get a clear idea of the NAAQS exceedances, as DFW exceeded the National Ambient Air Quality Standard (NAAQS) for ozone for decades. Figures 2-3, 2-4, 2-5, 2-6, and 2-7 show the air quality index levels of both ground level ozone and $PM_{2.5}$ in DFW from the years 2010 through 2014. As mentioned earlier, PM, including $PM_{2.5}$, is frequently strongly correlated with ozone (Guarnieri & Balmes, 2014). As seen in Figure 2-5, in 2012, the AQI value for $PM_{2.5}$ was at an unhealthy level for at least the sensitive groups during November and December, being unhealthy for all at one point in November. Figure 2-6 shows that the AQI value for $PM_{2.5}$ was at an unhealthy level for sensitive groups in August 2013, and Figure 2-7 shows that the AQI value for $PM_{2.5}$ was at an unhealthy level for sensitive groups in July 2014.

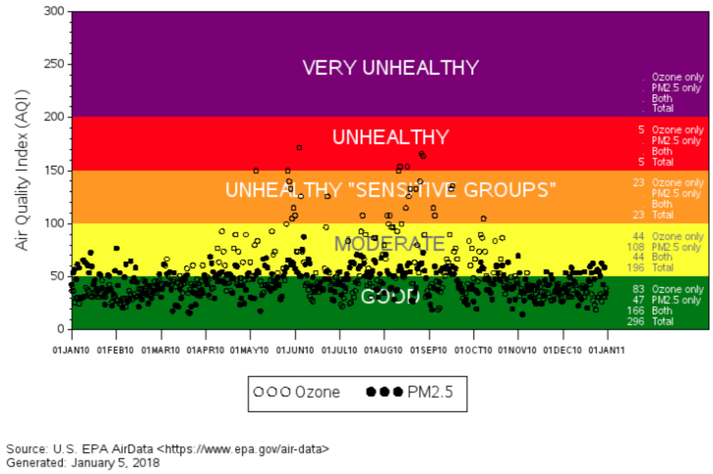


Figure 2-3. Daily ozone and $PM_{2.5}$ AQI values in the Dallas Fort-Worth metroplex in 2010.

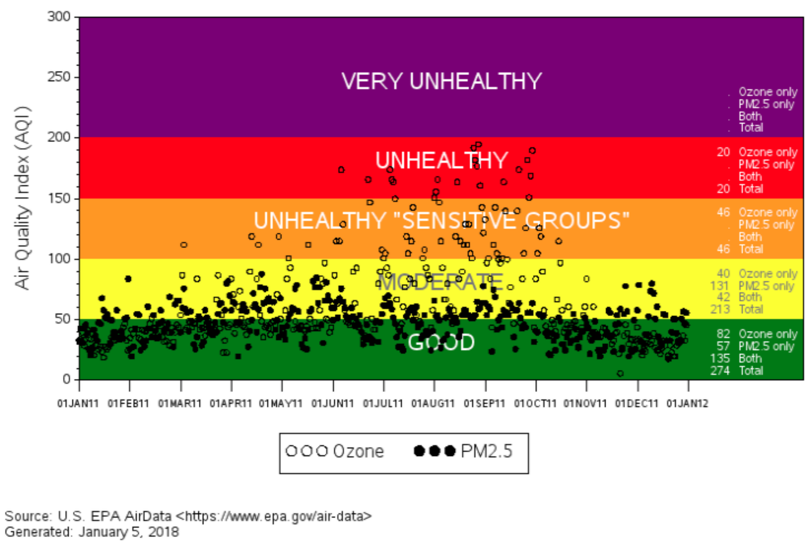
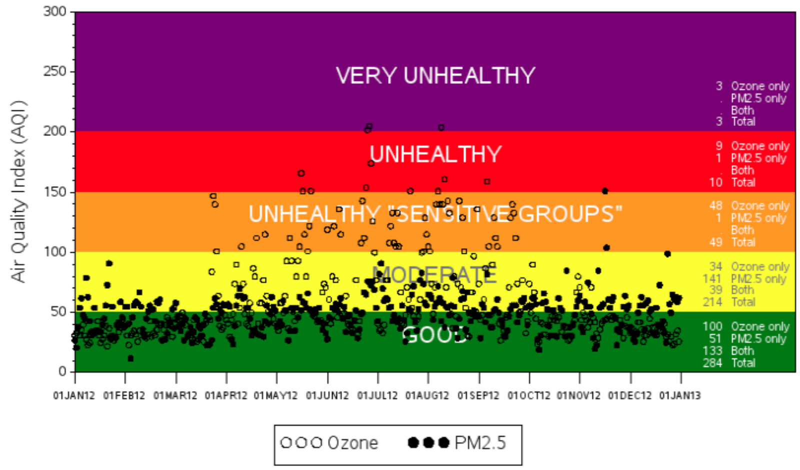
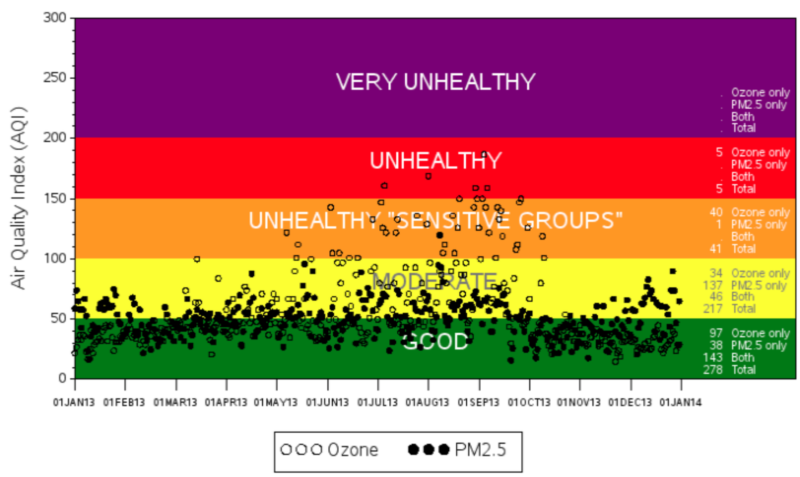


Figure 2-4. Daily ozone and $PM_{2.5}$ AQI values in in the Dallas Fort-Worth metroplex 2011.



Source: U.S. EPA AirData <https://www.epa.gov/air-data>
Generated: January 5, 2018

Figure 2-5. Daily ozone and $PM_{2.5}$ AQI values in the Dallas Fort-Worth metroplex in 2012.



Source: U.S. EPA AirData <https://www.epa.gov/air-data>
Generated: January 5, 2018

Figure 2-6. Daily ozone and $PM_{2.5}$ AQI values in the Dallas Fort-Worth metroplex in 2013.

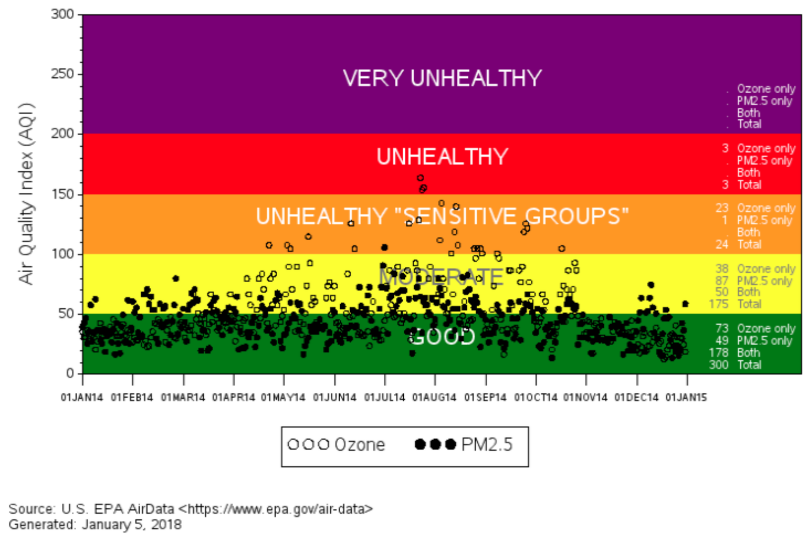


Figure 2-7. Daily ozone and $PM_{2.5}$ AQI values in the Dallas Fort-Worth metroplex in 2014.

Figure 2-8 reveals levels of ground-level ozone in the air from the years 2000 through 2017. The levels in DFW have been quite high for many years—over 0.070 ppm, with 0.071-0.085 ppm of ground level ozone being dangerous for sensitive groups (U.S. EPA, 2017). The figure does show lower levels in recent years, although at unhealthy levels for sensitive groups. Figures 2-9 and 2-10 also show the mean concentrations of $PM_{2.5}$ and ozone, respectively, from 2010 through 2014. From the figures, it is seen that $PM_{2.5}$ is not typically considered to be at extremely unhealthy levels as ozone is based on the mean concentrations, but it does show relatively high concentrations periodically.

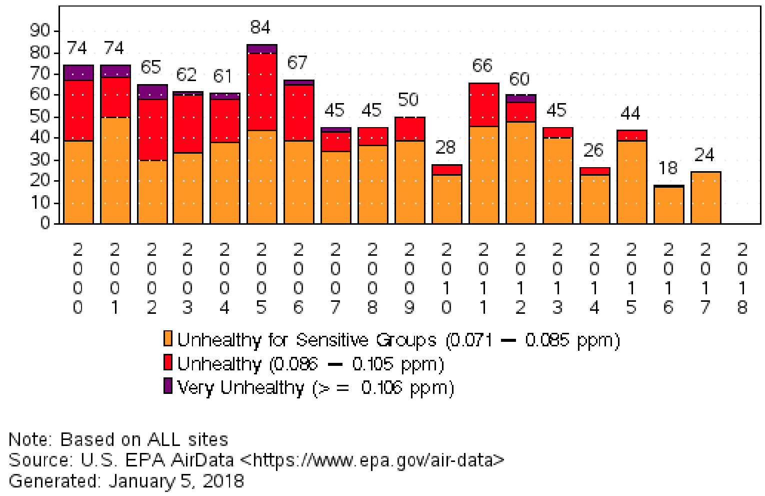


Figure 2-8. Number of days the 8-hr ozone daily maximum exceeded 0.070 ppm in the Dallas-Fort Worth area from 2000 to 2018 (U.S. EPA, 2017).

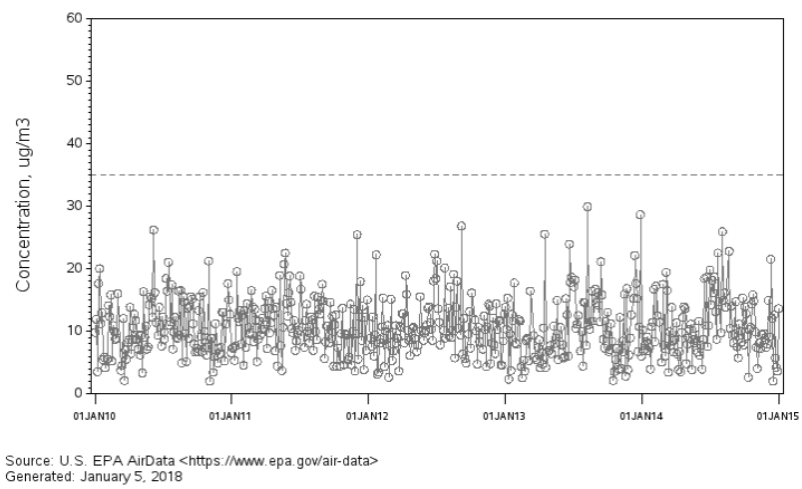


Figure 2-9. Daily mean $PM_{2.5}$ concentrations in the Dallas-Fort Worth area from 2010 through 2014 (U.S. EPA, 2017).

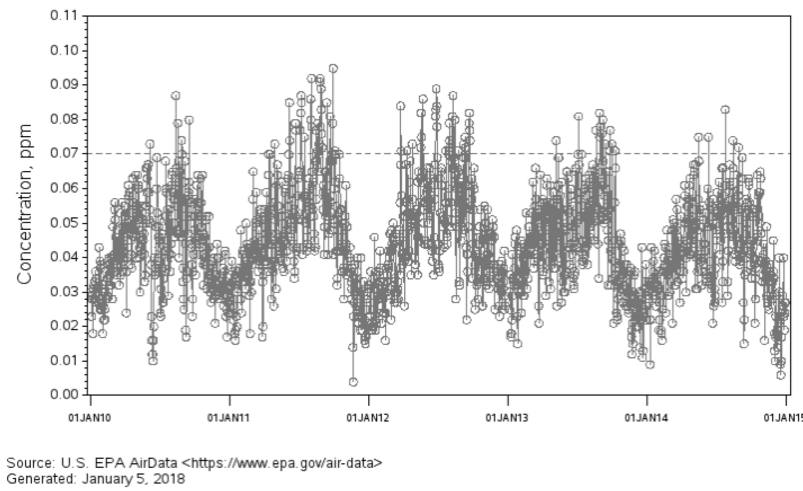


Figure 2-10. Daily maximum 8-hour ozone concentrations in the Dallas-Fort Worth area from 2010 through 2014 (U.S. EPA, 2017).

Pollutants and Health Effects

Because oxidative stress is associated with exposures to ozone, nitrogen dioxide, and $PM_{2.5}$ (specifically $PM_{2.5}$ which is made up of transition metals, polycyclic aromatic hydrocarbons, and environmentally persistent free radicals), exposure to those pollutants is thought to be linked to exacerbations of and likely the onset of asthma (Guarnieri & Balmes, 2014). Those same pollutants are also known to induce airway inflammation, and ozone and nitrogen dioxide are known to induce airway hyper-responsiveness (Guarnieri & Balmes, 2014). Other studies have shown similar results. Lu and Fang (2014) stated that besides high air pollution exposure causing an increase in illness and mortality, accrued exposure even to low levels of PM and ground-level O_3 can result in severe illness and death. Lu and Fang (2014) are presumably lumping all PM together in their article. PM_{10} does not pose the same risk of adverse effects on health as $PM_{2.5}$; $PM_{2.5}$ is more detrimental to human health (Jacobson, 2012, p. 123; Friis, 2012, p. 253). This is because $PM_{2.5}$ particles can circumvent the body's typical defenses, and they can be inhaled and deposited deep in the lungs (Friis, 2012, p. 253). If the particles do then dissolve, the body cannot efficiently remove them with its natural processes (Friis, 2012, p. 253). Therefore, it has become important to differentiate between the two. Also, unlike Guarnieri and Balmes (2014), who clearly focus on asthma, Lu and Fang (2014) are not specific about the illness in question. Air pollutants have been associated with different illnesses (i.e. $PM_{2.5}$ with both respiratory and cardiovascular disease) so one needs to be clear about the particular health concern in question. More focused research with results pointing to effects on a particular health concern, i.e. asthma, is necessary in order to further solidify claims that $PM_{2.5}$ has an adverse effect on it.

It is the case that PM is typically strongly correlated with O_3, NOx, and SOx (Guarnieri & Balmes, 2014). In New York, there was a positive correlation between the annual mean $PM_{2.5}$ concentration and the concentration of SO_2 and between the annual mean $PM_{2.5}$ concentration and the annual rate of asthma-related emergency room visits from 2005 to 2007 (Gorai et al., 2014). However, the correlation between the annual mean concentrations of ground-level ozone and asthma discharge and emergency visits was negative for the same time period (Gorai et al., 2014). $PM_{2.5}$, particularly ultrafine particles (PM less than 100 nm in diameter) like diesel exhaust particles and residue oil fly ash, can infiltrate the lung deep into the alveolar regions (Huang et al., 2015). Thus, short-term exposure to ambient $PM_{2.5}$ and PM_{10} has been linked to asthma symptoms in both children and adults (Guarnieri & Balmes, 2014). Research by Guarnieri and Balmes (2014) and Jacquemin et al. (2012) show that long-term exposure to PM is associated with uncontrolled adult asthma, leading to increased symptoms, reduced lung function, and increased hospitalization. Jacquemin et al. (2012) refer to only PM_{10}, whereas Guarnieri and Balmes (2014) refer to both PM_{10} and $PM_{2.5}$. According to Huang et al.

(2015) on page 27, PM may be shown to affect asthmatic patients because “combustion-derived PMs are known to be highly oxidizing and are capable of generating free radicals, through, in part, their surface metals involved in redox cycling or the depletion of anti-oxidant glutathione and protein-bound sulfhydryl groups.” Huang et al. (2015) do not specify that they are referring to $PM_{2.5}$, so it is difficult to know for certain that they mean $PM_{2.5}$ and not PM_{10}. As discussed by Khamutian et al. (2015), Jacobson (2012), and Friis (2012), PM_{10} may differ in its effect on asthma, so research which clearly separates the two must be done in order to back up any claims that $PM_{2.5}$ has an adverse effect on asthma, or that PM_{10} does not.

Pollutants and Asthma

When it comes to air pollution and its link to asthma cases, there is plenty of literature that focuses on ozone as it pertains to asthma aggravation worldwide. The U.S. EPA (2015) links ozone to the aggravation of asthma and possibly to asthma development. Other pollutants, including particulate matter, sulfur dioxide (SO_2), and nitrogen dioxide (NO_2), among others, have been considered for their health impacts as well in recent literature. In fact, the Global Burden Study of 2010 listed outdoor air pollution in general among the top ten worldwide health risks (Robichaud et al., 2016).

Particulate matter (PM) refers to particles in the atmosphere, and it can be derived from different sources. Particulate matter can be described as PM_{10} or $PM_{2.5}$, and as either primary or secondary. PM_{10} is particulate matter that is less than 10 μm in diameter, while $PM_{2.5}$ is particulate matter that is less than 2.5 μm in diameter. $PM_{2.5}$ is often called fine PM. Fine particulate matter can be referred to as aerosols as well. Primary PM is emitted directly into the atmosphere by a source, while secondary PM is often formed via gas-to-particle conversion within the atmosphere (Zhang et al., 2015).

Particulate matter can be derived from natural sources or anthropogenic activities and sources.

Natural sources of PM include emissions of gases and aerosols from vegetation (e.g. release of pollen), soil (e.g. windblown dust, dust storms, and nitrogen dioxide and carbon monoxide from microbial processes), ocean, wildfire, sea spray, and lightning (Zhang et al., 2015). In urban areas, most PM emissions have anthropogenic origins and natural sources such as wildfire, sea spray, and lightning (Zare et al., 2014). Wang et al. (2013) suggest that $PM_{2.5}$, in the form of smoke aerosols, is released from fire. Although the articles listed above are focused on fine PM, different PM sources may produce different particle size categories. For example, certain sources produce a certain percentage of coarse PM versus fine PM. Therefore, the authors could have been more diligent in their specification of PM sizes.

As far as anthropogenic sources, primary PM is usually derived from industrial and traffic-related sources—chiefly from coal and oil fuel combustion (Guarnieri & Balmes, 2014), but also from diesel soot, welding fumes, black carbon, or oil fly ash (Huang et al., 2015). Vehicle emissions (oil fuel combustion) are the most significant primary source of particulate matter in the urban environment (Ristovski et al., 2012), producing 31% of primary PM in Los Angeles, California (Zhang et al., 2015). Due to vehicle emissions, it is suggested that proximity to busy roads plays a role in the concentration of certain pollutants in an area. For example, Li et al. (2015) reports that areas in which there is abundant motor vehicle traffic, due to vehicle emissions, contain a higher concentration of air pollution, whereas areas with more green space and fewer vehicles passing through have less air pollution. Unfortunately, when stating this, Li et al. (2015) did not specify which pollutants are higher or lower in these areas, which makes it difficult to discern, from their work, the relevance to people with asthma. Huang et al.

(2015) were able to pinpoint multiple sources of primary PM, though their article was unclear in explaining the proportions of primary PM being produced by each source. The article by Ristovski et al. (2012) was successful in expanding on the proportion of primary PM produced by vehicle emissions in Los Angeles. The article by Guarnieri and Balmes (2014) was not specific about the individual types of pollutants which are derived from these sources. There are several pollutants that could be in question here, such as O_3. It is not limited to $PM_{2.5}$. More details about these sources and some pollutants associated with them will be discussed further later in this section.

Other anthropogenic sources of primary PM originate from domestic heating, meat cooking, and biomass burning (Zhang et al., 2015). Biomass burning releases $PM_{2.5}$ in the form of smoke aerosols (Wang et al., 2013) and ozone, and it entails activities such as fireplace wood burning, open wood burning, and straw burning (Zhang et al., 2015). While Zhang et al. (2015) and Wang et al. (2013) were successful in conveying the specific processes by which PM is released by burning of materials, Wang et al. (2013) were more successful in expanding on the specific details of how $PM_{2.5}$ is released. Neither article, however, was effective in explaining where these activities would occur, i.e. in rural or urban settings, or in a geographic sense. Relating this to DFW, a lot of biomass burning likely takes place in more rural areas, in agricultural settings. This is likely true mostly of open wood burning and straw burning. However, fireplace wood burning can take place all over the DFW area, in urban, suburban, and rural areas—wherever there are homes with fireplaces. Even open wood burning can take place in urban and suburban areas—presumably, this may be associated with outdoor cooking.

Secondary PM includes organic matter, sulfate, nitrate, and ammonium, the formation of which is caused by emissions of VOCs (volatile organic compounds), SO_2, NOx (nitrogen oxides), and ammonia (Zhang et al., 2015). The formation of secondary PM is more complicated than the release of primary PM. In urban settings, there can be high VOC emissions from both anthropogenic and natural sources. The VOCs go through photochemical oxidation, which leads to the formation of semi-volatile and nonvolatile gases. These gases go through gas-to-particle conversion processes, which results in organic particles (Zhang et al., 2015). Gas-phase VOCs are oxidated, driven by reactions with different radicals (e.g. OH, NO_3, or O_3). In the daytime, VOC oxidation initiated by OH yields "aldehyde, ketone, alcohol, carboxylic acid, hydroperoxide, percarboxylic acid, and peroxyacyl nitrates" (Zhang et al., 2015, p. 3809). The resulting particles depend on solar radiation intensity, ambient temperature, relative humidity, VOC structure, and NOx levels (Zhang et al., 2015).

In Houston, Texas, secondary inorganic aerosols represent 42% of the ambient fine PM, followed by vehicle emissions (31%), and because of the large amount of vehicles, road dust represents another significant source of $PM_{2.5}$ (11%) (Zhang et al., 2015). Secondary PM makes up a significant amount of the total mass of urban fine PM in the atmosphere. Vehicle emissions contribute to both primary and secondary PM concentrations. However, an important point to note is that determining the percentages of pollutants emitted by a source is difficult due to the abundance of natural and anthropogenic sources for urban PM. Zhang et al. (2015) includes secondary PM formation process as well as the proportions of $PM_{2.5}$ emitted from significant sources to the atmosphere (Figure 2-11).

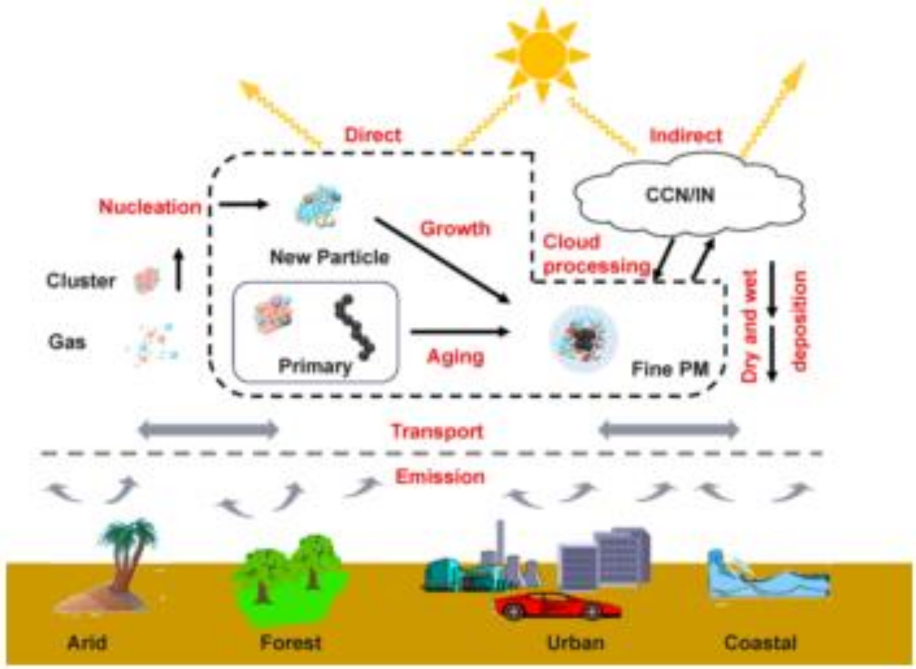


Figure 2-11. Formation of atmospheric particulate matter (Zhang et al., 2015).

Exposure of those individuals with asthma to pollutants, including $PM_{2.5}$, NO_2 (nitrogen dioxide), and O_3 can induce airway inflammation (a characteristic of asthma), and airway hyper-responsiveness (another characteristic of asthma) can be caused by exposure to NO_2 and O_3 (Guarnieri & Balmes, 2014). Oxidative stress, a characteristic of severe asthma, can be caused by exposure to O_3, NO_2, and $PM_{2.5}$ (Guarnieri & Balmes, 2014). Those pollutants (O_3, NO_2, and $PM_{2.5}$) are associated with both exacerbation and onset of asthma, and in the case of childhood asthma in particular, researchers found that 15% of exacerbations were due to exposure to primary pollutants emitted directly (including $PM_{2.5}$, NOx, and VOCs) and the secondary pollutants (e.g. O_3) that are formed by photochemical reactions with vehicle-emitted NOx and VOCs (Guarnieri & Balmes, 2014). Although they were not specific about the ways in which asthma was affected, their focus on hospitalization indicates that they were focused on subjects whose asthma was severely aggravated. While Guarnieri and Balmes (2014) were successful in showing how $PM_{2.5}$, among other pollutants, can affect asthma, they left room for expansion on what components of traffic-related pollution could contribute to asthma being exacerbated.

Even though some studies have pointed to the larger PM_{10} being associated with asthma exacerbation, a study done in Kermanshah, Iran showed that PM_{10} had no significant association with the number of asthma-related hospitalizations (Khamutian et al., 2015). Instead, gaseous pollutants (CO [carbon monoxide], O_3, NO [nitric oxide], NO_2, and SO_2) played an important role in asthma patients' hospitalizations (Khamutian et al., 2015). This goes along with the accepted view that $PM_{2.5}$ is more detrimental to human respiratory health than is PM_{10}, as explained by Jacobson (2012) and Friis (2012). The study by Khamutian et al. (2015) was not as descriptive about sources of PM_{10} or other pollutants.

The pervasiveness of asthma has increased since the 1960s, especially in westernized countries (Baldacci et al., 2015). In fact, as of 2015, an estimated 23 million people had asthma in the US (U.S. EPA, 2015). It is suggested that this cannot be explained only by genetics; increased exposure of western populations to air pollution due to urbanization and industrialization is believed to be a contributor to the rise (Baldacci et al., 2015). Baldacci et al. (2015) did not explain what urbanization and industrialization specifically release as far as pollutants.

Urbanization and industrialization entail increased air pollution, such as traffic-related air pollution. Traffic-related air pollution includes those pollutants released due to fossil fuel combustion: PM, SO_2, NO_2 and CO, and the greenhouse gases carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O) (DeSario, Katsouyanni, & Michelozzi, 2013). As the population of an area grows, one consequence is that there will typically be more vehicles on roads, thus leading to increased air pollution. DeSario et al. (2013) effectively specified what pollutants are released into the air due to fossil fuel combustion; however, they did not specify which particulate matter is being released (whether it is PM_{10}, $PM_{2.5}$, or a combination). This is important in that, as discussed by Khamutian et al. (2015), PM_{10} may not be significant in terms of asthma, whereas other literature points to $PM_{2.5}$ having a noticeable impact on asthma.

Weather Elements and Pollutants

Several meteorological variables are often shown to have combined effects on air pollution concentrations. For example, in a study based in Shanghai, China, Cai et al. (2014) found that PM_{10} and black carbon concentrations decreased with increasing outdoor temperature and humidity (Cai et al., 2014). However, in another study conducted in China, it was found that PM_{10} concentrations increased with increasing daily maximum temperatures (Li et al., 2014). While they did include PM_{10} in their focus, Cai et al. (2014) did not explicitly mention $PM_{2.5}$ in their study, though black carbon is typically considered to be in the category of fine particulate matter. Li et al. (2014) actually included daily average temperature, relative humidity, precipitation and maximum wind speed as variables in their study. Notably, Li et al. (2014) and Zhang et al. (2015) considered other meteorological variables in their research (i.e. solar radiation and precipitation, to be explained later in this section, *Weather Elements and Pollutants*), which is quite important. There are many meteorological events and processes which take place daily, and as many as feasible must be considered to get a clear idea of what processes may affect the concentrations of ambient $PM_{2.5}$ for an area.

A study from Poland found that high ozone levels were observed with higher levels of radiation, air temperature, and wind speed; however, atmospheric pressure had unclear effects on the ozone levels (Kalbarczyk et al., 2015). It is found that cloudiness tends to also have an effect on ozone and other secondary pollutant formation, as the clouds can limit incoming solar radiation (Wałaszek et al., 2017). With what is known about the formation of ozone (i.e. the necessity of solar radiation in order for the photochemical reactions to take place), one can hypothesize that the extreme heat, usually associated with high amounts of sunlight, may cause increased risk of hospitalization from asthma because of its effect on ozone. It is interesting to again note the studies from Toronto, Canada (Feldman et al., 2014) and Maryland, USA (Soneja et al., 2016) mentioned in the *Weather Elements and Asthma* section, in which it was found that extreme heat is associated with increased asthma exacerbation.

There are some studies which have found patterns between air pollutant concentrations and meteorological variables such as precipitation and wind speed, rather than just surface temperature and/or relative humidity alone. Often, precipitation and wind are associated with removal or dispersion of air pollutants, including $PM_{2.5}$. Both primary and secondary PM undergo chemical and physical transformations in the atmosphere as well as transport, cloud processing, and removal from the atmosphere, according to Zhang et al. (2015) and Brunner et al. (2015). Zhang et al. (2015) points out that PM formed in urban areas is transported downwind, with [primary PM] being transported 20 – 30 km. Also, PM precursors (which eventually form secondary PM) are transported to the urban areas from areas upwind (Zhang et al., 2015). As far as further removal processes, Zhang et al. (2015) and Brunner et al. (2015) agree that fine PM may be removed by dry deposition or wet deposition (via in-cloud scavenging and below-cloud scavenging), with wet deposition involving fine PM being incorporated in water droplets in clouds or raindrops, thus being removed from the atmosphere and deposited on the ground. While both Zhang et al. (2015) and Brunner et al. (2015) are aligned in their assessment of the processes by which PM may be removed from the atmosphere, Zhang et al. (2015) go into more detail about the transport and removal processes of fine PM. This gives a clear picture of how natural meteorological processes may reduce the fine PM concentrations in the atmosphere, which is important to note when comparing the concentrations of fine PM in the atmosphere to the meteorological events that have taken place around a given time.

There is evidence, as mentioned, that wind-induced mixing affects air pollutant concentrations via dispersion of the pollutants. Increase in wind speed and shear enhances vertical mixing as does thermal convection (Pesic et al., 2014). In the case of fire pollutants, which include ozone and particulate matter, dispersion of the pollutants is controlled by their buoyancy in low wind velocity situations, and by the wind intensity in high wind velocity situations (Pesic et al., 2014). While Pesic et al. (2014) were successful in shedding light on the effects of wind speed on dispersion of pollutants/aerosols produced from fires, a more in-depth look at the dispersion of different sizes of PM would have served them well. It would be helpful to know if different particle sizes are affected differently by different wind speeds.

Wind direction is a meteorological variable that has been shown to contribute significantly to the dispersion of air pollutants (Contreras & Ferri, 2016). Ahmadi and John (2015) and Bella et al. (2016) agree that the wind transports air pollutants such as ozone from one county to another. Ahmadi and John (2015) consider that the drilling for natural gas in the Barnett Shale area, which is situated on the west side of DFW, is a major source of ozone for the rest of DFW. Figure 2-12 shows the area that was referenced as Barnett Shale, as well as where the drilling takes place (Ahmadi & John, 2015). In addition to a few other counties to the west, some of the counties from the study area of this current study are at least partially situated on the Barnett Shale: Palo Pinto, Erath, Somervell, Hood, Parker, Wise, Denton, Collin, Tarrant, Johnson, Hill, Dallas, and Ellis Counties. Those counties which are situated on the shale and are a part of the drilling activities, according to Ahmadi and John (2015), experience a higher rate of ozone exceedances than other nearby counties in which there is no drilling activity (including Collin, Rockwall, Hunt, and Kaufman Counties). Bella et al. (2016) indicate that CO from fires as far away as the Pacific Northwest has made its way to the Houston, Texas area, as well as ozone and its precursors being transported from other distant locations into Texas. However, the source location(s) of ozone and its precursors are not pinned down in the discussion from this study. Also, the specific precursors are not explicitly stated.

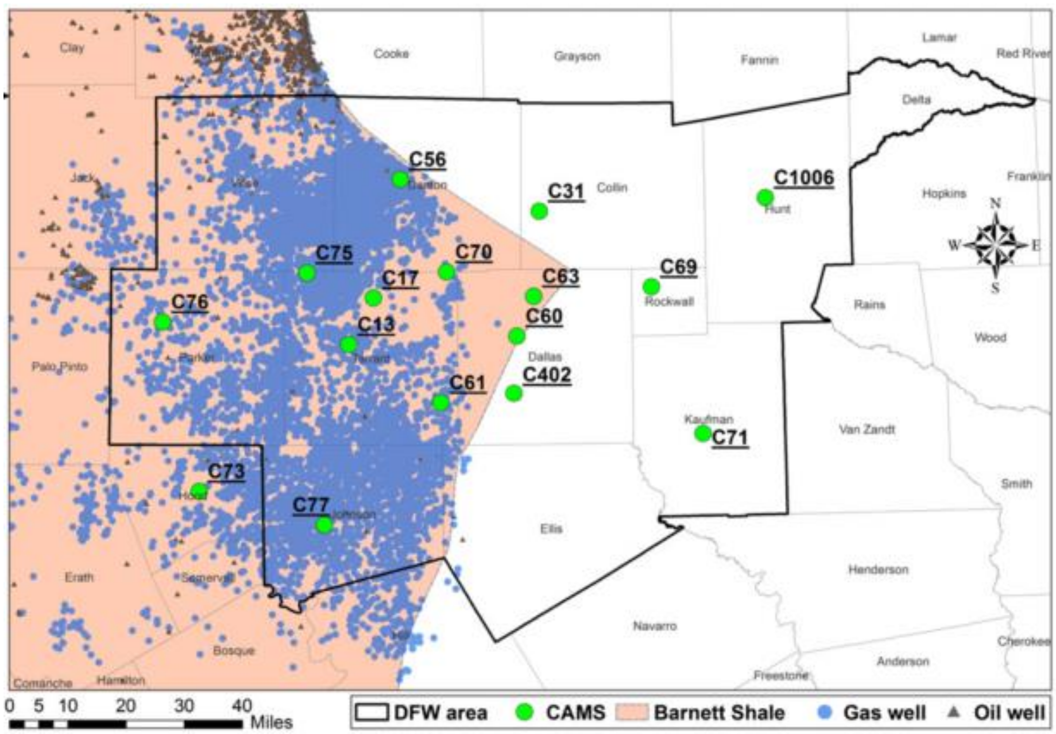


Figure 2-12. Barnett Shale drilling activity in North Texas (Ahmadi & John, 2015).

In Hong Kong, between 2000 and 2011, researchers found that changes in wind and emissions are two of the most important variables to consider in variations in local air quality, focusing on PM_{10} and SO_2 concentrations (Y. Li et al., 2014). They did not specify which type(s) of emissions; however, there is a fair amount of evidence to back up this statement as far as the effects of wind on transport and dispersion of pollutants, as seen above. Ahmadi and John (2015) focused on ozone being transported downwind, but did not mention particulate matter at all, let alone $PM_{2.5}$. Bella et al. (2016) also focused on O_3 and CO but did not mention $PM_{2.5}$ either. Y. Li et al. (2014) focused on PM_{10} and SO_2, but not $PM_{2.5}$.

Brunner et al. (2015), Zhang et al. (2015), Zhen et al. (2013), and Lai (2013) suggest that heavy precipitation contributes to the dispersion and removal of some water soluble trace gases (e.g. formaldehyde, carbon dioxide and nitrogen oxide) and aerosols (fine PM) via wet deposition. Zhen et al. (2013) did report on PM_{10} concentrations in their study, but not $PM_{2.5}$. Lai (2013) further explained that in all, high humidity, low precipitation, and low wind speed are associated with higher concentrations of $PM_{2.5}$ in the atmosphere, which may back up that high precipitation does cause deposition of air pollutants, and that it could deposit $PM_{2.5}$ specifically. Contrary to other findings regarding precipitation, Veremchuk et al. (2016) found that there was not a significant correlation found between precipitation and PM_{10} and PM_1 (a smaller form of PM than $PM_{2.5}$). This is likely because of the atmospheric circulation along with the rough topography and suburban development of the area (Veremchuk et al., 2016). They instead found that the season, actual humidity, actual temperature, actual dew point, and wind direction were significantly positively correlated with the PM concentrations in Vladivostok, Russia (Veremchuk et al., 2016). Although it was difficult to discern exactly how the season and wind direction were correlated with the PM concentrations, Veremchuk et al. (2016) were successful in conveying that the individual meteorological variables of humidity, temperature, and dew point are involved in the concentrations. It is important to know which individual pollutants may be removed by the purifying nature of precipitation, so it is helpful that Veremchuk et al. (2016) included various gaseous pollutants as well as two sizes of PM in their study, covering fine PM and coarser PM. Due to the findings of some of the research on the correlation between precipitation (and other weather variables) and fine PM concentrations differing, it is necessary to gather more evidence through more research, and in different locations, as the conflicting findings are often in different locations.

L. Li et al. (2014) state that some variables, being temperature, relative humidity, precipitation, and wind speed, were negatively correlated with the air pollution index for PM_{10}, NO_2, and SO_2, and that atmospheric pressure was positively correlated with the air pollution index for PM_{10} in the annual cycle. The study highlighted the correlation between the air pollution index and the atmospheric pressure. L. Li et al. (2014) explained that in an area with a low atmospheric pressure system, the air in the lower atmosphere "converges and rises". During that process, pollutants from the surface (ground-level pollutants) rise to higher altitudes, which results in the dispersion and dilution of the pollutants (L. Li et al., 2014). However, when there is a high-pressure system in the surrounding area, the air becomes stable. This limits the dispersion and dilution of pollutants rather keeping them in place in the lower atmosphere (L. Li et al., 2014). That description defines what is known as an inversion as it relates to air pollution (in regard to high atmospheric pressure). Low pressure systems are associated with stormy weather, which entails more turbulent winds, and the opposite effect from that of high pressure systems.

The study in Hungary by Makra et al. (2015) indicated that thunderstorm events tend to increase the frequency of asthma attacks; the researchers point to the thunderstorms' particular conditions circulating pollutants. In the case of Makra et al.

(2015), the specific conditions referenced were an “anticyclonic ridge” (Makra et al., 2015, p. 1284). Another example of the effects of a low pressure system is a study done in Massachusetts, in which it was found that low pressure days (which included high precipitation) resulted in low concentrations of ozone (Austin et al., 2015). As far as the effects of high pressure systems, the results of a study in Taipei revealed that photochemical smog days (high ground-level ozone days) took place during episodes of high surface air pressure, high air temperature, low relative humidity, and low wind speed (Lai, 2012). Again, high surface air pressure by nature entails a sunny day with low winds, the opposite of a low pressure system, which is a condition for stormy weather. None of these articles focus on $PM_{2.5}$, so more research needs to be done in order to determine if $PM_{2.5}$ is affected by storms.

Some studies found that a number of different meteorological factors impact air pollution concentrations. A study which took place in the southeastern United States showed that ground level ozone in particular is affected by temperature, humidity, surface pressure, wind speed, and wind direction, but that correlations between ground level ozone and those meteorological parameters vary with region and season (Zhang & Wang, 2016). Specifically, high temperatures (especially in the summer), high daytime relative humidity (especially in the fall), and low wind speeds are associated with high ozone concentrations (Zhang & Wang, 2016). Zhang and Wang (2016) do not, however, go into detail about the effects of surface pressure or wind direction. This information, especially since it was mentioned, would have clarified the factors which affect ozone concentration and how they affect it.

Some researchers focus on synoptic scale weather types (large, regional scale affected by pressure systems) as the basis for meteorological conditions in their studies of air pollution which may be affected by weather. Liu et al. (2017) found that in the contiguous United States, the concentration of ambient $PM_{2.5}$ underwent the largest increase when the synoptic weather type changed from dry-polar to moist-tropical air masses, and that a change from moist-tropical to dry-polar weather type caused the largest decrease in ambient $PM_{2.5}$ concentrations. It is important to note that the findings in the same study found that the effects of atmospheric moisture on $PM_{2.5}$ tend to be subtle compared to the effects of air temperature such that when the temperature is moderate, neither dry nor moist air, in most cases, are associated with significantly high or low concentrations of $PM_{2.5}$ (Liu et al., 2017). While these findings are interesting, focusing on synoptic weather types can be problematic in that it typically leaves out variables such as precipitation and wind speed, among other meteorological variables. Considering weather data from the NCEP reanalysis (Kalnay et al., 1996) allows for a more detailed possible explanation for the fluctuations in $PM_{2.5}$ concentrations on the regional scale. Seasonal changes in weather patterns influence concentrations of air pollutants such as PM and O_3. The levels of PM are generally higher in summer and fall months when the ambient temperature is typically warmer, and lower in winter and spring, according to a study in Los Angeles (Delamater, Finley, & Banerjee, 2012). On the outskirts of Santiago, Chile, research results showed that when the maximum temperature exceeds 30°C in the summer, ozone episodes tend to take place (Rubio & Lissi, 2014). Rubio and Lissi (2014) do not mention PM, however. There is much research done on ozone and its seasonal concentrations. However, research which mentions how weather affects other pollutants, such as $PM_{2.5}$, is needed.

While scientists are beginning to provide proof of the notion that weather does indeed have effects on the concentrations of air pollutants in a given area, Makra et al. (2015) and Vanos et al. (2013) stress that further studies must be carried out in order to determine which specific environmental factors (e.g. weather) affect air pollutant concentrations and how much those factors do affect pollutant concentrations. In future research, focusing on $PM_{2.5}$ in particular and how it is affected by weather variables will aid in the understanding of whether $PM_{2.5}$ is in higher concentrations at certain times based on meteorological factors, and in turn what to expect during certain meteorological events as far as health concerns like asthma.

Weather Elements and Asthma

Asthma is characterized by airway inflammation (Fitzpatrick et al., 2009), airway smooth muscle hyper-responsiveness, and oxidative stress (Guarnieri & Balmes, 2014). There is research that shows that certain elements of weather aggravate asthma symptoms. For example, in Toronto, Canada (Feldman et al., 2014), and in Maryland, USA (Soneja et al., 2016), researchers found that increasing temperatures correspond with increased risk for asthma-related hospital admission. Although Feldman et al. (2014) do not go into detail about other weather variables, Soneja et al. (2016) found that exposure to extreme precipitation also corresponds with increased risk for asthma-related hospital admission. DeSario et al. (2013) emphasize other weather-related variables such as humidity, visibility, cloud cover, air pressure and wind speed also need to be further examined as possible causes of respiratory disease exacerbation.

Weather influences on asthma have been discussed in various studies. Even though the study in Maryland (mentioned above) associated increased asthma-related hospitalization with extreme heat, there are studies which report cold temperatures are related to increased rates of asthma-related hospitalization. Studies in Iran (Khamutian et al., 2015) and Spain (Roye et al., 2016) revealed results which showed that there were higher rates of asthma cases during cooler months. Makra et al. (2015) suggest that the reason behind the cold air causing the aggravation of asthma is that “inhalation of cold air in hyper-reactive bronchi induces inflammation of the mucous membrane. Furthermore, the inhalation of dry and cold air also activates the so-called cold receptors on the nasal mucous membrane, which contributes to the development of the respiratory hyper-reactivity" (p. 1281). It is useful that a possible reason for the cold air causing exacerbation of asthma is presented, as those previously-mentioned articles linking warm outdoor air to asthma do not go into such detail. It is important to determine why certain weather may be causing the aggravation of asthma, but many articles do not explore the possible reasons; they instead simply point out the external conditions which are evidently present when there are outbreaks of exacerbated asthma. Interestingly, the results of research conducted by Tsangari et al. (2016) in Cyprus were on both sides as far as warm and cold air. Tsangari et al. (2016) highlighted that patients experienced increased hospital admissions due to respiratory conditions in the wake of certain meteorological events, namely warm, rainy days with high humidity and cold, cloudy days with increased precipitation. Again, the reasons behind this, specific to the effects on the human respiratory system, are not explicitly stated here, so there are still questions about these results. However, the article did bring up elements to consider besides temperature: precipitation and humidity. This advances their study, as there are of course more variables in weather than the temperature. The Cyprus study by Tsangari et al. (2016) was based on weather on the synoptic scale (large, regional scale affected by pressure systems). However, it is suggested that climate is more variable on a sub-regional scale than on a hemispheric or global scale, especially in the case of precipitation (Ramos, Cortesi, & Trigo, 2014). Therefore, local scale weather conditions (those conditions which are influenced by variables such as ground temperature and winds on the sub-regional scale), may be more useful in assessing the impact of weather on air pollutant concentrations.

In Hungary, researchers observed that the highest daily mortality due to asthma was during times of high relative humidity conditions (Makra et al., 2015). However, the same study cites previous research which shows that lower relative humidity is associated with increased emergency room visits related to asthma (Makra et al., 2015). Also, although heavy rain is associated with lower rates of asthma cases in Europe according to Makra et al. (2015), thunderstorms in particular are associated with increased asthma aggravation in other studies (Makra et al. 2015). Makra et al. (2015) were good, in this article, about covering many bases. They pointed out where conflicting results were seen between their research and previous research. It is helpful to see that there are such differences, but it does beg the question of why there are such differences between the studies on similar subject matter.

Influence of Weather Elements and Pollutants on Asthma

Meteorological variables (such as surface temperature, relative humidity, wind, and anticyclonic storm events) and air pollution (in particular ground-level ozone) individually have effects on human health (Vanos et al., 2015). This includes effects on asthma. There is, however, more work to be done in determining which particular weather conditions and events, if any, do affect $PM_{2.5}$ concentrations and how. There is one study of note in which researchers found that between temperatures of 1.1 to 80.5°F, each 1 $\mu g/m^3$ increase in $PM_{2.5}$ concentration was associated with an increased asthma symptom pervasiveness in adult women (Mirabelli et al., 2016). Focusing on temperature as the only weather variable, this suggests that the $PM_{2.5}$ concentration could be the driving factor for asthma symptom prevalence on its own. However, the findings are limited due to the testing only involving adult women and not adult men. Studies by Delamater et al. (2012) and Pleijel et al. (2016) show that pollutant concentrations are often highly correlated with seasonal changes and climate, not just pollutant emissions alone. Makra et al. (2015) and Chen et al. (2016) found that air temperature and relative humidity are positively correlated with both pediatric and adult asthma-related hospitalizations, and that air pollution effects on human health vary with season and the overall weather circumstances. Makra et al. (2015) focused on PM_{10} and O_3, but not $PM_{2.5}$. Chen et al. (2016) focused on several pollutants, including O_3, NO_2, pollen, $PM_{2.5}$ and PM_{10}. However, they only included synoptic scale weather conditions in their study, which negates local scale weather variables such as wind speeds, precipitation events, and urban heat island effect.

It is suggested that the contrasts between different circulation weather types (i.e. cyclones and anticyclones), in the case of human health impacts, could be more important than the synoptic situation (Roye et al., 2016). Because of this, it may be time to examine more local scale weather patterns in terms of air pollutants which negatively impact human health. Due to findings in eastern Texas being that positive correlations between $PM_{2.5}$ and asthma discharge rates not being statistically significant, it is suggested that the local weather conditions be considered as another variable possibly affecting asthma (Gorai, Tchounwou, & Tuluri 2016). Gorai et al. (2016) focus on what they call Eastern Texas for their study (Figure 2-13). Although their definition of Eastern Texas includes DFW as defined by the current study, the area covered by Gorai et al. (2016) is too large. There still may be differences in the weather events, $PM_{2.5}$ sources and subsequent concentrations, and asthma exacerbation in the two areas, which can only be determined with more testing in the individual regions on a smaller scale.

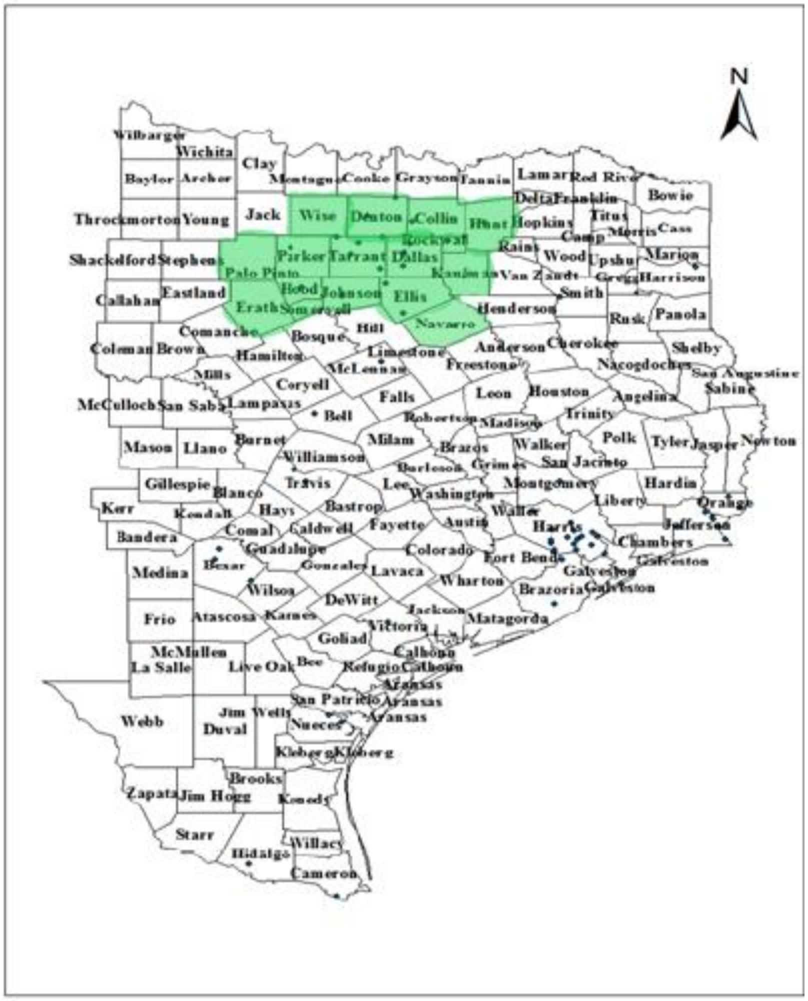


Figure 2-13. Study area (Eastern Texas) of Gorai et al. (2016). The counties in the study area of the current study are highlighted in green.

Focusing on specific weather-related variables such as humidity, visibility, cloud cover, air pressure, temperature, and wind speed, combined with the concentrations of air pollutants in areas in which variations of those factors occur, will further the understanding of how asthma symptoms are apparently increasing in frequency. Most of the available literature on these topics focuses on large areas, or on a select few cities around the world. Examples which focus on Texas are scant. Out of the 84 literary sources which were relevant enough to be cited in this study, 9 of them are from studies based in some part of Texas. Only five of those focus on north Texas or DFW. Other articles focus on other cities around the world, in Europe, Asia, South America, Australia, and other parts of North America, as seen in the literature reviewed for this research. Vanos et al. (2013) suggest that other cities be studied further due to the variation in pollutant concentrations which have already been found.

Chen et al. (2016) suggested that the influence of weather on asthma is yet poorly understood other than the apparent correlations between ambient temperatures and asthma symptoms. Perhaps some weather-related correlations with asthma symptoms, as well as air pollutant concentrations and their effect on asthma, may be further explained by combining pollutant concentration measurements with weather data.

Urban-Induced Turbulence

Something that may be important in the case of the more urbanized portions of DFW is the effect of buildings on wind turbulence. The flow and turbulence of air at ground level and above urban areas can be disturbed by structures such as buildings and by rough terrain (Castelli et al., 2014). In certain counties, such as Dallas and Tarrant counties (where the cities of Dallas and Fort Worth are located), this concept may be worth considering due to the abundance of buildings in and around the downtown areas. The presence of many tall buildings and other structures in these areas leads to the possibility of “street canyons,” which cause the phenomenon of turbulent winds. The findings of Castelli et al. (2014) are very interesting and can be useful in determining the effects that differences in wind turbulence due to the presence of buildings may have on air pollutants. However, the research was limited to only suburban areas rather than expanding into urban and rural areas for comparison.

The rapid urbanization in DFW has contributed to notable urban heat island effect (Winguth & Kelp, 2013), with the intensity of the effect—meaning the temperature difference at 2 meters between urban and rural zones—reaching 5.48°C in July of 2011 (Hu & Xue, 2016). With the predicted population growth and expected furthering of urbanization in DFW, future urban heat island circumstances are predicted to be even more severe (Hu & Xue, 2016). In general, the urban heat island effect displays a diurnal cycle with lower intensity during daytime and higher intensity at night because of the stored heat being released from buildings during the night, making the urban heat island effect a primarily nocturnal occurrence (Hu & Xue, 2016). Urban heat island intensity typically increases around sunset, staying at a relatively constant level through the night until the convective boundary layer begins rapid development early the next morning (Hu & Xue, 2016). It was found that secondary ozone peaks are reached at night due to vertical mixing brought on by a sea breeze reaching DFW from coastal areas of Texas on the Gulf of Mexico (Hu & Xue, 2016). Notably, Hu and Xue (2016) focused heavily on DFW. The origin of the ozone is not extensively discussed in the article, and the article lacked any mention of the possible correlation between the urban heat island effect itself and ambient air pollutant concentrations, i.e. $PM_{2.5}$ concentrations.

Built Environment, Weather Elements, Pollutants, and Asthma

L. Li et al. (2014) acknowledge that the urban heat island effect exacerbates pollution originating from vehicle emissions due to the implied temperature inversions and “static wind speeds” associated with the effect. Based on that statement, it appears that the urban heat island effect, which is generally known to be associated with high maximum temperatures, may also play a role in wind speed. L. Li et al. (2014) are more successful in explaining the way the urban heat island effect may exacerbate air pollution, however, they are not specific about what pollutants are being discussed.

The static wind speeds reported by L. Li et al. (2014) are in contrast to another concept: that of street canyons. Urbanization is typically accompanied by the presence of tall buildings, which ties into street canyons. Pesic et al. (2014) and Castelli et al. (2014) find that the presence of such buildings contribute to the mixing and dispersion of pollutants from vehicular, industrial, and domestic pollutant emissions (i.e. domestic heating). With wind speed increasing at the roof level of a street canyon, the strong turbulence caused by the increased velocity causes more intensive mixing of the air at that level and of pollutants and in turn, lowering local concentrations of pollutants in the air (Pesic et al., 2014). Pesic et al. (2014) are discussing aerosols in this research. Castelli et al. (2014) focus exclusively on suburban areas in this research, which limits the scope of their findings to that particular setting, negating rural and urban settings.

Because the Dallas-Fort Worth area (the focus of the proposed study) is growing rapidly in population (Hu & Xue, 2016) and, in turn, vehicular traffic, air pollutant concentrations could be exacerbated (including $PM_{2.5}$). This could lead to possible increased symptoms of respiratory illnesses, including asthma symptoms, which are typically associated with traffic-related air pollutant concentration increases (Guarnieri & Balmes, 2014). When it comes to the DFW area, there is some literature on air pollution in general as well as on asthma in relation to air pollution concentrations. The DFW area is presently the fourth largest metropolitan area in the United States due to rapid urbanization and industrialization (Hu & Xue, 2016). The area is expected to grow more populated and urbanized in the future, with the projection being that DFW will have a population of 15 million by 2050, making it a “megacity” (Hu & Xue, 2016). It is important that Hu and Xue (2016) brought this up, as discussing the projected future of DFW in terms of population helps put into perspective how much air pollution, including $PM_{2.5}$, may increase (as population growth leads to increased air pollution). This demonstrates the need to further research the formation and dispersion of $PM_{2.5}$ among the other pollutants being produced (i.e. O_3).

In 2014, when the eight-hour ozone standard set by the Environmental Protection Agency was 75 ppb, a ten-county area in DFW was classified by the EPA as a moderate non-attainment area for ozone—Wise, Denton, Collin, Parker, Tarrant, Dallas, Rockwall, Kaufman, Johnson, and Ellis Counties were the ten counties (Hudak, 2014). This means the daily maximum eight-hour ozone concentrations for each county, averaged over three years (so approximately 2011 through 2013), exceeded 75 ppb (Hudak, 2014). In fact, DFW notably exceeded the National Ambient Air Quality Standard (NAAQS) from 2003 to 2011 as well (Goodman et al., 2017). Between 2007 and 2010, Dallas and Harris Counties reported the highest number of asthma-related hospital admissions in Texas (Goodman et al., 2017). It is helpful to look again at the air quality index for ozone and $PM_{2.5}$ for DFW in order to get a clear idea of the NAAQS exceedances from 2010 through 2014, shown in Figures 2-3 through 2-7. Orange (unhealthy for sensitive groups), red (unhealthy), and violet (very unhealthy) represent exceedances in the figures.

The future of DFW—and other places which are similar in population and urbanization—is of concern due to global climate change. DeSario et al. (2013) and Guarnieri and Balmes (2014) found that due to climate change, among other variables, air pollution patterns have been changing in many urbanized areas like DFW. DeSario et al. (2013) and Guarnieri and Balmes (2014) explain that climate change will lead to increasing atmospheric concentrations of pollutants including O_3, PM (e.g. $PM_{2.5}$), SO_2, NO_2, and CO. This will be due to higher temperatures and less precipitation as well as an increase in frequency of extreme weather events like heatwaves, wildfires, and dust storms (DeSario et al., 2013). DeSario et al. (2013) are not specific about the PM size, however. As has been covered previously, it has become important to differentiate as

$PM_{2.5}$ and PM_{10} tend to have different connotations associated with health effects. Guarnieri and Balmes (2014) specify that $PM_{2.5}$ will increase due to climate change. The effects of climate change, such as on air pollutant concentrations and asthma exacerbations, should be explored more in future research (Guarnieri & Balmes, 2014). Other research also shows that climate change could cause an increase in regional summer ozone-related asthma exacerbation and hospital visits—the projected increase is 7.3% for children between 0 and 17 years of age in the New York City metropolitan area alone by the 2020s (Sheffield, Knowlton, Carr, & Kinney, 2011). Guarnieri and Balmes (2014), as well as Sheffield et al. (2011), are successful in indicating what the future may hold in terms of pollutant concentrations due to climate change. Sheffield et al. (2011) took it a step further by projecting the effects on asthma; however, the focus for their research was ozone rather than $PM_{2.5}$. Projections remain to be shown for the fate of DFW in terms of asthma, and in terms of $PM_{2.5}$, in the coming years marked by climate change.

Tools for Modeling and Analysis

It has been suggested that determining the percentages of pollutants emitted by given sources is difficult, in part, due to the limitations of current technology in efficiency and accuracy (Zhang et al., 2015). In this study, we apply geographic information systems (GIS) tools, as main analysis tools. Ordinary kriging is one tool that can be used for determining spatial relationships and to properly understand and resolve issues that are complex in relationships (Gorai et al., 2014). However, for ordinary kriging to be truly useful, there must be uniformly distributed data (e.g. $PM_{2.5}$ monitors) (Gorai et al., 2014).

Ahmadi and John (2015) used spatial interpolation of ozone concentration data from TCEQ's air quality monitoring sites from GIS analysis tools. While their data came from the same place as that from which the $PM_{2.5}$ concentration data for this current study was derived (TCEQ), TCEQ's ozone monitoring sites are more abundant than $PM_{2.5}$ monitoring sites. This leads to more reliable results. Since there are fewer sites for $PM_{2.5}$ in the DFW Metropolitan area an interpolation method must be selected that adequately interpolate the data in space and time.

An ArcGIS space-time extension toolset named Activity Pattern Analyst (APA) may be also suitable to map air pollutant concentrations (ozone, in this case) is described by Lu and Fang (2014). Lue and Fang (2014) enlisted an adult volunteer to travel through Houston, Texas, using GPS to track his trajectory, and using an ozone monitor to track ozone concentrations along his trajectory. APA was developed previously by other scientists to visualize and analyze individual space-time behavior, aiming at exploring the hidden aggregate patterns in large spatiotemporal datasets. ArcScene (from the ArcGIS software package) was used to process space-time travel data. While this is an innovative way to use GIS in order to test air pollution concentrations, it may be more useful in a smaller area. It may also have been a more reliable method if more than one person was enlisted in order to gather data. Because it was not done that way, Lu and Fang (2014) missed the possibility of more extensive data. The study by Ahmadi and John (2015), mentioned before, was able to report data from a more spread-out area since they used stationary sites which were located throughout the study area. So, although there were spaces in between monitors for which data would not have been reported, the spread of the data was wider than the straight-line trajectory of the Lu and Fang (2014) study. Given the amount of space which would need to be covered for this current study, for example (16 counties), this technique is not feasible due to cost and time constraints.

Machine learning, the study of algorithms and statistical tasks that is performed by a computer system without using explicit instructions, has been applied for assessment of $PM_{2.5}$ concentrations (e.g. Kleine-Deters et al., 2017). G. Zhang, Rui, & Fan (2018) suggested that machine learning may be well-suited approach to predicting $PM_{2.5}$ concentrations and is comparable to other spatial interpolation, remote sensing, and dynamic air quality model approaches. Kleine-Deters et al. (2017) were able to use an artificial neural network tool in order show that wind speed, wind direction, and precipitation data were able to successfully predict $PM_{2.5}$ concentrations in Ecuador. They also found that $PM_{2.5}$ concentration predictions are better when extreme climatic conditions are input (i.e. strong winds and high levels of precipitation) (Kleine-Deters et al., 2017). This type of modelling can be further tested with additional weather variables as well as traffic-related and land-use variables, and its use can be expanded to other parts of the world.

Another example of machine learning, using a neural network tool, is the research done by Zou et al. (2015). The neural network toolbox in Matlab was used in their study, and they focused on the state of Texas. The weather variables on which they focused were annual precipitation, temperature, humidity, and wind speed, and they also input road length, road distance, land use type, and population density (Zou et al., 2015). The predictions of their model were consistent with the actual $PM_{2.5}$ concentrations in the state at the times for which the predictions were made (Zou et al., 2015). However, it is necessary to focus on a smaller study area, as weather conditions can differ on a small scale such as the block level. Focusing on a smaller study area on a more disaggregate scale would account for the intricate differences from block group to block group in weather conditions, land use, and air pollutant-releasing human activities in the prediction of ambient $PM_{2.5}$ concentrations.

In all, much of the existing literature points to $PM_{2.5}$ having adverse effects on those diagnosed with asthma, and to meteorological factors of various kinds having an effect on $PM_{2.5}$ concentrations and on asthma as well. There is not much research that has been done of the proposed kind in the Dallas-Fort Worth area, although the closest-related research by Zou et al. (2015) focuses on Texas as a whole. A more populated and urban area such as DFW or Houston will likely have different levels of air pollution, different land cover, etc. from a more rural and less populated area such as Amarillo. Focusing on a smaller study area within Texas can pinpoint how these differences may affect air pollution as well as human health. Different regions have different weather patterns and seasonal variation as well. A study from the U.S. reported that the effects of the synoptic weather type on $PM_{2.5}$ concentrations indeed tend to vary based on season and geographical area (Liu et al., 2017). Therefore, the current study focuses on the DFW area as a smaller study area than similar preceding research. The study tested the hypothesis that $PM_{2.5}$ concentrations in DFW in 2014 were positively correlated with maximum temperatures and average station pressure, and that they were negatively correlated with average relative humidity, average and sustained wind speed, and total precipitation. It also tested the hypothesis that the $PM_{2.5}$ concentrations and asthma-related hospital admissions were positively correlated.

There is scientific evidence showing a relationship between asthma and air pollution, including $PM_{2.5}$. High temperatures are often found to be associated with high concentrations of air pollutants, including ozone and PM (L. Li et al., 2014; Veremchuk et al., 2016; Kalbarczyk et al., 2015; Lai, 2012). This is due to chemical reactions that form ozone and fine PM occurring faster with temperature, according to basic chemical theory. High pressure areas are associated with inversions—sinking air, which traps pollutants near the ground, so higher levels of $PM_{2.5}$ would be expected (L. Li et al., 2014; Lai, 2012). Wind typically removes pollutants from an area via dispersion, hence lower $PM_{2.5}$ concentrations are expected when the wind speed is higher (Pesic et al., 2014; Ahmadi &

John, 2015; Bella et al., 2016; Zhang et al., 2015). Relative Humidity has been found in some studies to be associated with lower PM concentrations as it increases (Cai et al., 2014; L. Li et al., 2014; Lai, 2012). This could be due to the increase of humidity before the onset of precipitation events. In other cases, higher relative humidity leads to higher PM concentrations, because more water vapor condenses onto the particles, increasing their weight. Precipitation causes removal of pollutants due to wet deposition, which would lead to lower concentrations of $PM_{2.5}$ (Brunner et al., 2015; Zhang et al., 2015; Zhen et al., 2013; Lai, 2013; Jacobson, 2012, p. 294).

Chapter 3

Methodology

Instead of another aggregate-scale study on the topic at hand (i.e. on the county or state level), research needs to be conducted on a more disaggregate scale. A study at the block group level, for example, will account for the intricacies which are more apparent when looking at an area from this smaller scale. Such intricacies include how populations are concentrated and how traffic is spread, which are some of the variables which can be used determine the ambient $PM_{2.5}$ concentration. Other complexities include how weather events such as thunderstorms are spread through an area of interest, which may have an effect on $PM_{2.5}$ concentrations. This is part of what the study aims to determine.

As far as asthma being affected by $PM_{2.5}$ exposure, more research is needed on a more disaggregate scale as well. Many existing studies of the kind cover a large area comprising dozens of counties or even entire states. This only allows for data to be examined from a large-scale perspective, such as on the county-level scale. Because $PM_{2.5}$ concentrations, as well as weather variables, will be looked at on the block group level for the current study, this allows for the asthma-related hospital admission data to be examined on the same scale. This allows for the intricacies associated with weather and $PM_{2.5}$ concentration on the block level to be considered in relation to the asthma-related hospital admissions on the same level.

The main reason for testing whether asthma is exacerbated by $PM_{2.5}$ is that there is still recent research which suggests that it may not be. For example, Gorai et al. (2016) found that in eastern Texas, positive correlations between $PM_{2.5}$ and asthma discharge rates were not statistically significant. This research has served to test the hypothesis that $PM_{2.5}$ concentrations in DFW in 2014 were positively correlated with maximum temperatures and average station pressure, and that they were negatively correlated with average relative humidity, average and sustained wind speed, and total precipitation. It has also served to test the hypothesis that the $PM_{2.5}$ concentrations and asthma-related hospital admissions were positively correlated.

Study Area and Data

The study area for this research is the Dallas-Fort Worth metropolitan area of north Texas, which includes Collin, Dallas, Denton, Ellis, Erath, Hood, Hunt, Johnson, Kaufman, Navarro, Palo Pinto, Parker, Rockwall, Somervell, Tarrant, and Wise Counties. These counties were the extent of the available asthma data, hence their inclusion in this study. The boundaries were determined by the North Central Texas Council of Governments (NCTCOG), the agency from which county boundary spatial data was obtained. The time period on which the research was focused is the year 2014, using daily air quality data and daily weather data. This year was chosen because of the years of asthma data provided (2010 – 2014), the weather data was most complete for 2014 for the study area. The hospital visit data used for this research was sourced from the Dallas-Fort Worth Hospital Council Foundation (DFWHCF). It was based on the reported home address for each patient. The patients represented in this study are adults.

The daily $PM_{2.5}$ concentration and weather data were used for this study. Known $PM_{2.5}$ concentration data for the Dallas-Fort Worth area, which was used as input data for the RBF, was obtained from the Texas Council on Environmental Quality (TCEQ) database online. This database contains the daily air pollution concentration measurements from monitors throughout the DFW area, seven of which specifically displayed $PM_{2.5}$ data throughout 2014. Those monitoring sites are named CAMS 52 (at Midlothian OFW, C52/A137), CAMS 56 (at Denton Airport South, C56/A163/X157), CAMS 3002 (at Dallas Hinton St., C401/C60/AH161), CAMS 61 (at Arlington Municipal Airport, C61), CAMS 71 (at Kaufman, C71/A304/X071), CAMS 1044 (at Italy, C1044/A323), and CAMS 1051 (at Corsicana Airport, C1051). The data from those seven sites was used for this study. In Table 3-1, the coordinates of each station are listed.

STATION	STATION NAME	LATITUDE	LONGITUDE
CAMS 52	Midlothian OFW C52/A137	32.482083	-97.026899
CAMS 56	Denton Airport South C56/A163/X157	33.219069	-97.196284
CAMS 3002	Dallas Hinton St. C401/C60/AH161	32.820061	-96.860117
CAMS 61	Arlington Municipal Airport C61	32.656357	-97.088585
CAMS 71	Kaufman C71/A304/X071	32.564968	-96.317687
CAMS 1044	Italy C1044/A323	32.175417	-96.870189
CAMS 1051	Corsicana Airport C1051	32.031934	-96.399141

Table 3-1. Locations of $PM_{2.5}$ monitoring sites

Weather and climate variability and change effects can exacerbate air pollution. However, it is suggested that the local weather conditions be considered (Gorai et al., 2016), in part because the contrasts between different circulation weather types, in the case of human health impacts, could be more important than the synoptic situation (Roye et al., 2016).

In this study, only local meteorological measurement stations from the National Oceanic and Atmospheric Administration (NOAA) database (NOAA National Centers for Environmental Information, 2020) are considered including daily maximum temperature, average wind speed, sustained wind speed, average station pressure, average relative humidity, and total precipitation. The daily sustained wind speed and daily total precipitation were included due to their association with storms. Sustained winds are surface winds which are typically measured at a height of 10 m (33 ft) with no obstructions (i.e. trees or buildings) and averaged for either 1- or 2-minute intervals

(NOAA Hurricane Research Division, 2006). It must be noted that the DFW airport measures at a height of 6.7 m rather than the 10 m defined by NOAA. According to the NOAA Hurricane Research Division (2006), the 1- and 2-minute averages are essentially interchangeable. High sustained wind speeds, high precipitation, and low pressure typically indicate storm activity. However, it is due to the complications of inversion, which is caused by high pressure systems, that the hypothesis includes that average station pressure would be positively correlated with $PM_{2.5}$ concentrations.

Nineteen meteorological stations have been selected, the data from which were used as input data for the RBF neural network prediction, were chosen for this study based on their location within the study area. Those were located at the Arlington Municipal Airport, Fort Worth Alliance Airport, Fort Worth Meacham Field, Cleburne Municipal Airport, Dallas-Fort Worth WSCMO Airport, Denton Municipal Airport, Fort Worth NAS, Dallas FAA Airport, Dallas Redbird Airport, McKinney Municipal Airport, Terrell Municipal Airport, Mid Way Regional Airport Midlothian Waxahachie, Stephenville Clark Field, Granbury Municipal Airport, Greenville Municipal Airport Majors Field, Corsicana Campbell Field, Mineral Wells Airport, Bridgeport Municipal Airport, and Decatur Municipal Airport. These were chosen as they represent the extent of the study area in which the seven air quality monitors are located, as well as the hospital patients. They include all the weather monitoring sites within the specified counties, with the exception of those which did not report the specified weather data during 2014. In Table 3-2, each weather station's coordinates are displayed.

STATION	STATION NAME	LATITUDE	LONGITUDE
WBAN:53907	ARLINGTON MUNICIPAL AIRPORT TX US	32.66361	-97.09389
WBAN:53976	BRIDGEPORT MUNICIPAL AIRPORT TX US	33.17528	-97.82833
WBAN:53981	CLEBURNE MUNICIPAL AIRPORT TX US	32.35389	-97.43389
WBAN:53912	CORSICANA CAMPBELL FIELD TX US	32.03111	-96.39889
WBAN:03927	DAL FTW WSCMO AIRPORT TX US	32.8978	-97.0189
WBAN:13960	DALLAS FAA AIRPORT TX US	32.8519	-96.8555
WBAN:03971	DALLAS REDBIRD AIRPORT TX US	32.68083	-96.86806
WBAN:53964	DECATUR MUNICIPAL AIRPORT TX US	33.25444	-97.58056
WBAN:03991	DENTON MUNICPAL AIRPORT TX US	33.20611	-97.19889
WBAN:53909	FORT WORTH ALLIANCE AIRPORT TX US	32.97333	-97.31806
WBAN:13961	FORT WORTH MEACHAM FIELD TX US	32.81917	-97.36139
WBAN:13911	FORT WORTH NAS TX US	32.76667	-97.45
WBAN:53977	GRANBURY MUNICIPAL AIRPORT TX US	32.44444	-97.81694
WBAN:13926	GREENVILLE MUNICIPAL AIRPORT MAJORS FIELD TX US	33.06778	-96.06528
WBAN:53914	MCKINNEY MUNICIPAL AIRPORT TX US	33.19028	-96.59139
WBAN:53966	MID WAY REGIONAL AIRPORT MIDLOTHIAN WAXAHACHIE TX US	32.45611	-96.9125
WBAN:93985	MINERAL WELLS AIRPORT TX US	32.7816	-98.0602
WBAN:03969	STEPHENVILLE CLARK FIELD TX US	32.21528	-98.1775
WBAN:53911	TERRELL MUNICIPAL AIRPORT TX US	32.71	-96.26722

Table 3-2. Locations of weather monitoring sites

The weather monitoring site for Rockwall County was not included due to having collected no data for 2014, and the sites at Dallas Hensley Field (Dallas County), Dallas Fort Worth Spinks Airport (Tarrant County), Grand Prairie Municipal Airport (Dallas County), Dallas Addison Airport (Dallas County), and Lancaster Airport (Dallas County) were not included for the same reason. The only county which was examined for this study that did not physically have a weather monitoring site (as of 2014) is Somervell. Palo Pinto and Parker Counties share the same single monitoring site. Figure 3-1 shows the locations of the air quality and weather monitors from which data were acquired for 2014.

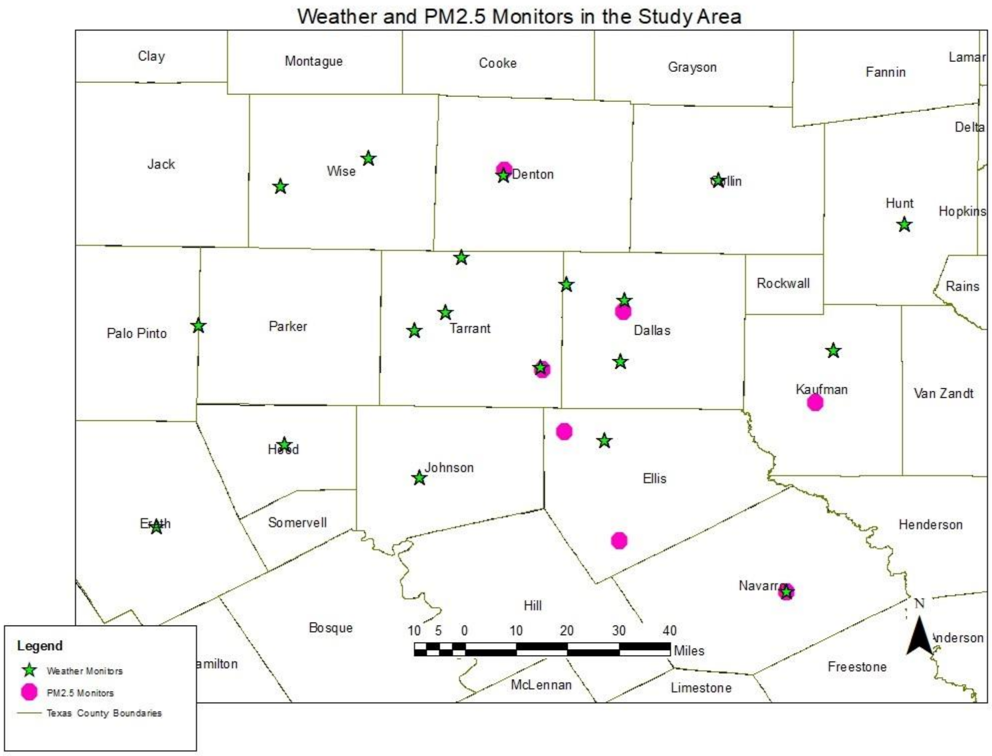


Figure 3-1. Locations of air quality monitoring and weather monitoring sites for 2014.

The weather data and limited known $PM_{2.5}$ concentration data (from the few monitors available) were used in creation of the RBF network to model the $PM_{2.5}$ concentrations for the whole study area, including spaces in which there were no monitors. The air quality monitoring sites seen in Figure 3-1 are the following: CAMS 52 Midlothian OFW C52/A137, CAMS 56 Denton Airport South C56/A163/X157, CAMS 3002 Dallas Hinton St. C401/C60/AH161, CAMS 61 Arlington Municipal Airport C61, CAMS 71 Kaufman C71/A304/X071, CAMS 1044 Italy C1044/A323, and CAMS 1051 Corsicana Airport C1051.

Land use data was included for estimation of $PM_{2.5}$ concentrations due to the implications of certain land use types regarding $PM_{2.5}$ and $PM_{2.5}$ precursor release into the atmosphere. Populated areas would include land use types such as industrial, commercial, and residential. Industrial land use areas would be likely have more industrial emissions, which in the study area would include sources like cement kilns that emit NOx and power plants that emit NOx and VOCs (Zhang et al., 2015). Commercial areas would include many scattered area sources of VOCs, like auto body paint shops, bakeries, and gas stations (Zhang et al., 2015). There would also be varying levels of vehicular traffic within the study area, which entails release of primary $PM_{2.5}$ (Ristovski et al., 2012; Li et al., 2015; Zhang et al., 2015) and VOCs (Zhang et al., 2015). Agricultural land (planted vegetation) would likely have ammonia emissions as well as VOCs (Zhang et al., 2015). Open space and natural vegetation areas would have VOCs from the vegetation (Zare et al., 2014; R. Zhang et al., 2015).

Land use, road type, and average daily traffic (ADT) data was sourced from the North Central Texas Council of Governments. The road data (road type and ADT) is from 2014. Land use data is from 2015—the closest available year to the study time period. The 2014 ecological land cover data, from the Ecological Mapping Systems of Texas of the Texas Parks & Wildlife Department, was also used to determine dominant land use. The population data was based on the 2014 estimates from the US Census Bureau.

One date per month in 2014 was tested: January 1st, February 7th, March 15th, April 27th, May 3rd, June 5th, July 7th, August 23rd, September 17th, October 29th, November 5th, and December 3rd. After a process of eliminating dates which had missing data for one or more weather or $PM_{2.5}$ monitors, these dates were selected so that there would be a mix of days with precipitation and days without. While the dates without precipitation were selected randomly, those dates with precipitation, since there were few, were chosen intentionally in order to compare them to the non-precipitation days.

This is because of precipitation being an important part of the hypothesis. Only 12 dates were selected (one from each month) due to time constraints.

Modeling and Analysis Tools

Some of the literature features new ways to mathematically and graphically present the correlations discussed. Similarly, for this study, a radial basis function (RBF) neural network was used via the Matlab Neural Network Toolbox in order to model the $PM_{2.5}$ concentrations in the DFW area which were not reported by $PM_{2.5}$ monitors.

A feed-forward artificial neural network—a variation of which was also used in this study— is comprised of an input layer, a hidden layer, and an output layer. The input layer acts as a set of “neurons,” which are fed into the hidden layer (Mishra, Goyal, & Upadhyay, 2015). The hidden layer acts as a “feature detector,” and the output is determined once it collects those detected features (Mishra, Goyal, & Upadhyay, 2015). Figure 3-2 illustrates how an artificial neural network works.

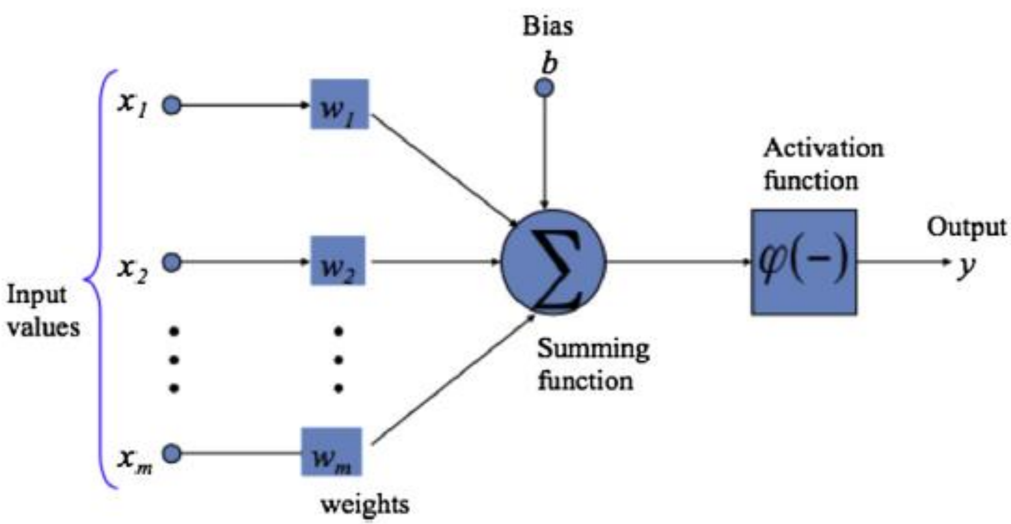


Figure 3-2. Artificial neural network schema (Mishra et al., 2015).

According to Zou et al. (2015), a radial basis function (RBF) neural network can interpolate in “high-dimensional spaces” (Zou et al., 2015). Such a function contains an input layer, a hidden layer, and an output layer (Zou et al., 2015), just like the basic artificial neural network structure. The RBF is named as such due to the part of the process in which a “radial basis version of the Gaussian function is employed to represent the distribution of variable values in the input layer” (Zou et al., 2015, p. 10398). Figure 3-3 shows the structure of an RBF neural network.

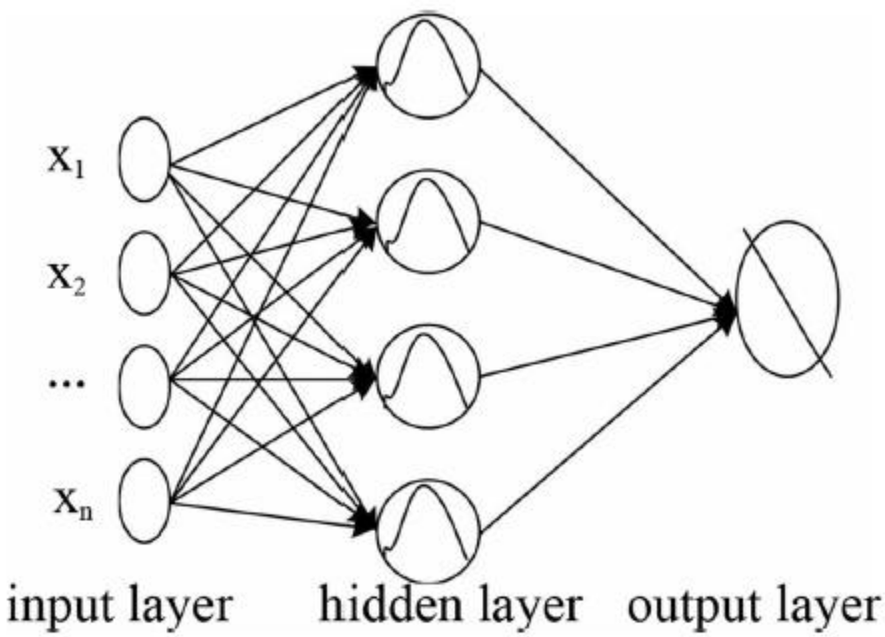


Figure 3-3. RBF neural network structure (Zou et al., 2015).

The creation of an RBF neural network or any ANN consists of a training and testing process, during which the RBF neural network tries to replicate the target values. Once that process has been completed, the model itself is ready to use and can have new inputs added in for estimation.

The RBF network was created using the known daily maximum dry-bulb temperature, daily average wind speed, daily sustained wind speed, daily average station pressure, daily average relative humidity, daily total precipitation, road types, ADT, dominant land use types, and known $PM_{2.5}$ concentrations. There were 100 neurons used in the hidden layer of the model. A more in-depth description of how the RBF network was used in this study will be found in the next section of this chapter, entitled *Procedure.*

For similar research to the current study, a tool within GIS which was used for the research described by Gorai et al. (2014) was the ordinary kriging tool. It was "used to estimate the spatial distribution of pollutant levels in each county from 2005 to 2007 for each of the three pollutants: SO_2, O_3, and $PM_{2.5}$," according to Gorai et al. (2014) (p. 4854). Gorai et al., (2014) explain that "in Kriging, a smooth surface is estimated from irregularly spaced data points based on the assumptions that the spatial variation in the feature (O_3, $PM_{2.5}$, and SO_2) is homogeneous over the domain depends only on the distance between sites" (p. 4854). Given that the air quality monitoring stations which collect $PM_{2.5}$ data in DFW are quite scarce (being that there are only 7 such monitors which can be used for the study area and dates), this method was very useful for the current study, as it filled in the gaps in the coverage of both $PM_{2.5}$ and weather monitors. Ordinary kriging, in order to work well, requires many location points with known data. Therefore, it is not a reliable method to use by itself for making such estimations. A more in-depth description of how ordinary kriging was used in this study will be found in the next section of this chapter, entitled *Procedure.*

Spatial statistical analysis consisted of the Getis-Ord G Statistic and Local Moran's I Coefficient. Because the two analysis techniques interpret the data in different ways, both were necessary. The Getis–Ord G Statistic is a global measure that summarizes the pattern of spatial autocorrelation in the area; it can be used to effectively define the location of hot spots and cold spots in a study area (Oyana & Margai, 2015).

This was useful in determining the hotspots and cold spots among the reported asthma cases in the study, which can show the relevance of the $PM_{2.5}$ concentrations on the map as they relate to human health.

Local Indicators of Spatial Autocorrelation (LISA) are measures that disaggregate global measures of spatial autocorrelation into location-specific measures such as the Local Moran's I Coefficient (Oyana & Margai, 2015). The Local Moran's I Coefficient enables one to focus on individual spatial units and compare their data values relative to the neighboring units to assess the degree of similarity or dissimilarity (Oyana & Margai, 2015). The coefficient is represented by a scatterplot or cluster map that can be used to effectively show spatial anomalies in the distribution (Oyana & Margai, 2015). LISA can be aggregated to summarize the measures for the individual units and can be used as a global indicator of spatial autocorrelation (Oyana & Margai, 2015). The Local Moran's I Coefficient was also useful for analyzing the asthma-related hospital visit data—it is helpful to see whether points are generally clustered or dispersed and if there are any spatial anomalies within the data.

Procedure

The first step taken was to determine spatial correlations. The Getis-Ord G and Local Moran's I analyses were run using ArcMap software for the point data for the hospital admissions. A Kernel Density analysis tool was also used via ArcMap in order to visualize the density of the reported asthma cases. After that, the process of estimating $PM_{2.5}$ began.

Using ordinary kriging, all weather variables were interpolated based on the daily weather reported by the weather monitors in the study area, thus creating a raster data set for each of the weather variables. The process of ordinary kriging was repeated for each of the 6 weather variables and for each of the 12 dates separately. The weather variables are daily maximum temperature, daily average station pressure, daily precipitation, daily average relative humidity, daily average wind speed, and daily sustained wind speed. Figure 3-4 shows an example of how ordinary kriging displayed the maximum temperatures in the study area.

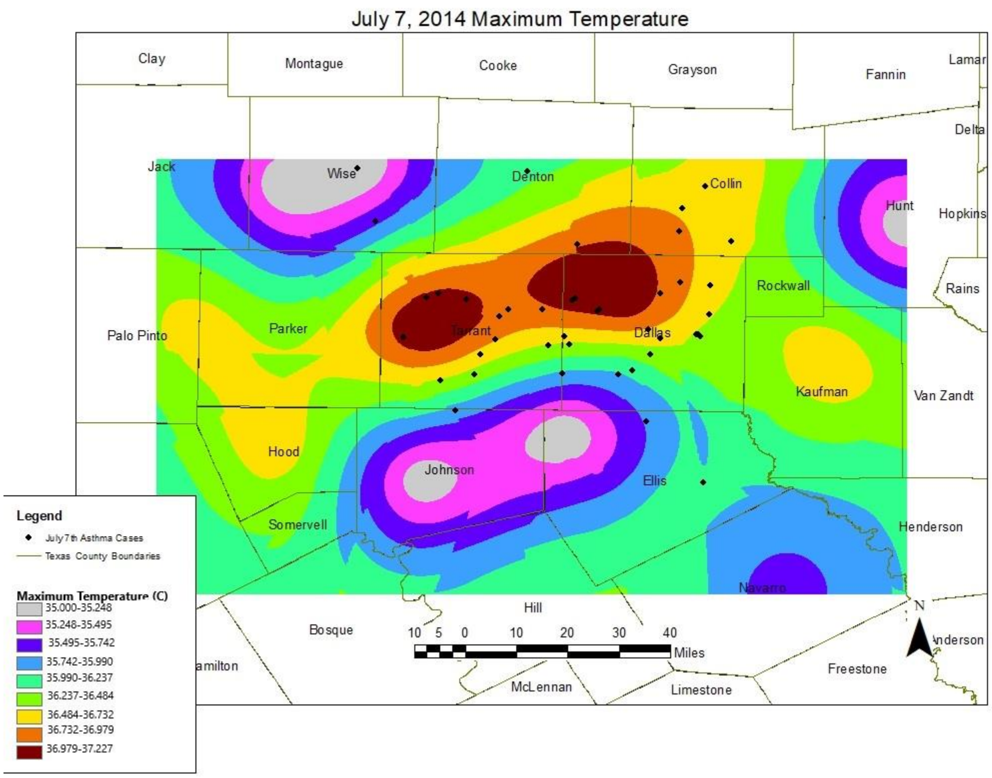


Figure 3-4. July 7, 2014 maximum temperature in north Texas.

Following the ordinary kriging process, the “zonal statistics as table” tool in ArcMap was used in order to pinpoint in which zone the points from the asthma case data fell in terms of the distribution of weather variables (i.e. maximum temperature, amount of precipitation, etc.). The input layer was the asthma case points, and the zone layers were the raster layers (the result of ordinary kriging) for each of the weather variables for each date. This process was repeated for each weather variable and for each selected date. This data was added as separate variables to the table used as the input for the neural network estimation.

In order to determine the dominant land use type for each asthma case point, a 500-meter buffer was applied to each of the asthma case points. This distance was chosen based on previous research—the 500m buffer was associated with better results from artificial neural network models. For example, Zou et al. (2015) used a 500m buffer for land use determination, and the model created for the study yielded a MAE of 0.99 and MSE of 1.44. When tested for the current study, smaller buffer radii caused nearly homogeneous land use rankings across the reported locations of each asthma patient. The majority of them were in residential areas, so a buffer of a smaller distance would show most of the patients being surrounded by nearly exclusively the populated areas land use type. Without more variation, the neural network model would lose predictive accuracy.

The intersect tool was next used with the buffer and the NCTCOG land use feature class as inputs and the area and percentage of the 500m buffer was calculated for each land use type in the resulting attribute table. This table was then exported, and the dominant land use type within the buffer was determined based on the percentages of each land use type within each buffer area, as derived from the table. The same process was used to find where the points from the asthma case points fell in terms of ecological land cover. The ecological land cover data showed whether areas were urban or vegetated land cover as well as the vegetation types within vegetated areas. The resulting table was used to confirm the dominant land use types for each asthma case point. The land use types are populated areas, open space, planted vegetation, natural vegetation, and water. They were assigned ranks as follows: 1 = water, 2 = natural vegetation, 3 = planted vegetation, 4 = open space, and 5 = populated areas. These ranks were based on the presence or potential for human activity in or around the land in question, with 5 being the highest level, and 1 being the lowest. The ranks assigned for dominant land use type within the buffer of each asthma case point were added to the table for neural network training.

Land use types were specifically defined as follows: “Populated areas” includes commercial land, industrial land, hotels, airports, utilities, offices, institutional land, schools, and residential land including single- and multi-family homes, mobile homes, and group quarters. “Open space” includes vacant land adjacent to land categorized as populated areas, as well as residential acreage and improved acreage. Vacant lots, according to the NCTCOG (2017), are undeveloped land and are therefore considered by the EPA to be “open space.” Improved acreage is “land that is mostly undeveloped yet includes a non-residential structure with road access as a minor part of the use” (NCTCOG 2017). Residential acreage, according to the NCTCOG (2017), is “land that is mostly undeveloped yet includes a mobile home, house, or other residence as a minor part of the use.” Because residential and improved acreage areas are mostly undeveloped but also associated with human alteration, they were included in the “open space” category. “Planted vegetation” includes farmland and parks. In other words, these are lands that are mostly vegetation, but are planted or otherwise disturbed by human activity to some extent. “Natural vegetation” includes wetlands, ranchland and other grasslands, and timberland. “Water” includes bodies of water (i.e. rivers, lakes, and ponds).

In order to determine the ADT for each asthma case point, a 100m buffer was applied to each of the asthma case points. The 100m buffer was chosen because when the 500m radius was used, some traffic data (i.e. road class) was the same for nearly all of the patient points. When tested, this led to lower accuracy of the predictions from the model. The intersect tool was next used, with the buffers and road feature class as inputs. The resulting attribute table showed the roads and their traffic count data within 100m of each point from the asthma case feature class. This table was then exported, and ADT for the road with the highest traffic count within 100m of each asthma case point was entered into the table for the neural network.

The table from the above 100m buffer and intersect process was also used to assign the road class to each data point from the asthma case feature class. The road classes were assigned as ranks based on the average traffic count for each road: 1 = local, 2 = collector, 3 = arterial, 4 = highway, and 5 = freeway. These ranks for each of the asthma case points were entered into the table for the neural network. The definitions of the roads are outlined in the next paragraph.

Road information used for this study includes the nearest average daily traffic count (ADT) and nearest road class. The road classes are “local,” “collector,” “arterial,” “highway,” and “freeway” (Setton, Hystad, & Keller, 2005). “Local” roads are residential roads, and the mean traffic count is 3,976 (Setton et al., 2005). “Collector” roads are those which connect areas to cross town, and usually have one lane each way, and the mean traffic count is 8,953 (Setton et al., 2005). “Arterial” roads are those which are considered thoroughfares—they generally have a large traffic capacity and are multilane, and the mean traffic count is 18,457 (Setton et al., 2005). A “highway” refers to a primary or secondary state highway, and the mean traffic count is 27,961 (Setton et al., 2005). They can be single or multilane (Setton et al., 2005). A “freeway” refers to a highway with controlled access; these tend to be divided, and the mean traffic count is 113,789 (Setton et al., 2005).

Once all of the steps above were completed and the table was ready for running the RBF neural network, the network was put through the training and testing process.

After that process was completed, the RBF network was used to model the average $PM_{2.5}$ concentration for the day for each asthma case point (a detailed description of the coding can be seen in Appendix 2, and sample $PM_{2.5}$ estimations can be found in Appendix 3). In order to test the accuracy of the created model, the Mean Absolute Error (MAE) was calculated. Wang & Lu (2018) and Willmott & Matsuura (2005) show that the MAE—which shows the average magnitude of error of a given model—is the best model for assessing accuracy of models.

Chapter 4

Results

In the following sections, the results of the RBF neural network and the correlations between the input and output variables are reported. The correlation results are in three parts. There are results which are inclusive of all 12 test dates, and results for test dates in with precipitation, and results for test dates in without precipitation. The dates with precipitation had varying precipitation levels by location within the study area. In fact, on these days, some areas had no precipitation or only trace amounts, while others had some measurable amount of it.

RBF Model Results

The RBF neural network model performance from the training and testing process is displayed in Figure 4-1. The regression model in figure 4-1 shows a R value of 0.868 for the outputs of the RBF model versus the targets. The targets were the actual average $PM_{2.5}$ concentrations which were measured by the $PM_{2.5}$ monitors. During the training and testing process, the RBF model tries to replicate the target values, and the regression shows the accuracy with which the model performed that task.

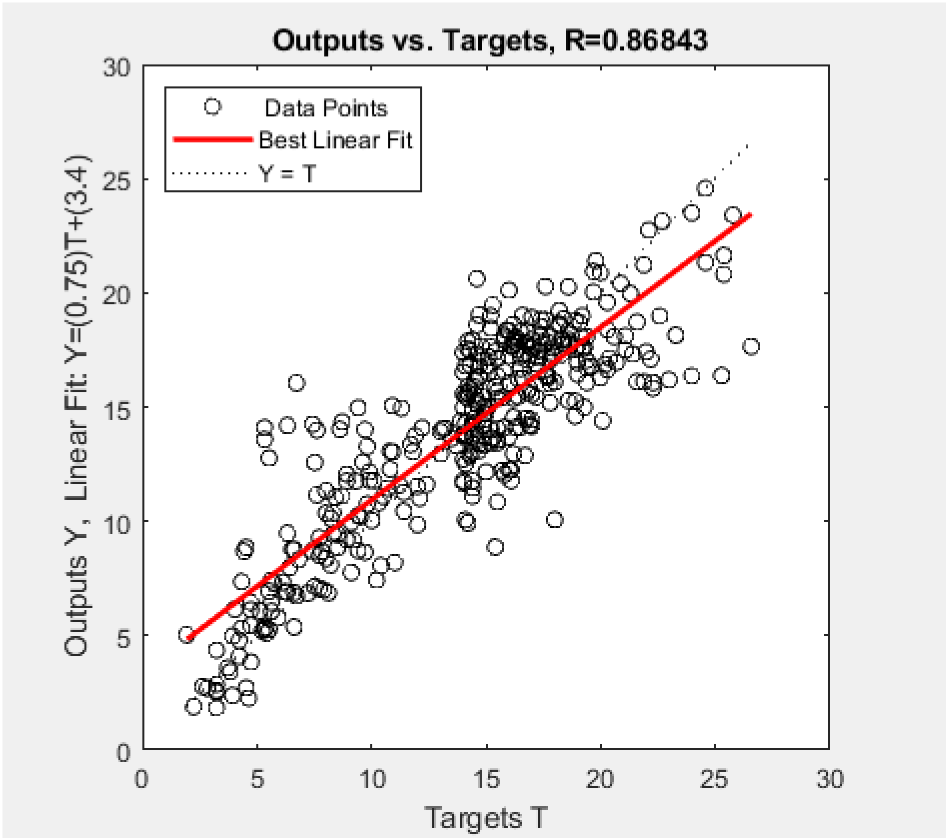


Figure 4-1. Performance (regression) of the RBF model.

In the case of this current study, the MAE is 1.94 µg/m^3. In other words, the model is accurate within 1.94 µg/m^3 of $PM_{2.5}$. Table 4-1 has the comparison of the MAE for this created model versus previous artificial neural network models created in other studies. Most studies which reported a MAE did not report the MSE, which is why only the MAE is shown in Table 4-1. The other studies were focused on hourly or annual $PM_{2.5}$ concentrations, whereas this study was focused on the daily average. That may be part of the cause for the large differences in MAE. Also, some studies were focused on areas, i.e. Beijing, China, where the $PM_{2.5}$ was hundreds of µg/m^3 on some days, which may also contribute to relatively high MAE.

Model	**MAE (μg/m³)**
Zou et al. (2015)	0.99
Zhou et al. (2014)	19.80
Feng et al. (2015)	10.62
Oprea, Mihalache, and Popescu (2016)	1.93
Ding, Zhang, and Leung (2016)	18.5
Current	1.94

Table 4-1. Comparison of MAE for $PM_{2.5}$ concentration models.

The RBF neural network that was initially created based on the example from Zou et al. (2015) caused repeated overfitting. This may have been the case for Zou et al. (2015) as well, given the very low MAE as compared to other studies. Because of this, the RBF neural network would predict very low $PM_{2.5}$ concentrations on days when the actual concentration was in the "moderate" range. It could also be the case that the difference in study area—i.e. Zou et al. (2015) focusing on the county level rather than the block group level—causes the difference in model performance and MAE. When the final version of the RBF model was used for the current study, the model was able to predict $PM_{2.5}$ concentrations from different datasets with the same accuracy as with the training dataset.

Meteorological Variables and $PM_{2.5}$ Concentration

Figures 4-2 – 4-7 display the relationships between the average $PM_{2.5}$ concentration for the DFW area and each weather variable for all test dates combined. As seen in Figure 4-2, an increase in daily maximum temperature typically coincides with an increase in $PM_{2.5}$ concentration. Chemical reaction rates increase with higher temperatures, so reactions that form secondary PM would be faster at higher temperatures. The R^2 value is 0.140, which means that 14% of the variance around the mean can be explained by the regression. Figure 4-3 shows that there is a slight negative trend with regard to precipitation versus $PM_{2.5}$ concentration, but it is closer to showing no correlation. The R^2 value is 0.006, meaning that only 0.6% of variance around the mean can be explained by the regression. Figure 4-4 illustrates that an increase in average relative humidity typically indicates a decrease in $PM_{2.5}$ concentration, with an R^2 value of 0.065, meaning that 6.5% of variance around the mean can be explained by the regression. Looking at Figure 4-5, there is not as clear a trend as the previous figures regarding average station pressure versus $PM_{2.5}$ concentration. Figure 4-5 displays a low R^2 value of 0.008. So only 0.8% of variance around the mean can be explained by the regression. Figures 4-6 (R^2 of 0.252) and 4-7 (R^2 of 0.108) show that when there is a very pronounced increase in average wind speed and sustained wind speed, there is typically an increase in $PM_{2.5}$ concentration.

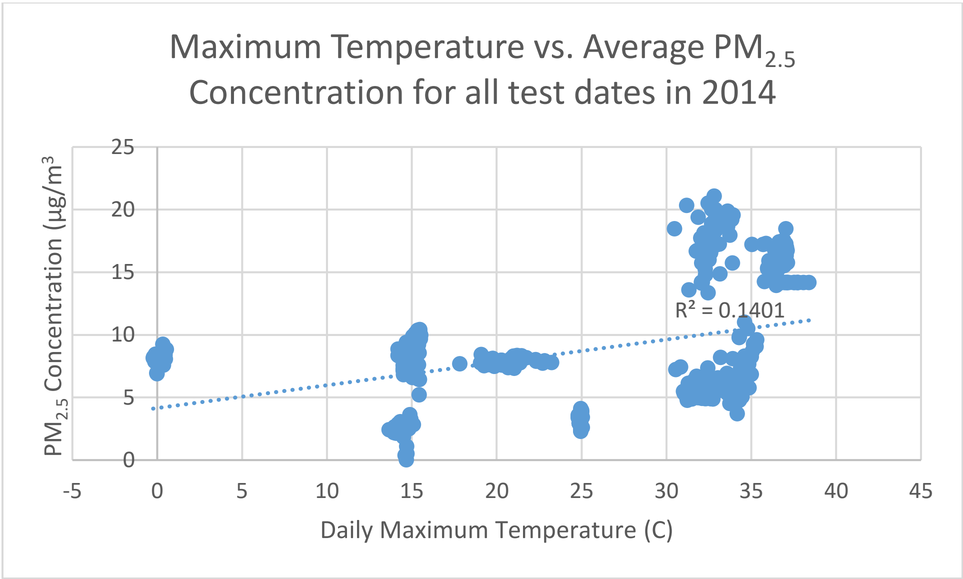


Figure 4-2. Maximum temperature vs. average $PM_{2.5}$ concentration for all test dates in 2014.

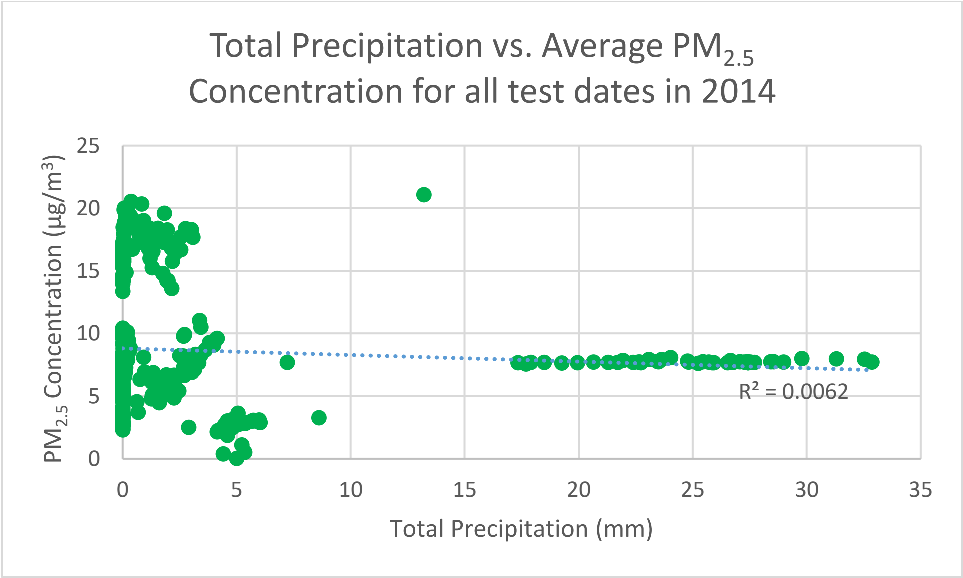


Figure 4-3. Total precipitation vs. average $PM_{2.5}$ concentration for all test dates in 2014.

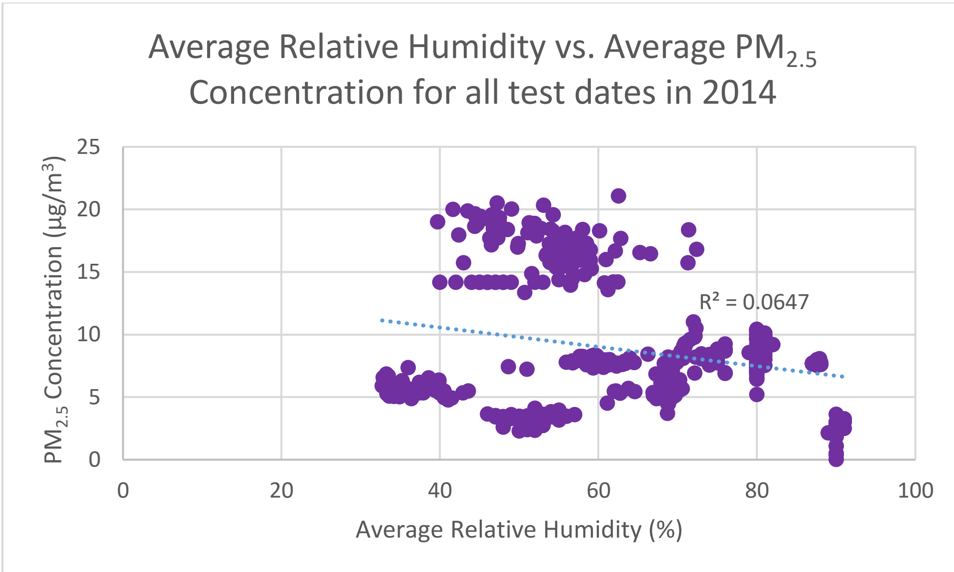


Figure 4-4. Average relative humidity vs. average $PM_{2.5}$ concentration for all test dates in 2014.

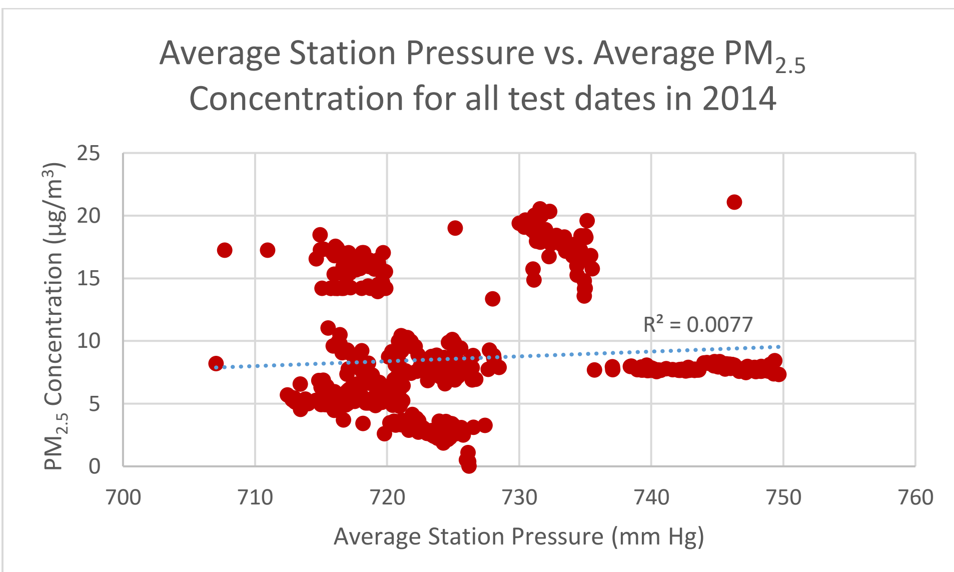


Figure 4-5. Average station pressure vs. average $PM_{2.5}$ concentration for all test dates in 2014.

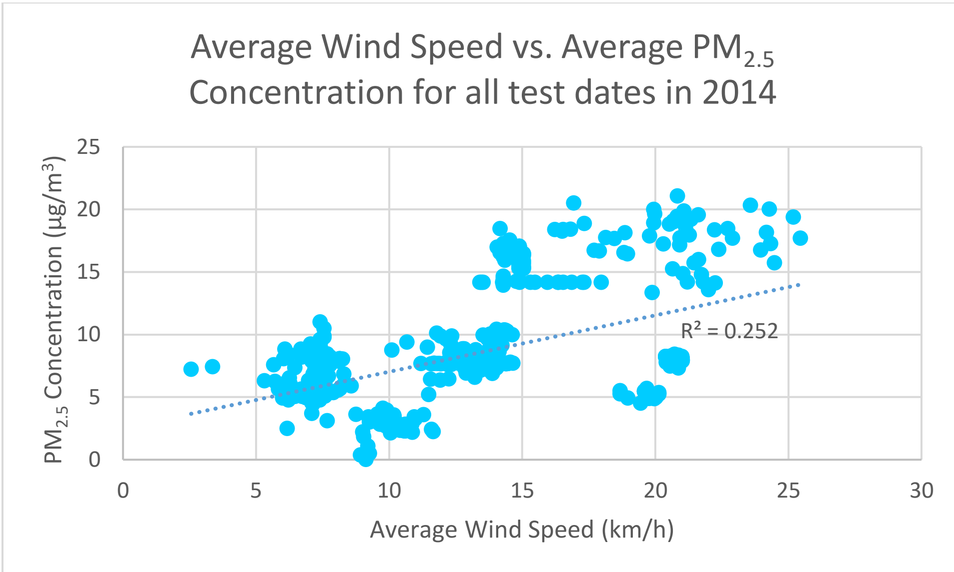


Figure 4-6. Average wind speed vs. average $PM_{2.5}$ concentration for all test dates in 2014.

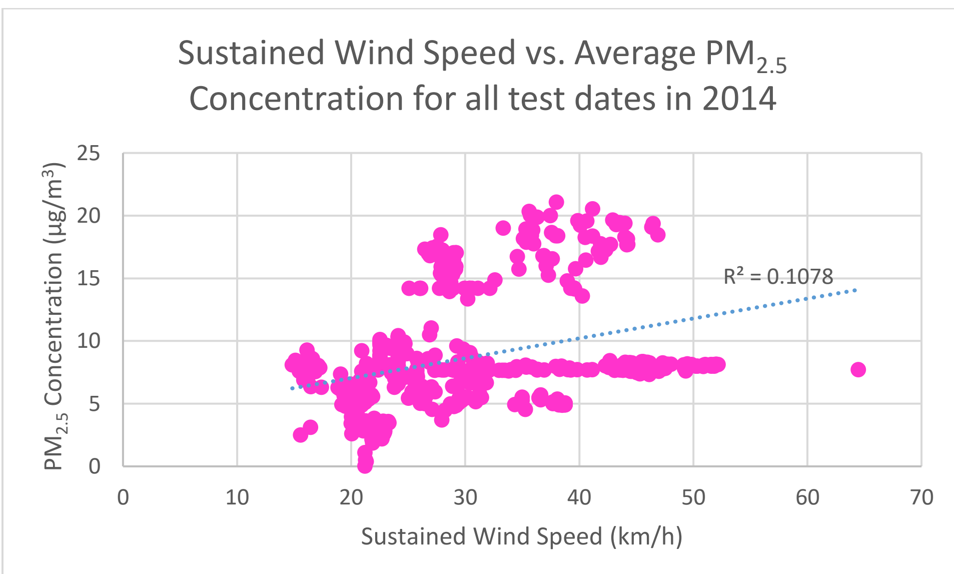


Figure 4-7. Sustained wind speed vs. average $PM_{2.5}$ concentration for all test dates in 2014.

Table 4-2 shows the Pearson's correlation between each weather variable and the $PM_{2.5}$ concentration for all test dates. The Pearson values are the square roots of the R^2 values shown in Figures 4-3 through 4-7 above. As seen in Table 4-2, there is a relatively weak positive correlation between maximum temperature and $PM_{2.5}$ concentration (0.374) and between sustained wind speed and $PM_{2.5}$ concentration (0.328). The Pearson correlation coefficient between average station pressure and $PM_{2.5}$ concentration is 0.088, which indicates that there is really no correlation between the two. There is a moderately high positive correlation between average wind speed and $PM_{2.5}$ concentration (with a Pearson correlation coefficient of 0.502). Table 4-2 also shows that there is a relatively weak negative correlation between average relative humidity and $PM_{2.5}$ concentration (-0.254). It also shows that there is a very weak negative correlation between total precipitation and $PM_{2.5}$ concentration (-0.079); however, this finding is the only one shown on the table which is not statistically significant.

Table 4-2 also illustrates how the weather variables are correlated with each other. Daily maximum temperature is negatively correlated with average station pressure, total precipitation, and average relative humidity, with the respective Pearson correlation coefficients being -0.352, -0.161, and -0.599. Maximum temperature is positively correlated with average and sustained wind speed. The Pearson correlation coefficients are 0.136, and 0.213, respectively. Average station pressure is positively correlated with total precipitation, average relative humidity, average wind speed, and sustained wind speed, with Pearson correlation coefficients of 0.375, 0.174, 0.573, and 0.699, respectively). It is negatively correlated with maximum temperature (-0.352). Total precipitation has a very weak correlation with average wind speed, which is not significant. However, total precipitation does have a weak negative correlation with maximum temperature (with a Pearson correlation coefficient of -0.161) that is significant at the 0.01 level, and a positive correlation with average station pressure, average relative humidity, and sustained wind speed (0.375, 0.520, and 0.185, respectively). Average relative humidity is similar to total precipitation in its correlations with the other variables; it has a negative correlation with maximum temperature and average wind speed (-0.254 and -0.599, respectively), a very weak correlation with sustained wind speed which is not significant, and a positive correlation with average station pressure (0.174) and total precipitation (0.520). Average wind speed has a very strong positive correlation with sustained wind speed, with the Pearson correlation coefficient being 0.821.

		$PM_{2.5}$ Concentration (µg/m^3)	Maximum Temperature (degrees C)	Average Station Pressure (HPa)	Total Precipitation (mm)	Average Relative Humidity (%)	Average Wind Speed (km/h)	Sustained Wind Speed (km/h)
$PM_{2.5}$ Concentration (µg/m^3)	Pearson Correlation	1	0.374**	0.088*	-0.079	-0.254**	0.502**	0.328**
	Sig. (2-tailed)	-	0	0.04	0.065	0	0	0
Maximum Temperature (degrees C)	Pearson Correlation	0.374**	1	-0.352**	-0.161**	-0.599**	0.136**	0.213**
	Sig. (2-tailed)	0	-	0	0	0	0.001	0
Average Station Pressure (HPa)	Pearson Correlation	0.088*	-0.352**	1	0.375**	0.174**	0.573**	0.699**
	Sig. (2-tailed)	0.04	0	-	0	0	0	0
Total Precipitation (mm)	Pearson Correlation	-0.079	-0.161**	0.375**	1	0.520**	-0.057	0.185**
	Sig. (2-tailed)	0.065	0	0	-	0	0.186	0
Average Relative Humidity (%)	Pearson Correlation	-0.254**	-0.599**	0.174**	0.520**	1	-0.102*	-0.045
	Sig. (2-tailed)	0	0	0	0	-	0.017	0.296
Average Wind Speed (km/h)	Pearson Correlation	0.502**	0.136**	0.573**	-0.057	-0.102*	1	0.821**
	Sig. (2-tailed)	0	0.001	0	0.186	0.017	-	0
Sustained Wind Speed (km/h)	Pearson Correlation	0.328**	0.213**	0.699**	0.185**	-0.045	0.821**	1
	Sig. (2-tailed)	0	0	0	0	0.296	0	-

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 4-2. 2014 correlations between weather variables and $PM_{2.5}$ concentration for all test dates. N = 546.

Table 4-3 shows the multiple linear regression analysis results for the daily average $PM_{2.5}$ concentration versus all of the input variables—road ADT, road class, dominant land use, daily maximum temperature, daily average station pressure, daily total precipitation, daily average relative humidity, daily average wind speed, and daily sustained wind speed—with the addition of block group population. This analysis pertains to all test dates. The adjusted R square is 0.393. The adjusted R square value indicates that the combined variables have a fairly weak relationship with the $PM_{2.5}$ concentration. The p-value for this regression is <0.001, so it is statistically significant. Table 4-3 also displays the model coefficients for each variable. For dominant land use class, the coefficient is -0.802, which means that for every unit increase in dominant land use class (which entails an increase in anthropogenic activity), the $PM_{2.5}$ concentration decreases by -0.802 $\mu g/m^3$. Dominant land use class has the highest coefficient when all variables are considered for all test dates. The coefficient for total precipitation (0.0764) shows that total precipitation has the lowest impact on $PM_{2.5}$ with statistical significance. For every unit increase in total precipitation, the $PM_{2.5}$ concentration increases by 0.0764 $\mu g/m^3$.

Regression Statistics: $PM_{2.5}$ Concentration vs. All Variables for All Test Dates	
Multiple R	0.638
R Square	0.407
Adjusted R Square	0.396
Standard Error	3.644
Maximum Temperature Coefficient	0.192**
Average Station Pressure Coefficient	0.0247
Total Precipitation Coefficient	0.0764*
Average Relative Humidity Coefficient	-0.00819
Average Wind Speed Coefficient	0.740**
Sustained Wind Speed Coefficient	-0.240**
ADT Coefficient	-2.746×10^{-6}
Road Class Coefficient	0.180
Dominant Land Use Class Coefficient	-0.802*
Block Group Population Coefficient	4.917×10^{-5}
Intercept	-12.929
Observations	546

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 4-3. Regression statistics of $PM_{2.5}$ concentration vs. all variables for all test dates.

Table 4-4 shows the regression analysis results (for all test dates) for the daily average $PM_{2.5}$ concentration versus all weather variables: daily maximum temperature, daily average station pressure, daily total precipitation, daily average relative humidity, daily average wind speed, and daily sustained wind speed. The adjusted R square is 0.395. The adjusted R square value indicates that the combined weather variables have a relatively weak relationship with the $PM_{2.5}$ concentration. The p-value for this regression is <0.001, so it is statistically significant. The weather variables, when combined, have a stronger relationship with $PM_{2.5}$ concentration than they have individually: the adjusted R^2 value in Table 4-4 is greater than any of the individual R^2 values in Figures 4-3 through 4-7. When considering only the weather variables against

$PM_{2.5}$ concentration, average wind speed has the highest coefficient (0.745). For every unit increase in average wind speed, the $PM_{2.5}$ concentration increases by 0.745 μg/m^3. The coefficient for total precipitation is 0.0750, meaning that for every unit increase in total precipitation, the $PM_{2.5}$ concentration increases by 0.0750 μg/m^3.

Regression Statistics: $PM_{2.5}$ Concentration vs. Weather Variables for All Test Dates	
Multiple R	0.634
R Square	0.402
Adjusted R Square	0.395
Standard Error	3.646
Maximum Temperature Coefficient	0.194**
Average Station Pressure Coefficient	0.0307
Total Precipitation Coefficient	0.0750*
Average Relative Humidity Coefficient	-0.00767
Average Wind Speed Coefficient	0.745**
Sustained Wind Speed Coefficient	-0.245**
Intercept	-20.849
Observations	546

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 4-4. Regression statistics of $PM_{2.5}$ concentration vs. weather variables for all test dates.

Figures 4-8 – 4-13 display the relationships between the average $PM_{2.5}$ concentration for the DFW area and each weather variable for the test dates with precipitation. As seen in Figure 4-8, an increase in daily maximum temperature typically indicates an increase in $PM_{2.5}$ concentration. Figure 4-8 exhibits an R^2 value of 0.248. In Figure 4-9, the trend is that an increase in total precipitation is indicative of a decrease in $PM_{2.5}$ concentration—more-so than Figure 4-3 did for combined precipitation and non-precipitation days. The R^2 value in this case is 0.051. Similarly, as seen in Figure 4-10, an increase in average relative humidity is shown to lead to a decrease in $PM_{2.5}$

concentration. Figure 4-10 indicates that this relationship is more pronounced than the relationship between $PM_{2.5}$ concentration and precipitation; the R^2 value here is 0.695. Figure 4-11 shows that slight increases in average station pressure are met with a decrease in $PM_{2.5}$ concentration. The R^2 value for Figure 4-11 is 0.033. Figures 4-12 and 4-13 show the same basic tendency: when average wind speed and sustained wind speed increase, there is typically an increase in $PM_{2.5}$ concentration. The R^2 values for these are 0.6026 and 0.298, respectively.

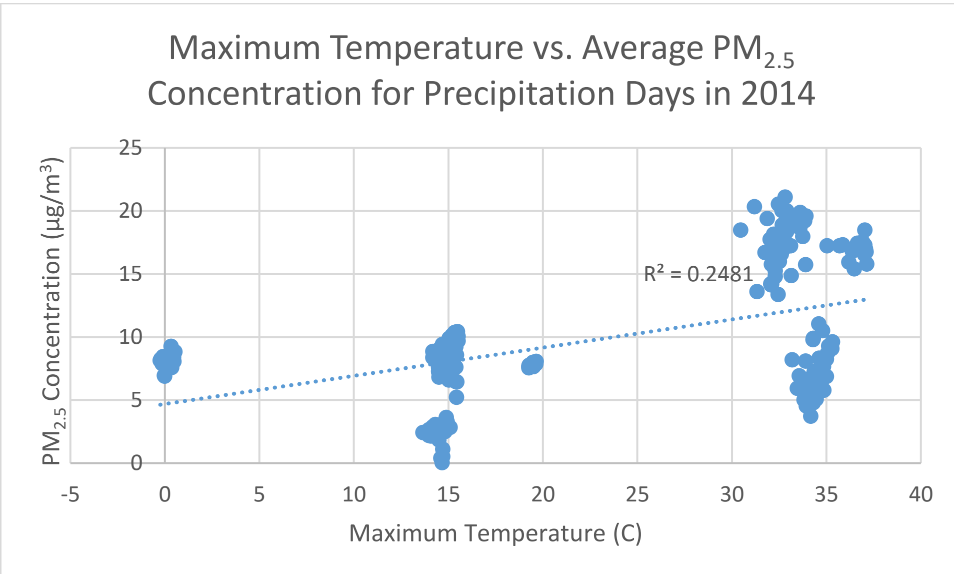


Figure 4-8. Maximum temperature vs. average $PM_{2.5}$ concentration for precipitation days in 2014.

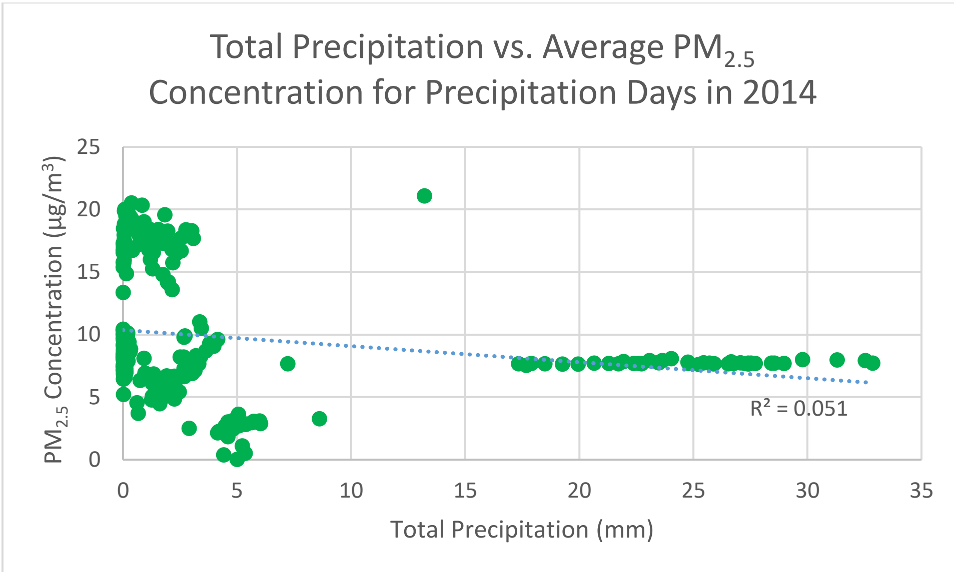


Figure 4-9. Total precipitation vs. average $PM_{2.5}$ concentration for precipitation days in 2014.

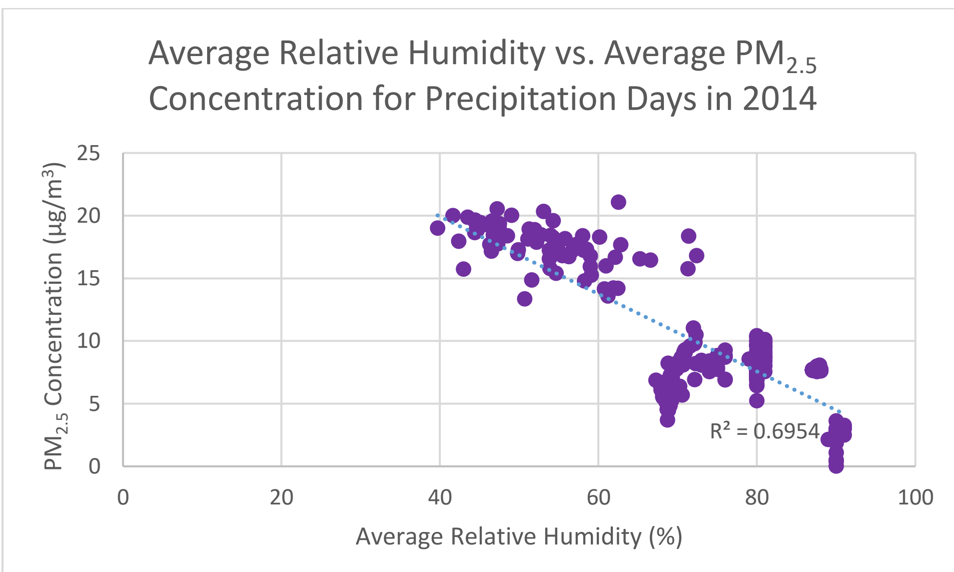


Figure 4-10. Average relative humidity vs. average $PM_{2.5}$ concentration for precipitation days in 2014.

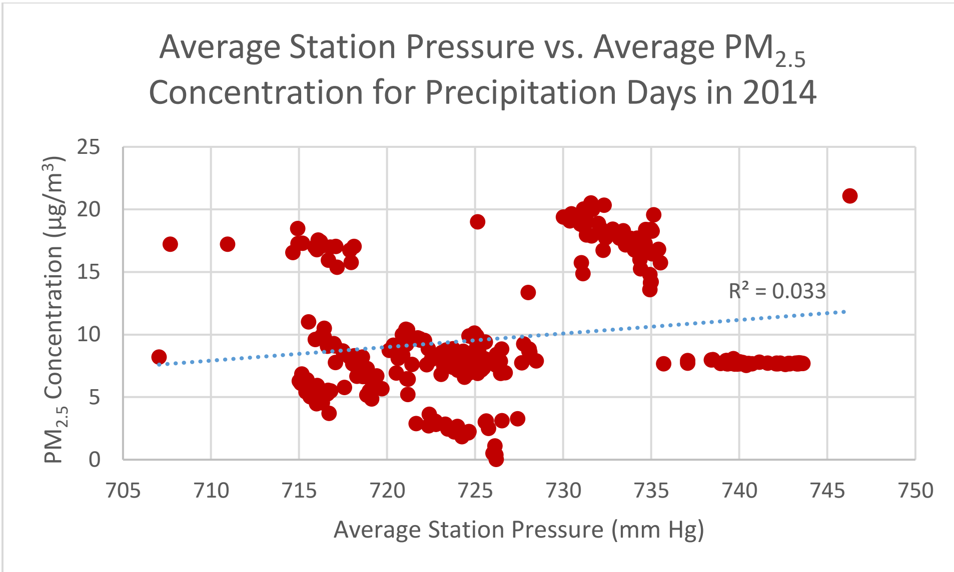


Figure 4-11. Average station pressure vs. average $PM_{2.5}$ concentration for precipitation days in 2014.

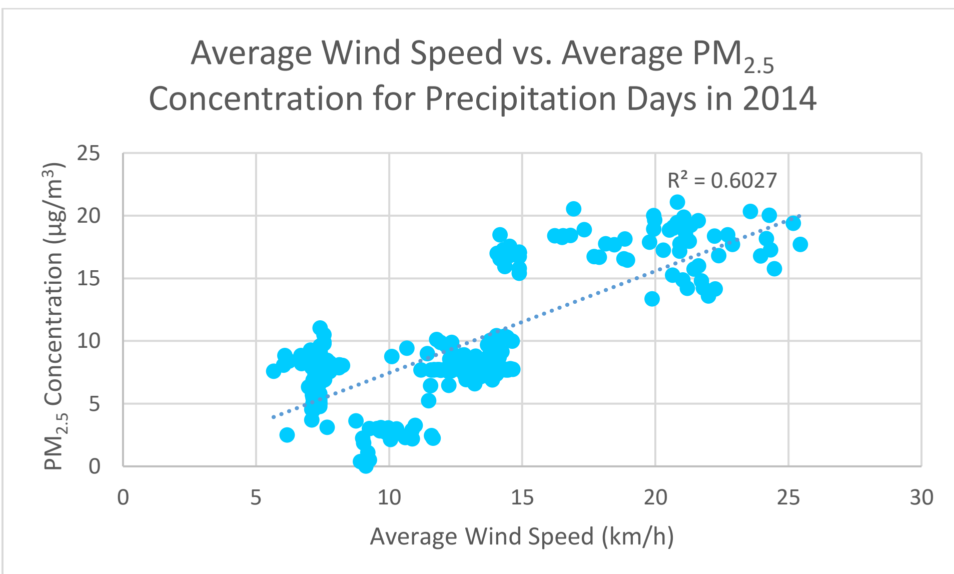


Figure 4-12. Average wind speed vs. average $PM_{2.5}$ concentration for precipitation days in 2014.

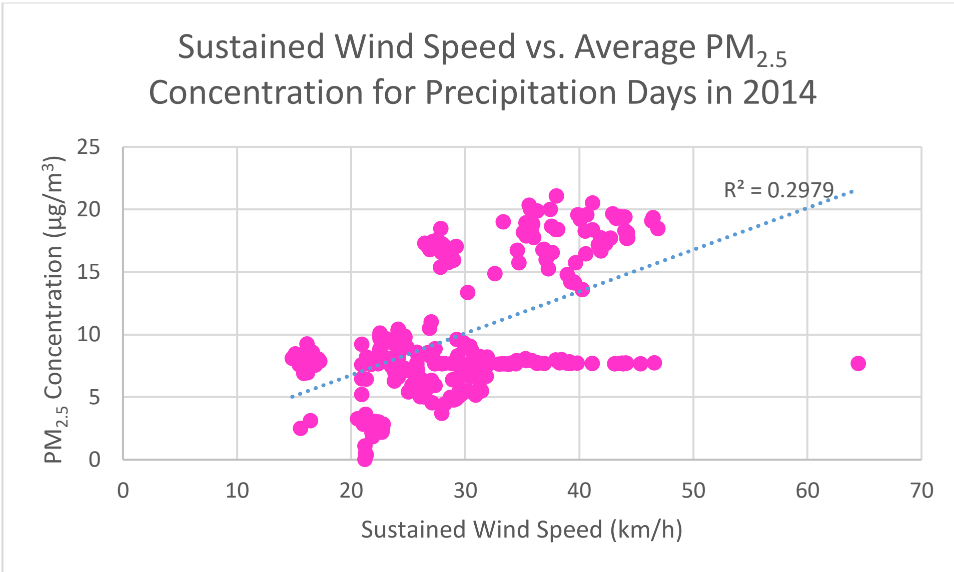


Figure 4-13. Sustained wind speed vs. average $PM_{2.5}$ concentration for precipitation days in 2014.

Table 4-5 shows the correlation between each weather variable and the $PM_{2.5}$ concentration on days with precipitation. Based on Table 4-5 and the above figures, maximum temperature, average wind speed, sustained wind speed, and average station pressure are shown to be positively correlated with $PM_{2.5}$ concentrations. Precipitation and average relative humidity are shown to be negatively correlated with $PM_{2.5}$ concentrations. Table 4-5 demonstrates that daily maximum temperature, daily average relative humidity, daily average wind speed, and daily sustained wind speed have the strongest correlations with $PM_{2.5}$ concentration out of the weather variables tested (with Pearson's correlation coefficients of 0.498, -0.834, 0.776, and 0.546, respectively). For those four correlation coefficients, $p < 0.001$, making the correlations significant. In all cases besides the average wind speeds and sustained wind speeds, results are consistent with the hypothesis that $PM_{2.5}$ concentrations in DFW in 2014 were positively correlated with maximum temperatures and average station pressure, and that they were negatively correlated with average relative humidity, average and sustained wind speed, and total precipitation.

Table 4-5 illustrates that daily maximum temperature is negatively correlated with average station pressure and average relative humidity, with the respective Pearson correlation coefficients being -0.178 and -0.640. Maximum temperature has an extremely weak correlation with total precipitation in this case, which is not significant at the 0.01 or 0.05 level. Maximum temperature is positively correlated with average and sustained wind speed. The Pearson correlation coefficients are 0.326, and 0.602, respectively. Average station pressure is positively correlated with total precipitation, average relative humidity, average wind speed, and sustained wind speed. The Pearson correlation coefficients are 0.713, 0.183, 0.495, and 0.551, respectively). Average station pressure is negatively correlated with maximum temperature (-0.178). Total precipitation has very weak correlations with average wind speed and maximum temperature, which are not significant at either the 0.01 or 0.05 level. Total precipitation does have a positive correlation with average station pressure, average relative humidity, and sustained wind speed (0.713, 0.494, and 0.407, respectively). Average relative humidity has a negative correlation with maximum temperature, sustained wind speed, and average wind speed (-0.640, -0.397, and -0.500, respectively). Average relative humidity has a positive correlation with average station pressure (0.183) and total precipitation (0.494). Average wind speed has a strong positive correlation with sustained wind speed, with the Pearson correlation coefficient being 0.663.

		$PM_{2.5}$ Concentration (µg/m^3)	Maximum Temperature (degrees C)	Average Station Pressure (HPa)	Total Precipitation (mm)	Average Relative Humidity (%)	Average Wind Speed (km/h)	Sustained Wind Speed (km/h)
$PM_{2.5}$ Concentration (µg/m^3)	Pearson Correlation	1	0.498**	0.182**	-0.226**	-0.834**	0.776**	0.546**
	Sig. (2-tailed)	-	0	0.001	0	0	0	0
Maximum Temperature (degrees C)	Pearson Correlation	0.498**	1	-0.178**	-0.085	-0.640**	0.326**	0.602**
	Sig. (2-tailed)	0	-	0.002	0.139	0	0	0
Average Station Pressure (HPa)	Pearson Correlation	0.182**	-0.178**	1	0.713**	0.183**	0.495**	0.551**
	Sig. (2-tailed)	0.001	0.002	-	0	0.001	0	0
Total Precipitation (mm)	Pearson Correlation	-0.226**	-0.085	0.713**	1	0.494**	0.012	0.407**
	Sig. (2-tailed)	0	0.139	0	-	0	0.834	0
Average Relative Humidity (%)	Pearson Correlation	-0.834**	-0.640**	0.183**	0.494**	1	-0.500**	-0.397**
	Sig. (2-tailed)	0	0	0.001	0	-	0	0
Average Wind Speed (km/h)	Pearson Correlation	0.776**	0.326**	0.495**	0.012	-0.500**	1	0.663**
	Sig. (2-tailed)	0	0	0	0.834	0	-	0
Sustained Wind Speed (km/h)	Pearson Correlation	0.546**	0.602**	0.551**	0.407**	-0.397**	0.663**	1
	Sig. (2-tailed)	0	0	0	0	0	0	-

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 4-5. 2014 correlations between weather variables and $PM_{2.5}$ concentration for days with precipitation. N = 307.

Table 4-6 shows the regression analysis results (for precipitation days only) for the daily average $PM_{2.5}$ concentration versus all of the input variables: road ADT, road class, dominant land use, daily maximum temperature, daily average station pressure, daily total precipitation, daily average relative humidity, daily average wind speed, and daily sustained wind speed. Additionally, block group population is included. The adjusted R square is 0.881, which indicates that the combined variables have a strong relationship with the $PM_{2.5}$ concentration on days with precipitation. The p-value for this regression is <0.001, so it is statistically significant. When considering all variables against $PM_{2.5}$ on precipitation days, average wind speed (with a coefficient of 0.522) has the most impact on $PM_{2.5}$. The variable with the least impact on $PM_{2.5}$ (with statistical significance) is the sustained wind speed, with a coefficient of -0.0823.

Regression Statistics: $PM_{2.5}$ Concentration vs. All Variables for Precipitation Days	
Multiple R	0.941
R Square	0.885
Adjusted R Square	0.881
Standard Error	1.722
Maximum Temperature Coefficient	-0.0306
Average Station Pressure Coefficient	-0.00791
Total Precipitation Coefficient	0.121**
Average Relative Humidity Coefficient	-0.289**
Average Wind Speed Coefficient	0.522**
Sustained Wind Speed Coefficient	-0.0823**
ADT Coefficient	8.940×10^{-6}
Road Class Coefficient	-0.0282
Dominant Land Use Class Coefficient	-0.356
Block Group Population Coefficient	8.220×10^{-5}
Intercept	33.988
Observations	307

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 4-6. Regression statistics of $PM_{2.5}$ concentration vs. all variables for precipitation days.

Table 4-7 displays the regression analysis results (for precipitation days only) for the daily average $PM_{2.5}$ concentration versus the weather variables: daily maximum temperature, daily average station pressure, daily total precipitation, daily average relative humidity, daily average wind speed, and daily sustained wind speed. The adjusted R square is 0.881. The adjusted R square value indicates that the combined weather variables have a strong relationship with the $PM_{2.5}$ concentration on days with precipitation. The p-value for this regression is <0.001, so it is statistically significant. When considering only weather variables on precipitation days, average wind speed has the highest impact on $PM_{2.5}$ concentration; its coefficient is 0.521. Sustained wind speed has the least impact on $PM_{2.5}$ concentration (with statistical significance), with a coefficient of -0.0830.

Regression Statistics: $PM_{2.5}$ Concentration vs. Weather Variables for Precipitation Days	
Multiple R	0.940
R Square	0.884
Adjusted R Square	0.881
Standard Error	1.723
Maximum Temperature Coefficient	-0.0311
Average Station Pressure Coefficient	-0.00658
Total Precipitation Coefficient	0.121**
Average Relative Humidity Coefficient	-0.291**
Average Wind Speed Coefficient	0.521**
Sustained Wind Speed Coefficient	-0.0830**
Intercept	31.600
Observations	307

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 4-7. Regression statistics of $PM_{2.5}$ concentration vs. weather variables for precipitation days.

Figures 4-14 – 4-18 display the relationships between the average $PM_{2.5}$ concentration for the DFW area and each weather variable for the test dates with no precipitation. As seen in Figure 4-14, an increase in daily maximum temperature typically indicates an increase in $PM_{2.5}$ concentration. For figure 4-14, there is an R^2 value of 0.174. Figure 4-15 shows that an increase in average relative humidity typically to leads to an increase in $PM_{2.5}$ concentration, and it has a low R^2 value of 0.0103. Figure 4-16 demonstrates that any trend is quite slight regarding the relationship between average station pressure and $PM_{2.5}$ concentration. In fact, it is closer to indicating no correlation. The R^2 value for Figure 4-16 is 0.0012. Figures 4-17 and 4-18 show that when average wind speed and sustained wind speed increase, there is typically an increase in $PM_{2.5}$ concentration. Figures 4-17 and 4-18 show R^2 values of 0.103 and 0.051, respectively. Further, Figure 4-18 shows that the R^2 value is much lower for sustained wind speed versus $PM_{2.5}$ concentration than it is for average wind speed and $PM_{2.5}$ concentration (shown in Figure 4-17).

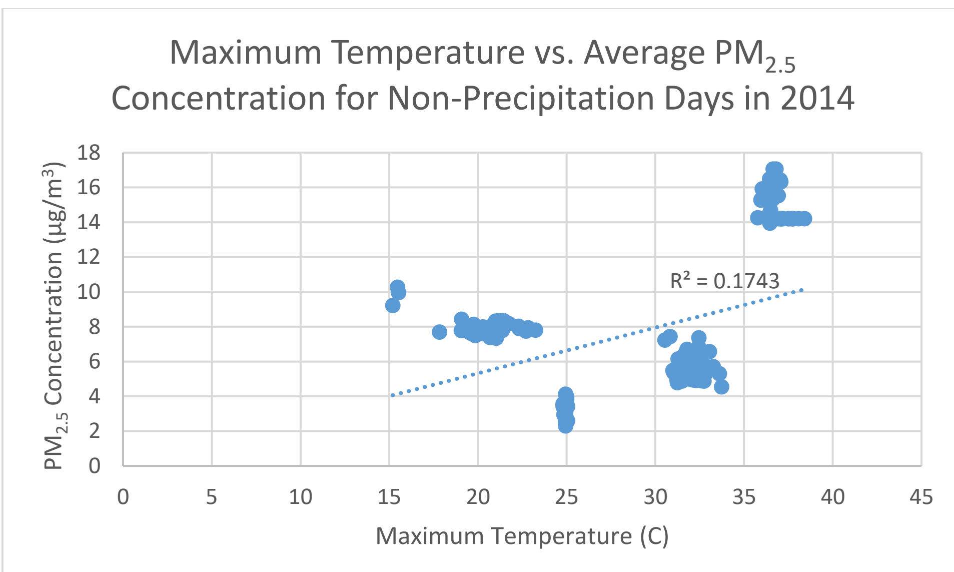


Figure 4-14. Maximum temperature vs. average $PM_{2.5}$ concentration for non-precipitation days in 2014.

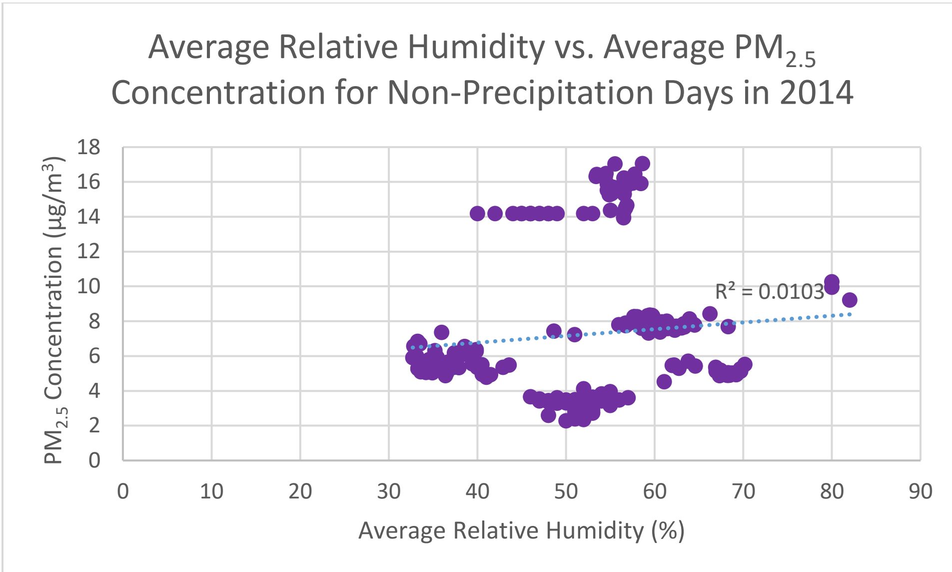


Figure 4-15. Average relative humidity vs. average $PM_{2.5}$ concentration for non-precipitation days in 2014.

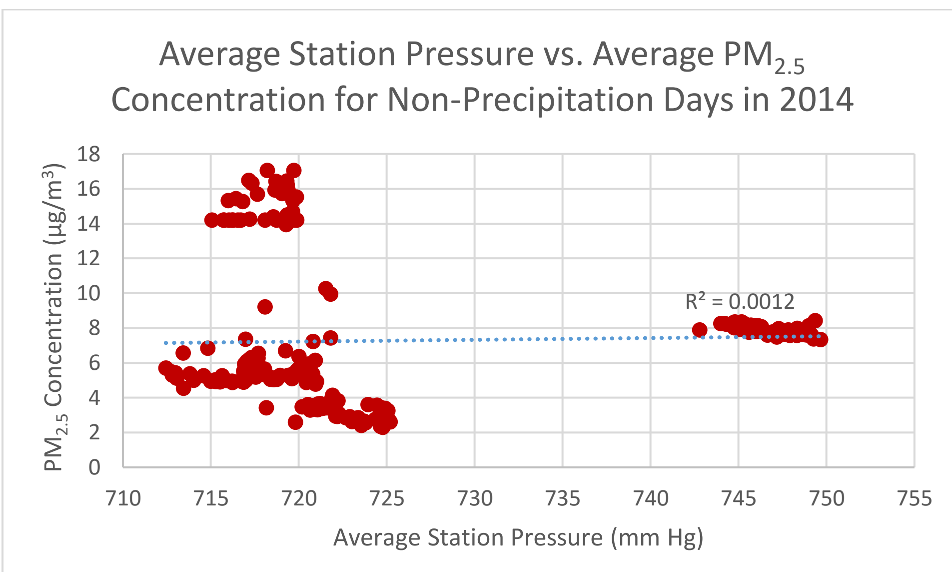


Figure 4-16. Average station pressure vs. average $PM_{2.5}$ concentration for non-precipitation days in 2014.

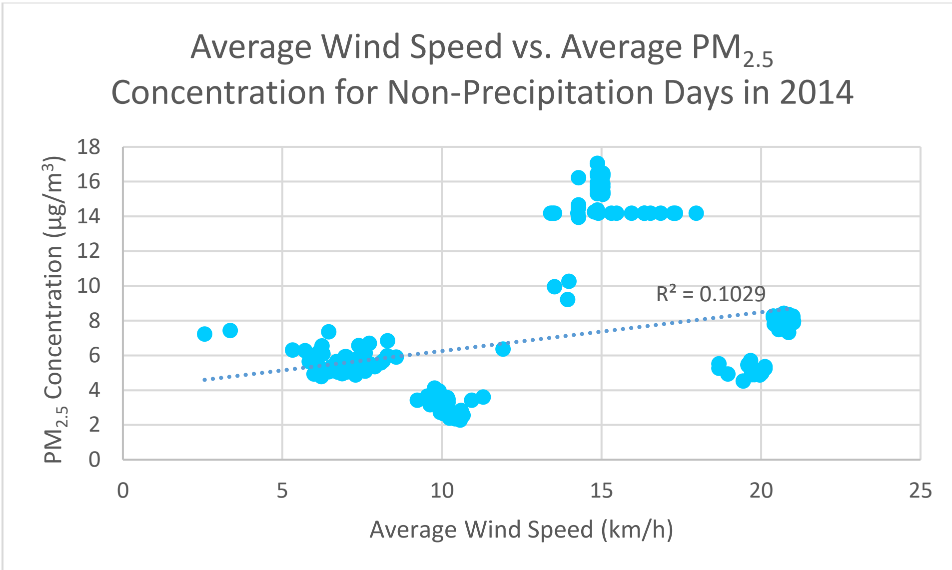


Figure 4-17. Average wind speed vs. average $PM_{2.5}$ concentration for non-precipitation days in 2014.

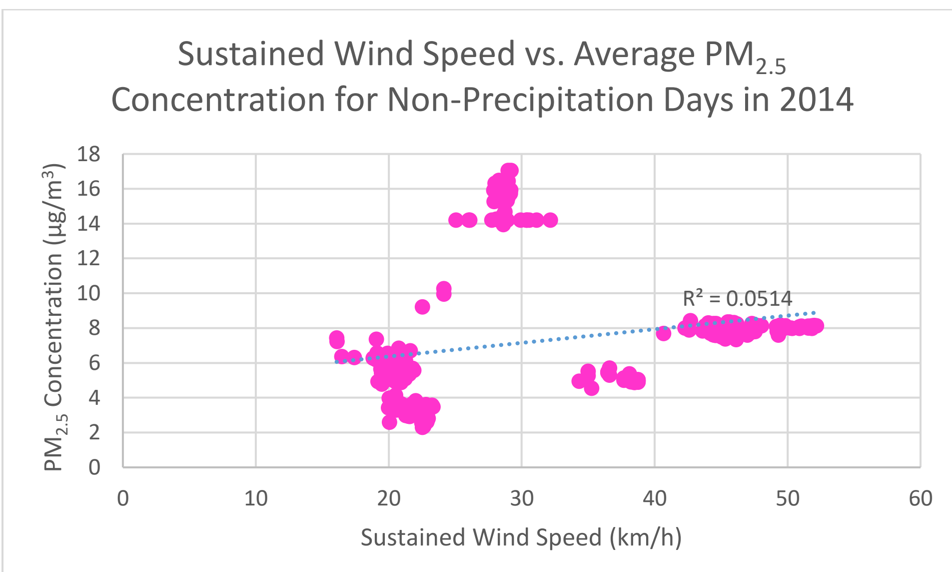


Figure 4-18. Sustained wind speed vs. average $PM_{2.5}$ concentration for non-precipitation days in 2014.

Table 4-8 shows the correlation between each weather variable and the $PM_{2.5}$ concentration on days with no precipitation. Based on Table 4-8 and the above figures, maximum temperature, average wind speed, sustained wind speed, and average relative humidity are all shown to be positively correlated with $PM_{2.5}$ concentrations. None of the variables have a very strong correlation with $PM_{2.5}$, however. In fact, average station pressure has a very low correlation coefficient of 0.034, which shows no correlation. It also has a p-value of 0.600, which shows that the very weak correlation is not statistically significant, again pointing to randomness. Table 4-8 demonstrates that daily maximum temperature has the strongest correlation with $PM_{2.5}$ concentration out of the weather variables tested (with a Pearson's correlation coefficient of 0.417). For that, $p < 0.001$, making the correlations significant. As far as average relative humidity, average wind speed, and sustained wind speed, the correlations are relatively weak, being 0.101, 0.321, and 0.227 respectively. For average relative humidity, the p-value is 0.120, making the result not statistically significant. The p-values for average and sustained wind speed are both <0.001, making the results statistically significant. For non-precipitation days, in all cases besides the maximum temperature, results are not consistent with the hypothesis that $PM_{2.5}$ concentrations in DFW in 2014 were positively correlated with maximum temperatures and average station pressure, and that they were negatively correlated with average relative humidity, average and sustained wind speed, and total precipitation.

Table 4-8 also shows how the weather variables are correlated with each other. Daily maximum temperature is negatively correlated with average station pressure, average relative humidity, average wind speed, and sustained wind speed. The respective Pearson correlation coefficients are -0.805, -0.400, -0.359, and -0.490. Average station pressure is positively correlated average relative humidity, average wind speed, and sustained wind speed, with Pearson correlation coefficients of 0.385, 0.641, and 0.793, respectively). It is negatively correlated with maximum temperature (-0.805). Average relative humidity has a negative correlation with maximum temperature, with a Pearson correlation coefficient of -0.400. It has a positive correlation with average wind speed, sustained wind speed, and average station pressure (with Pearson correlation coefficients of 0.775, 0.658, and 0.385, respectively). Average wind speed has a very strong positive correlation with sustained wind speed—the Pearson correlation coefficient being 0.945. All of the correlations between the weather variables are statistically significant.

		$PM_{2.5}$ Concentration (µg/m3)	Maximum Temperature (degrees C)	Average Station Pressure (HPa)	Average Relative Humidity (%)	Average Wind Speed (km/h)	Sustained Wind Speed (km/h)
$PM_{2.5}$ Concentration (µg/m^3)	Pearson Correlation	1	0.417**	0.034	0.101	0.321**	0.227**
	Sig. (2-tailed)	-	0	0.596	0.118	0	0
Maximum Temperature (degrees C)	Pearson Correlation	0.417**	1	-0.805**	-0.400**	-0.359**	-0.490**
	Sig. (2-tailed)	0	-	0	0	0	0
Average Station Pressure (HPa)	Pearson Correlation	0.034	-0.805**	1	0.385**	0.641**	0.793**
	Sig. (2-tailed)	0.596	0	-	0	0	0
Average Relative Humidity (%)	Pearson Correlation	0.101	-0.400**	0.385**	1	0.775**	0.658**
	Sig. (2-tailed)	0.118	0	0	-	0	0
Average Wind Speed (km/h)	Pearson Correlation	0.321**	-0.359**	0.641**	0.775**	1	0.945**
	Sig. (2-tailed)	0	0	0	0	-	0
Sustained Wind Speed (km/h)	Pearson Correlation	0.227**	-0.490**	0.793**	0.658**	0.945**	1
	Sig. (2-tailed)	0	0	0	0	0	-

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 4-8. 2014 correlations between weather variables and $PM_{2.5}$ concentration for non-precipitation days. N = 239.

Table 4-9 shows the regression analysis results (for non-precipitation days only) for the daily average $PM_{2.5}$ concentration versus all of the input variables: road ADT, road class, dominant land use, daily maximum temperature, daily average station pressure, daily total precipitation, daily average relative humidity, daily average wind speed, and daily sustained wind speed. Additionally, block group population is included. The adjusted R square is 0.677. The adjusted R square value indicates that the combined variables have a relatively strong relationship with the $PM_{2.5}$ concentration on days with precipitation. The p-value for this regression is <0.001, so it is statistically significant. When considering all variables against $PM_{2.5}$ on non-precipitation days, maximum temperature has the highest impact on $PM_{2.5}$ concentration. The coefficient is 0.980. Average relative humidity has the least impact on $PM_{2.5}$ concentration (with statistical significance), with a coefficient of 0.133.

Regression Statistics: $PM_{2.5}$ Concentration vs. All Variables for Non-Precipitation Days	
Multiple R	0.830
R Square	0.689
Adjusted R Square	0.677
Standard Error	2.193
Maximum Temperature Coefficient	0.980**
Average Station Pressure Coefficient	0.500**
Average Relative Humidity Coefficient	0.133**
Average Wind Speed Coefficient)	0.473**
Sustained Wind Speed Coefficient	-0.421**
ADT Coefficient	-8.900×10^{-6}
Road Class Coefficient	0.185
Dominant Land Use Class Coefficient	0.0501
Block Group Population Coefficient	0.000106
Intercept	-385.194**
Observations	239

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 4-9. Regression statistics of $PM_{2.5}$ concentration vs. all variables for non-precipitation days.

Table 4-10 displays the regression analysis results (for non-precipitation days only) for the daily average $PM_{2.5}$ concentration versus the weather variables: daily maximum temperature, daily average station pressure, daily total precipitation, daily average relative humidity, daily average wind speed, and daily sustained wind speed. The adjusted R square is 0.681. The adjusted R square value indicates that the combined weather variables have a relatively strong relationship with the $PM_{2.5}$ concentration on days with precipitation. The p-value for this regression is <0.001, so it is statistically significant. When only weather variables are measured against $PM_{2.5}$ on non-precipitation days, maximum temperature again has the highest coefficient (0.983) and thus the highest impact on $PM_{2.5}$ concentration. Average relative humidity has the least impact on $PM_{2.5}$ concentration, with a coefficient of 0.135.

Regression Statistics: $PM_{2.5}$ Concentration vs. Weather Variables for Non-Precipitation Days	
Multiple R	0.829
R Square	0.688
Adjusted R Square	0.681
Standard Error	2.180
Maximum Temperature Coefficient	0.983**
Average Station Pressure Coefficient	0.502**
Average Relative Humidity Coefficient	0.135**
Average Wind Speed Coefficient	0.468**
Sustained Wind Speed Coefficient	-0.421**
Intercept	-385.997**
Observations	239

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 4-10. Regression statistics of $PM_{2.5}$ concentration vs. weather variables for non-precipitation days.

$PM_{2.5}$ Concentrations and Asthma

When all dates in the study are assessed, there is essentially no correlation between $PM_{2.5}$ concentration and total number of asthma cases in the study area on a given date. Figure 4-19 shows an R^2 value of 0.0066, and as seen in Table 4-11, the Pearson correlation coefficient is 0.081. However, for days with precipitation, $PM_{2.5}$ concentration and the number of asthma cases have a Pearson correlation coefficient of 0.233 (Table 4-12). The p-value for that correlation is <0.001, making the result statistically significant. There is, therefore, a statistically significant relatively weak positive correlation between $PM_{2.5}$ concentration and reported asthma-related hospital visits when considering precipitation days. Figure 4-20, which shows $PM_{2.5}$ concentration vs. asthma cases for precipitation days, exhibits an R^2 value of 0.0541, which means that about 5.4% of cases can be explained by the correlation.

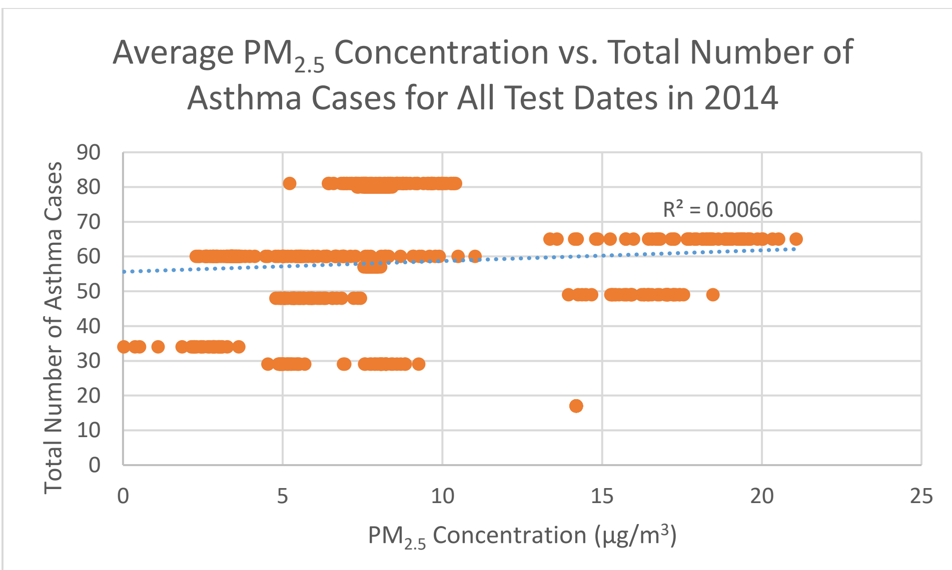


Figure 4-19. Average $PM_{2.5}$ concentration vs. total number of asthma cases for all test dates in 2014.

		Total Number of Asthma Cases (All Test Dates)
$PM_{2.5}$ Concentration ($\mu g/m^3$)	Pearson Correlation	0.081
	Sig. (2-tailed)	0.057

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 4-11. Average $PM_{2.5}$ concentration vs. total number of asthma cases for all test dates in 2014.

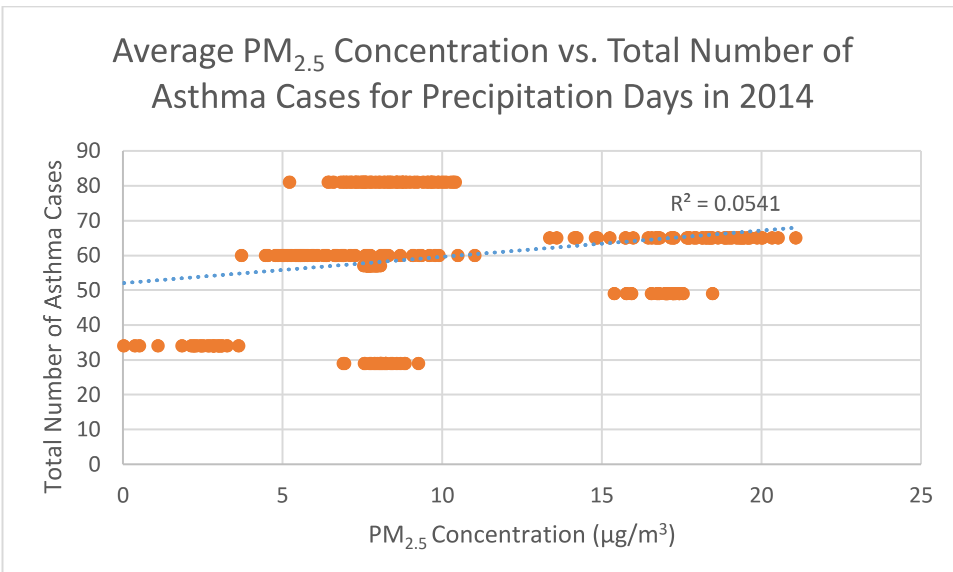


Figure 4-20. Average $PM_{2.5}$ concentration vs. total number of asthma cases for precipitation days in 2014.

		Total Number of Asthma Cases (Precipitation Days)
$PM_{2.5}$ Concentration ($\mu g/m^3$)	Pearson Correlation	0.233**
	Sig. (2-tailed)	0

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 4-12. Average $PM_{2.5}$ concentration vs. total number of asthma cases for precipitation days in 2014.

Figure 4-21 shows that about 2.6% of cases can be explained by the correlation, with an R^2 value of 0.0258. Table 4-13 demonstrates that for non-precipitation days, the Pearson correlation coefficient is -0.161, with a p-value of 0.014. On non-precipitation days, therefore, the results indicate that there is a very weak negative correlation between $PM_{2.5}$ concentrations and asthma cases. This is surprising because an increase in $PM_{2.5}$ concentrations would be expected to increase asthma cases.

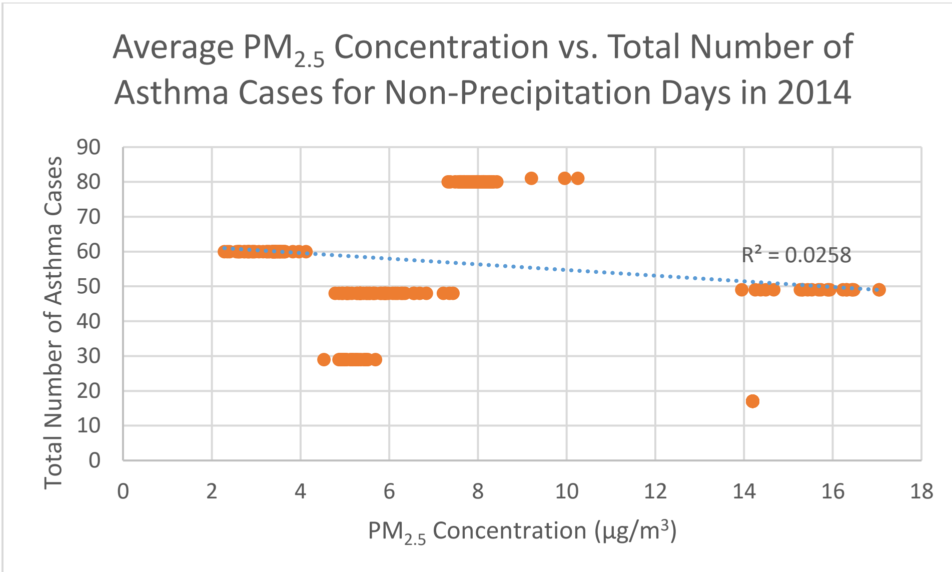


Figure 4-21. Average $PM_{2.5}$ concentration vs. total number of asthma cases for non-precipitation days in 2014.

		Total Number of Asthma Cases (Non-Precipitation Days)
$PM_{2.5}$ Concentration (µg/m^3)	Pearson Correlation	-0.161*
	Sig. (2-tailed)	0.014

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 4-13. Average $PM_{2.5}$ concentration vs. total number of asthma cases for non-precipitation days in 2014.

Figure 4-22 shows that there is no correlation between $PM_{2.5}$ concentrations and asthma cases within the block groups for all test dates combined—the R^2 value is 0.0014. Further, Table 4-14 shows that for daily average $PM_{2.5}$ concentration versus the number of asthma cases within the block group, the Pearson's correlation coefficient is 0.037. Similar to the data for total asthma cases, there is essentially no significant relationship between the number of asthma cases within the block group versus daily average $PM_{2.5}$ concentration.

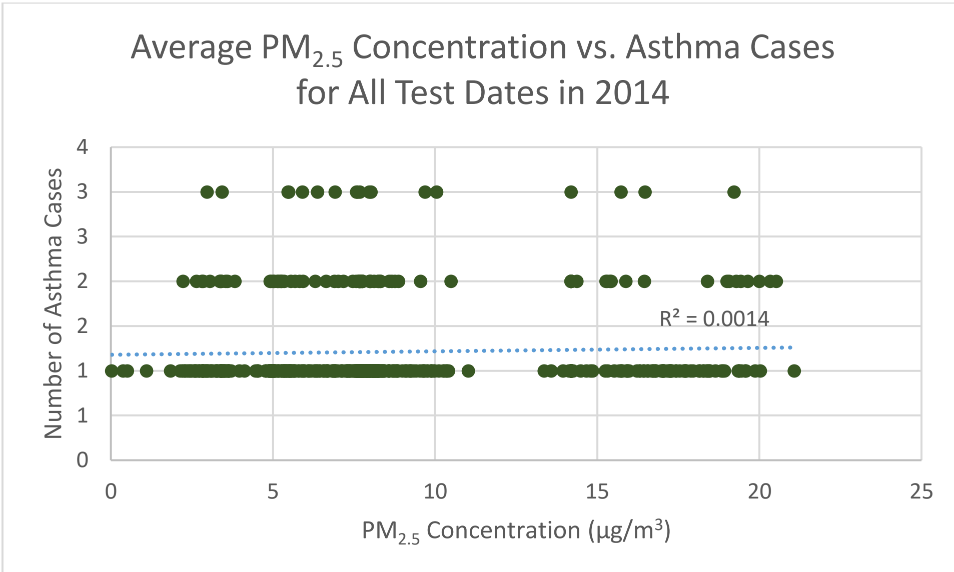


Figure 4-22. Average $PM_{2.5}$ concentration vs. asthma cases within the block group for all test dates in 2014.

		Number of Asthma Cases in Block Group (All Test Dates)
$PM_{2.5}$ Concentration (μg/m³)	Pearson Correlation	0.037
	Sig. (2-tailed)	0.386

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 4-14. Average $PM_{2.5}$ concentration vs. asthma cases within the block group for all test dates in 2014.

With an R^2 value of 0.005, Figure 4-23 does not illustrate that there is any notable correlation between $PM_{2.5}$ concentrations and asthma cases within the block groups when only considering precipitation days. Table 4-15 displays that the daily average $PM_{2.5}$ concentration versus the number of asthma cases within the block group for precipitation days. The Pearson's correlation coefficient is 0.023. Similar to the data for total asthma cases, the relationship between the number of asthma cases within the block group and daily average $PM_{2.5}$ concentration is a very weak positive relationship. However, unlike the data for total asthma cases, the finding is not statistically significant, as the p-value is 0.69. Again, this shows that the result could be due to chance.

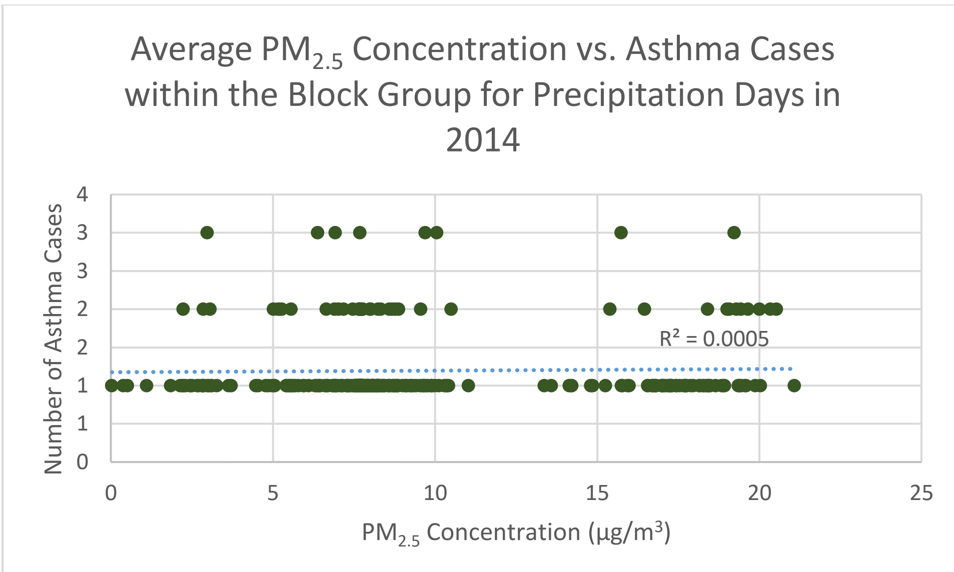


Figure 4-23. Average $PM_{2.5}$ concentration vs. asthma cases within the block group for precipitation days in 2014.

		Number of Asthma Cases in Block Group (Precipitation Days)
$PM_{2.5}$ Concentration ($\mu g/m^3$)	Pearson Correlation	0.023
	Sig. (2-tailed)	0.692

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 4-15. Average $PM_{2.5}$ concentration vs. asthma cases within the block group for precipitation days in 2014.

Figure 4-24 also demonstrates that there is no significant correlation between $PM_{2.5}$ concentrations and asthma cases within the block groups for non-precipitation days, and it shows an R^2 value of 0.0081. Table 4-16 shows a Pearson's correlation coefficient is 0.090 for the relationship between the number of asthma cases within the block group versus daily average $PM_{2.5}$ concentration for non-precipitation days. Like the data for total asthma cases, the Pearson's coefficient value indicates that there is no correlation.

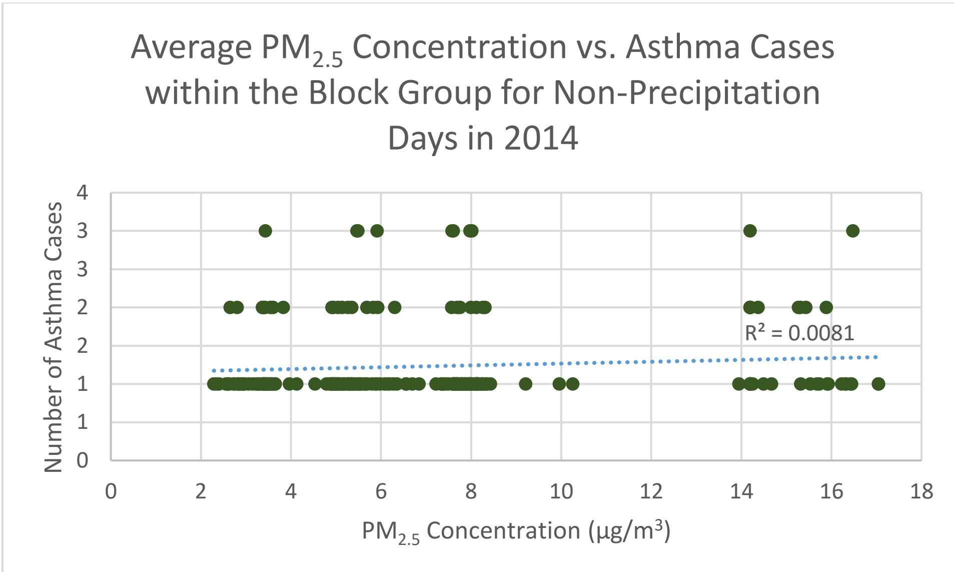


Figure 4-24. Average $PM_{2.5}$ concentration vs. asthma cases within the block group for non-precipitation days in 2014.

		Number of Asthma Cases in Block Group (Non-Precipitation Days)
$PM_{2.5}$ Concentration (µg/m^3)	Pearson Correlation	0.090
	Sig. (2-tailed)	0.167

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Table 4-16. Average $PM_{2.5}$ concentration vs. asthma cases within the block group for non-precipitation days in 2014.

The Spatial Pattern of Asthma-Related Hospital Visits

Figure 4-25, a Kernel Density analysis image, shows how dense the asthma patient locations were in their respective areas. Again, the density is increased in Dallas County, but it is also increased noticeably in Tarrant County. The city of Dallas is in Dallas County, while Fort Worth, another major city, is located in Tarrant County.

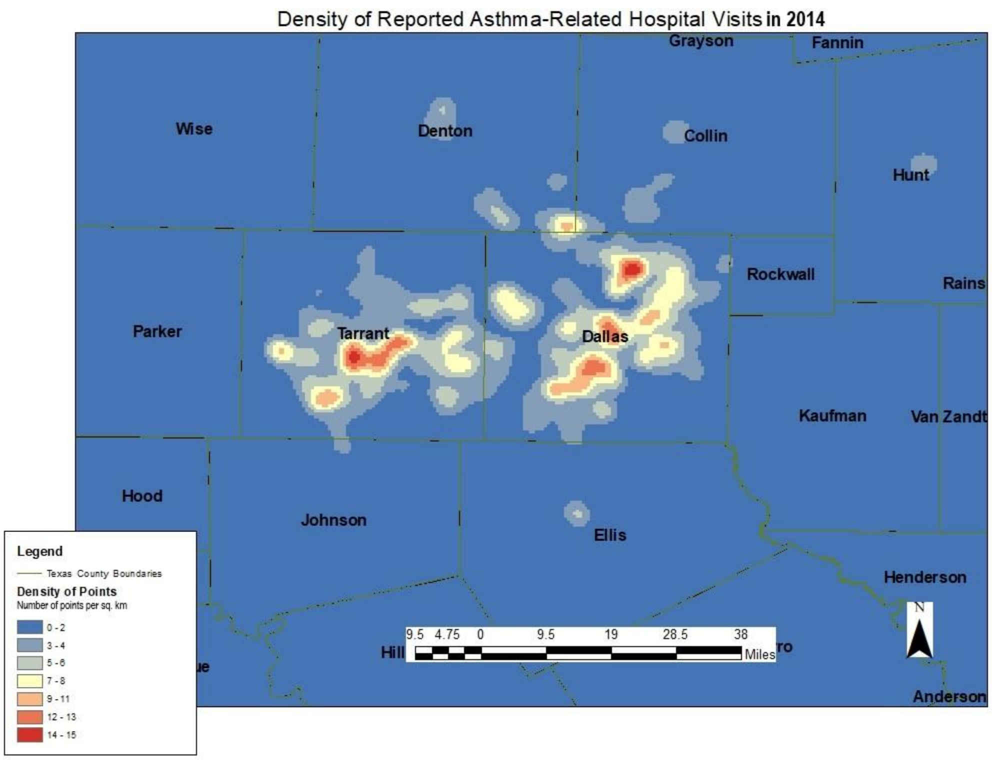


Figure 4-25. Density of reported asthma-related hospital visits in 2014.

The Anselin's Local Moran's analysis yielded clusters among the reported home locations of those admitted to hospitals due to asthma for all of 2014 (Figure 4-46). As seen in Figure 4-26, the clusters of reported asthma cases were mostly seen in Tarrant, Denton, Collin, Hunt, and Rockwall Counties. Tarrant county also has many outliers. Dallas County has many outliers, but there are still some clusters seen there. Figure 4-

27 shows the hot spots and cold spots of asthma cases within the study area as determined by the Getis-Ord G analysis. The hot spots are mostly seen in Dallas County, but there are noticeable numbers of hot spots in Denton, Collin, Rockwall, and Ellis Counties. There are a few in Tarrant County as well. Based on both figures, the city centers and surrounding areas (namely Fort Worth, Dallas, and Denton) have a high concentration of asthma-related hospital visits surrounding them.

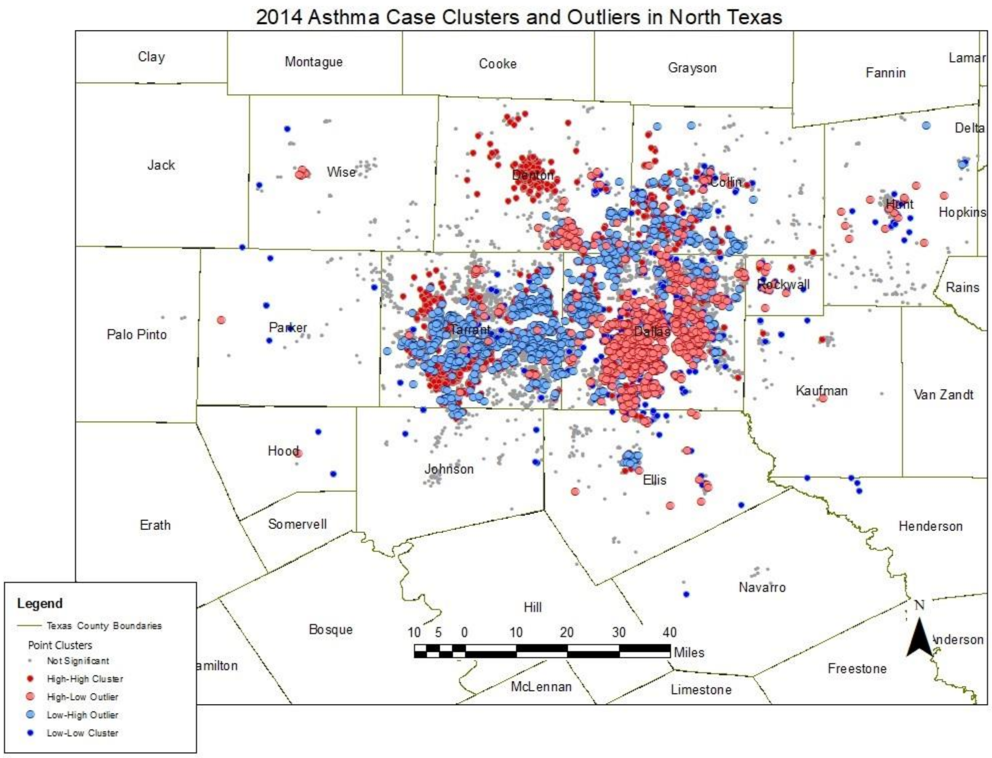


Figure 4-26. 2014 Asthma case clusters and outliers in north Texas.

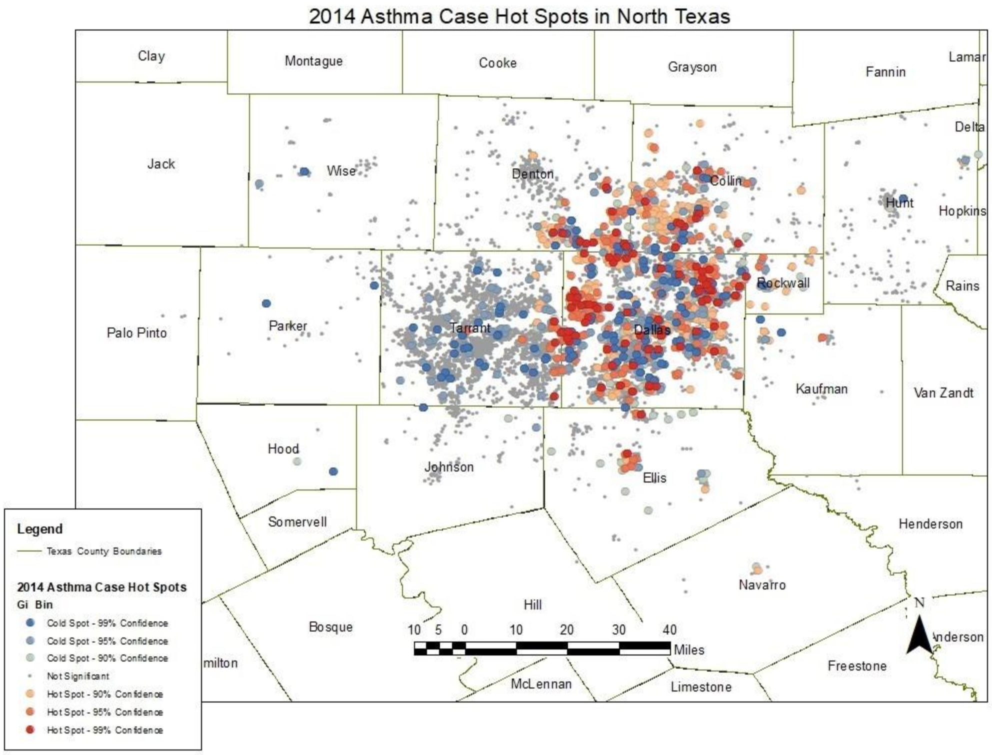


Figure 4-27. 2014 Asthma case hot spots in north Texas.

Figure 4-28 shows the population by block group within the study area, and it illustrates how busy the major roads are in the area. Areas with higher populations are seen in Figure 4-48 as surrounded by many roads with varying ADTs. Many of those ADTs are quite high. However, many of the highest ADTs are not in areas with high populations by block group. This shows that high traffic areas are not necessarily the same as high population areas. When compared to Figures 4-25, 4-26, and 4-27, it is apparent that most areas with higher populations (i.e. parts of Dallas and Tarrant Counties) are the same areas where clusters and hot spots are heavily concentrated.

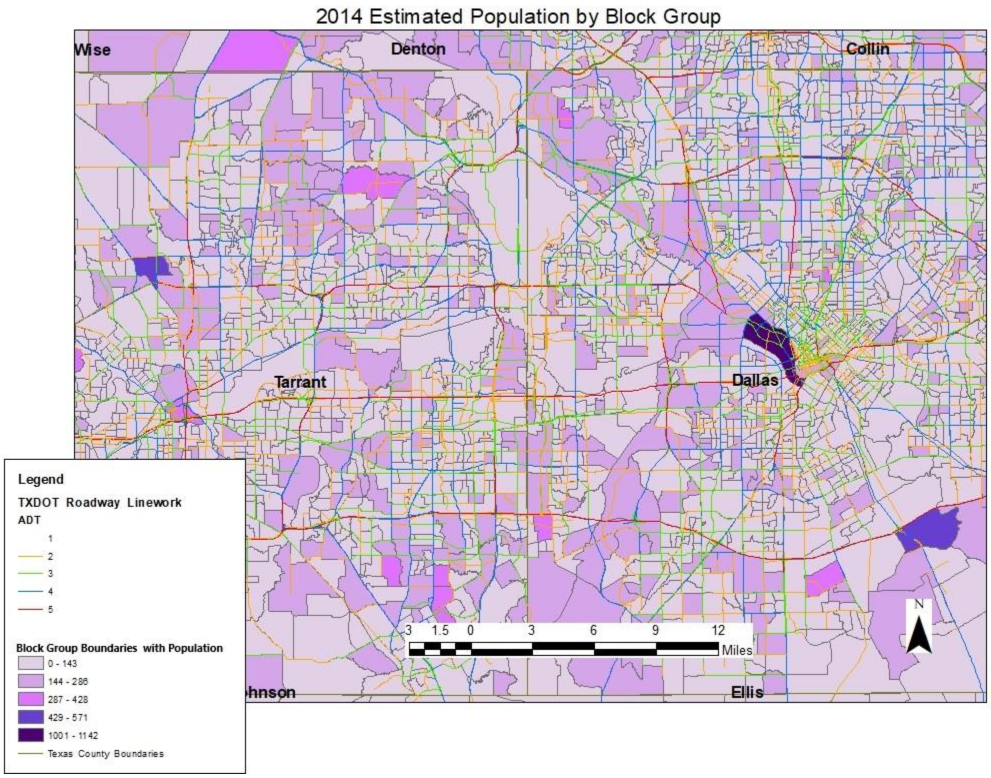


Figure 4-28. Population by block group with roads. The block groups are color-coded based on population. The roads are color-coded based on the ADT.

Chapter 5

Discussion

This section discusses the research constraints that may have influenced the results. There is also discussion of possible reasons for any results which did not go along with the hypotheses.

Limitations of the Analysis

Based on similar studies to this current one, there can be limitations based on the use of GIS tools (i.e. ordinary kriging). In general, GIS based studies face the challenge of uniformly distributed data, which limits certain data which is used for analysis (Gorai et al., 2014). This is true of this current study, as the weather and air quality monitoring sites are not as numerous and spatially diverse as the patient locations. Even the available air quality monitoring sites are not as abundant as the weather data sites. Looking at Figure 2-12, it is clear that even for Ahmadi and John (2015), there were relatively few TCEQ air quality monitors available for use for a very similar study area, although they were using monitors which reported ozone concentration data.

There are only 24 weather monitors which collected data for 2014 in the study area, and of those, 5 of them had large amounts of missing data and could not be used. There are only seven $PM_{2.5}$ monitors in the study area. Seeing how much variation there is in the average $PM_{2.5}$ concentration from station to station on the same given day, it is necessary to have more monitors that measure $PM_{2.5}$ concentrations. As far as weather monitors, there is a very noticeable difference in daily precipitation measurements in each given point within the study area. Because of this, it is necessary to have more weather monitors and more recorded data.

Another limitation that this research had is that some patients may have reported an address which is not truly where they live or have spent much time in, and a given address may not even be where they were when symptoms occurred. Some people experiencing asthma symptom aggravation may have gone to a private doctor rather than a hospital, or they may not have gone to a healthcare provider at all, which means their cases are not reflected in the data available (Gorai et al., 2014). That can be assumed for this research that took place in DFW.

Regarding the block-group level, one notable research constraint is that most of the block groups for the study area are quite small, so the number of asthma cases per block group did not exceed 3 for the study period. Another constraint is that the block groups are quite varied in size, as is evident in Figure 4-28. The most significant limitation is that not all meteorological variables were included, i.e. mixing height (indicates inversions) and stability (determined by solar insolation and wind speed). Stability is the main variable that affects dispersion of air pollutants (Jacobson, 2012, p. 137). Another limitation is that only 12 days were analyzed, which do not capture all combinations of weather conditions.

Regarding the modelling technique for $PM_{2.5}$ concentrations, a limitation is that the RBF neural network does not use the same dynamics as a weather forecast model with an atmospheric chemistry module. There are fewer variables involved with the RBF neural network model. Dynamic forecast models can be useful tools to assess the meteorological implications on the distribution of air pollutants (e.g. ozone and $PM_{2.5}$) due to their use of many variables.

Discussion of Results

The results point to the ambient $PM_{2.5}$ concentration being positively correlated with asthma cases when precipitation days are considered and when the total count of asthma-related hospital admissions for the study area are considered. This is consistent with previous studies' results (Huang et al., 2019; Mirabelli et al., 2016; Williams et al., 2019) and the proposed hypothesis. However, the results also indicate that $PM_{2.5}$ concentrations are negatively correlated with asthma cases on non-precipitation days, and that they are not correlated with asthma cases when all test dates are combined. This is not consistent with the proposed hypothesis; however, it is consistent with the results of Yamazaki et al. (2019), who also found no correlation between $PM_{2.5}$ and asthma exacerbation. Also, when just the number of asthma cases per block group are considered, there is not much of a correlation between asthma cases and $PM_{2.5}$ concentrations at all. It is possible that the block group level is too small for this research—the number of asthma cases per day per block group never exceeded three. As seen in Figure 4-28, many of the block groups are quite small areas. Perhaps the census tract level, which is the next step up in size, should be the next level on which to focus similar research.

Regarding the slightly higher positive correlation between $PM_{2.5}$ concentration and total asthma cases on precipitation days, it would be expected that $PM_{2.5}$ concentrations would vary between areas with little precipitation and those with more due to the washout effect. It would also be expected that the areas with higher $PM_{2.5}$ concentration would have higher cases of asthma on such days. It is also possible that some asthma symptoms are exacerbated from the patient remaining indoors, as indoor air quality may cause amplification of asthma symptoms (Habre et al., 2014; Liu et al., 2014). Indoor temperature and moisture levels also contribute to exacerbated asthma and allergy symptoms (Norbäck et al., 2019; J. Wang et al., 2017). Exposure to indoor conditions, therefore, may be contributing factors to asthma-related hospital visits happening on cooler days and/or days with more precipitation. Regarding the very weak negative correlation between $PM_{2.5}$ concentration and asthma cases on non-precipitation days, since other pollutants such as ozone (O_3) form from NOx and VOCs like $PM_{2.5}$ can, it may be that asthma cases could actually increase on days when $PM_{2.5}$ levels are lower due to the presence of other pollutants that exacerbate asthma.

Precipitation is shown to be negatively correlated with $PM_{2.5}$ when considering precipitation days only. This is consistent with the results of previous studies as well as with the proposed hypothesis. This makes sense due to the effects of precipitation leading to wet deposition of $PM_{2.5}$ (Brunner et al., 2015; Zhang et al., 2015; Zhen et al., 2013; Lai, 2013; Jacobson, 2012, p. 294). Average relative humidity is found to be negatively correlated with $PM_{2.5}$ on when considering all days or when considering precipitation days only, which is also consistent with previous studies' results and the hypothesis. Because high humidity is often associated with the onset of precipitation events, this makes sense if there are precipitation events (and wet deposition) surrounding the days with higher humidity. On non-precipitation days, average relative humidity is found to be positively correlated with $PM_{2.5}$ with no statistical significance. This indicates that the result for non-precipitation days regarding relative humidity could be due to chance. However, there are some studies which reported that humidity is positively correlated with $PM_{2.5}$ concentration (Veremchuk et al., 2016; Lai, 2013).

Maximum temperature, average station pressure, average wind speed, and sustained wind speed are positively correlated with ambient $PM_{2.5}$ concentration when days with precipitation are considered. Besides the results for average wind speed and sustained wind speed, these results are consistent with the results of previous studies as well as with the proposed hypothesis. In the case of the positive correlation of maximum temperature with $PM_{2.5}$ concentration, higher temperatures also lead to greater evaporative emissions of VOCs, one of the precursors of $PM_{2.5}$ (Zhang et al., 2015).

Therefore, increased $PM_{2.5}$ levels with increased temperature makes sense. Regarding average station pressure, higher pressure is typically associated with inversions, which result in high air pollution events (L. Li et al., 2014). As for average and sustained wind speeds, higher wind speeds would be expected to increase dispersal of $PM_{2.5}$ rather than increasing the concentration in a given area (Pesic et al., 2014; Ahmadi & John, 2015; Bella et al., 2016; Zhang et al., 2015).

Effects of Drought

Much of north Texas was in drought during 2014. In fact, according to the National Drought Mitigation Center (2019), since the start of the U.S. Drought Monitor in 2000, Texas had its longest bout of drought for 271 weeks from May 4, 2010 to July 7, 2015. A drought can be defined as "an interval of time, generally of the order of months or years in duration, during which the actual moisture supply at a given place rather consistently falls short of the climatically expected or climatically appropriate moisture supply" (Lloyd-Hughes, 2014, p. 607; Texas State Historical Association, 2018). During 2014, North Central Texas as a whole (which includes the study area) received 73% of its expected precipitation (Texas State Historical Association, 2018). Texas drought maps from 2014 can be found in Appendix 1.

In March, April, May, June, July, August, September, October, November, and December, parts of the study area, including Tarrant and Dallas Counties, were in severe, extreme, or exceptional drought (the three highest severities). Appendix 1 has figures which feature drought maps of Texas from 2014. The strong positive correlation between average and sustained wind speed and $PM_{2.5}$ is the opposite of the findings of B. Zhang et al. (2018), which indicates that strong wind speeds are associated with removal of 60% of $PM_{2.5}$ from the atmosphere. The strong positive correlations between average and sustained wind speeds and $PM_{2.5}$ concentration may be explained by the drought. Studies by Y. Wang et al. (2017) and Wang et al. (2015) found that there is an increase in ambient $PM_{2.5}$ in the form of wind-blown dust during drought conditions. Similarly, Achakulwisut, Mickley, and Anenberg (2018) found that drought conditions are a precursor to increased fine dust (fine PM) concentrations.

There was only one date (with complete data) within the study time period that exhibited heavy precipitation. Zalakeviciute, López-Villada, and Rybarczyk (2018) found that in urban areas, atmospheric $PM_{2.5}$ removal was significant during rainfall events with at least 9 mm of precipitation. Sun et al. (2019) found the same with rainfall events of at least 10 mm. Of the seven precipitation dates included in this dissertation study, there was one date which had greater than 10 mm of precipitation (March 15, 2014, with an average of 24.618 mm of precipitation among the reported asthma case locations). The strong negative correlation of relative humidity with $PM_{2.5}$ on rainy days is consistent with the research of Zalakeviciute et al. (2018), which found that $PM_{2.5}$ concentration decreases with increasing relative humidity among the outskirts of cities. Most of the asthma points were surrounding city centers in this case. The drought conditions may have been the cause for the finding of a very weak negative correlation between precipitation and $PM_{2.5}$.

Aeroallergens

It could be that aeroallergens, which consist of larger particles, cause exacerbation of asthma symptoms as well as allergic reactions, which also lead in turn to exacerbation of asthma symptoms (Sierra-Heredia et al., 2018). Aeroallergens include pollen grains and certain fungi. Mature pollen grains are typically released when there is a decrease in relative humidity, and they typically stay in the air as long as there is low humidity and wind speeds and high atmospheric pressure (Sierra-Heredia et al., 2018).

Fungi tend to grow well in wet conditions, and they produce spores in dry conditions (Sierra-Heredia et al., 2018).

According to Zhang et al. (2015) and Sierra-Heredia et al. (2018), precipitation often temporarily washes out aeroallergens from the atmosphere. However, according to Sierra-Heredia et al. (2018), it is possible that precipitation, i.e. rain, can even break pollen apart, thus releasing $PM_{2.5}$ in the form of the smaller particles of pollen in the atmosphere. Thunderstorms can carry whole and ruptured pollen grains to ground level, thus being distributed by the wind to areas outside of the area of the thunderstorm (Sierra-Heredia et al., 2018). It may be due to the breaking of pollen grains in spring that precipitation during the spring months was associated with higher hospital admissions for asthma symptoms. It is possible that this rupturing caused an increase in allergy symptoms, which could have exacerbated asthma symptoms. However, due to the unavailability of aeroallergen monitors (there was one found for the DFW area which has the necessary historic data), the effects of pollen count on asthma could not be assessed in this study. For non-precipitation days, it could be that the lack of interaction between the weather and pollen grains caused the slight decrease in asthma-related hospital admissions when $PM_{2.5}$ concentrations had increased.

Chapter 6

Conclusions and Recommendations for Future Work

An objective of this research was to determine the potential spatial correlations between the weather variables of daily maximum dry-bulb temperature, daily average wind speed, daily sustained wind speed, daily average station pressure, daily average relative humidity, and daily total precipitation with ambient $PM_{2.5}$ concentration. The other objective of this research was to determine the correlation between $PM_{2.5}$ concentration and adult asthma-related hospital admissions. To reach those objectives, a radial basis function model was used to model the $PM_{2.5}$ concentrations in the DFW area in the year 2014. The variables used within the model were weather variables—daily maximum dry-bulb temperature, daily average wind speed, daily sustained wind speed, daily station pressure, daily average relative humidity, and daily precipitation—road type, average daily traffic counts, dominant land use, and the known $PM_{2.5}$ concentrations. The 2014 reported asthma cases were assessed by using spatial autocorrelation analyses—the Getis-Ord G and Local Moran's I statistical analyses.

In this study, maximum temperature, average station pressure, average wind speed, and sustained wind speed were found to be positively correlated with ambient $PM_{2.5}$ concentration on precipitation days. The strong positive correlations between average and sustained wind speeds and $PM_{2.5}$ concentration may be explained by the drought of 2014. Apart from the results for average wind speed and sustained wind speed, those results are consistent with the results of previous studies and the hypothesis that the $PM_{2.5}$ concentrations in DFW in 2014 were positively correlated with maximum temperatures and average station pressure, and that they were negatively correlated with average relative humidity, average and sustained wind speed, and total precipitation. Such studies include L. Li et al. (2014), Kalbarczyk et al. (2015), and Veremchuk et al. (2016), who found that temperature was positively correlated with air pollution concentrations. L. Li et al. (2014) and Lai (2012) found that station pressure is positively correlated with air pollution concentrations, and that they were negatively correlated with average wind speed, sustained wind speed, relative humidity, and precipitation. In all cases, the correlations are shown to be much stronger when considering only precipitation days than when considering combined precipitation and non-precipitation days.

Precipitation and average relative humidity are shown to be negatively correlated with $PM_{2.5}$ concentration on precipitation days. This is consistent with the results of previous studies—i.e. Cai et al. (2014), who found that relative humidity was negatively correlated with air pollution concentrations; Austin et al. (2015) and Zhai et al. (2019), who found that precipitation was negatively correlated with air pollution concentrations; and Lai et al. (2012) and Li et al. (2014) who found that both precipitation and average relative humidity were negatively correlated with air pollution concentrations. It is also consistent with the proposed hypothesis. In both cases, the correlations are shown to be much stronger when considering only precipitation days than when considering combined precipitation and non-precipitation days. The differences between the results on precipitation days versus combined precipitation and non-precipitation days indicate that $PM_{2.5}$ concentration is sensitive to precipitation events. Kleine-Deters et al. (2017) similarly found that their machine-learning-based model was sensitive to precipitation events. Due to the variation in literature about whether humidity is positively or negatively correlated with $PM_{2.5}$ concentration, more research should be done in the future on how humidity affects $PM_{2.5}$ concentrations.

This research has found that there is a relatively weak positive correlation between $PM_{2.5}$ concentration and reported asthma-related hospital visits on precipitation days. This is consistent with the results of Mirabelli et al. (2016), Williams et al. (2019), and Huang et al. (2019), who specifically focused on $PM_{2.5}$ and found that it is positively correlated with asthma exacerbation. Gorai et al. (2016) also found a positive correlation between the two, but they found that it was not statistically significant. It is also consistent with the hypothesis that $PM_{2.5}$ concentrations and asthma-related hospital admissions were positively correlated. The correlation for all test dates including non-precipitation days showed a no correlation which, like the results of Gorai et al. (2016), was not statistically significant. It is also consistent with Yamazaki et al., (2019), who found essentially no correlation between $PM_{2.5}$ and asthma exacerbation. Regression analyses also show that the relationship is weak, and those results were not statistically significant. Due to those findings, further research is needed to determine whether $PM_{2.5}$ concentrations and asthma exacerbation are related in different study areas and/or different time periods.

There is a lot of focus in the literature on ambient ozone concentration as it relates to asthma exacerbation. However, as seen in this study, $PM_{2.5}$ concentration is positively correlated with asthma exacerbation as well, although weakly, when precipitation is considered. More extensive research should be done to confirm whether $PM_{2.5}$ concentrations do exacerbate asthma. In the future, it would be helpful for TCEQ and/or the EPA to place more $PM_{2.5}$ monitors in the DFW region. $PM_{2.5}$ concentrations can fluctuate from station to station, so more $PM_{2.5}$ monitors will help with future research. It would also help with potentially better estimations of $PM_{2.5}$ for future research. More weather monitors would also be helpful for the same reasons. Not only would that help to better estimate weather variables for more locations—it would also aid in the estimation of $PM_{2.5}$. Perhaps with more $PM_{2.5}$ and weather monitors, prediction of $PM_{2.5}$ could be possible rather than only retrospective estimation.

More research should also be done of the same kind as this study, in the same study area, but during a year that is not a drought year. The complications of the drought may have impacted the results, so a year with more precipitation may show different results. Further research focusing on the effects of aeroallergens on asthma and allergies is also needed. North Texas does have vegetation which releases significant amounts of pollen, and that pollen may play a role in the exacerbation of asthma symptoms.

In future research in the DFW area, it would be beneficial to study the correlation between highways in general—or high-traffic roads and highways—and $PM_{2.5}$ concentrations and asthma cases. There are parts of certain roads in the metroplex that have very high volumes of traffic. It is also recommended that a potential correlation between areas of construction and $PM_{2.5}$ concentrations and asthma cases be studied. Windblown dust from construction could be contributing to $PM_{2.5}$ concentrations and asthma symptom exacerbation.

Based on the results of this study, daily maximum temperature, daily average station pressure, daily average wind speed, and daily sustained wind speed are positively correlated with ambient $PM_{2.5}$ concentration on days with precipitation. On days with precipitation, daily total precipitation and daily average relative humidity are negatively correlated with ambient $PM_{2.5}$ concentration. $PM_{2.5}$ concentration is positively correlated with asthma-related hospital admissions among adults in the DFW region of north Texas on days with precipitation, and negatively correlated with the same on days without precipitation. The findings of this study indicate that it is necessary to further study the relationships to determine whether $PM_{2.5}$ is detrimental to human respiratory health.

Appendix

Appendix 1: Drought Maps

Figures A1-1 – A1-12 show drought maps from each month in 2014, from the dates closest to the dates from the study. According to the National Drought Mitigation Center (2019), the intensity categories entail the following: D0, or “abnormally dry,” is actually a “precursor to drought” and entails “short-term dry conditions that may impede agriculture, some water shortages, and crops may not fully recover.” D1, or “moderate drought,” entails some crop damage due to dry conditions, the beginnings of water shortages, and requested water-use restrictions (National Drought Mitigation Center, 2019a). D2, or “severe drought,” means that it is likely that there will be loss of crops, that water shortages are common, and that there are required water restrictions (National Drought Mitigation Center, 2019a). D3, or “extreme drought,” means there is a “major” loss of crops and extensive water restrictions due to water shortages (National Drought Mitigation Center, 2019a). D4, or “exceptional drought,” entails extensive loss of crops and water emergencies due to water shortage (National Drought Mitigation Center, 2019a).

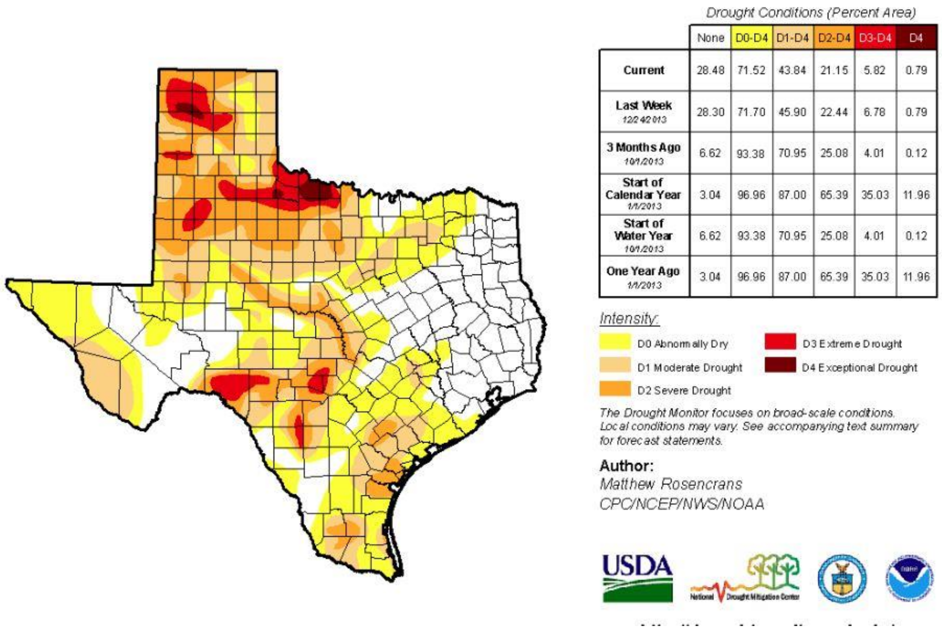


Figure A1-1. Drought areas in Texas during the week of January 1, 2014 (National Drought Mitigation Center, 2019b).

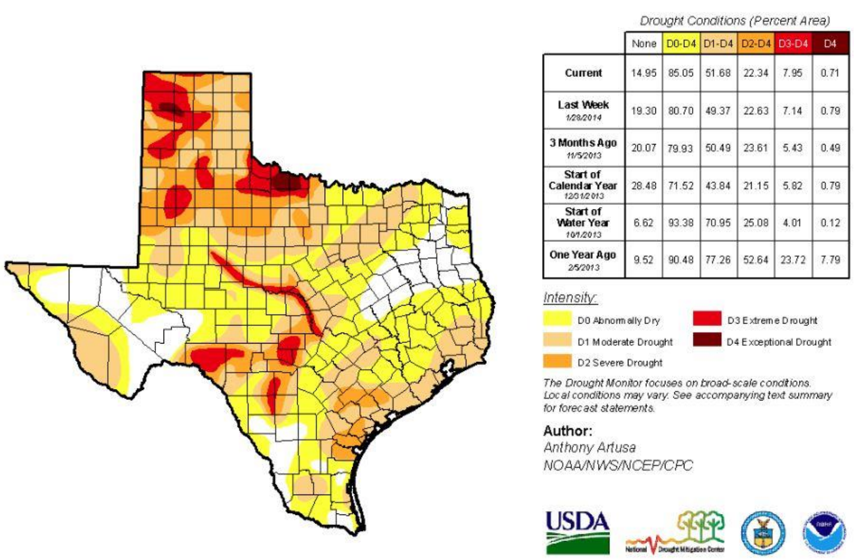


Figure A1-2. Drought areas in Texas during the week of February 7, 2014 (National Drought Mitigation Center, 2019b).

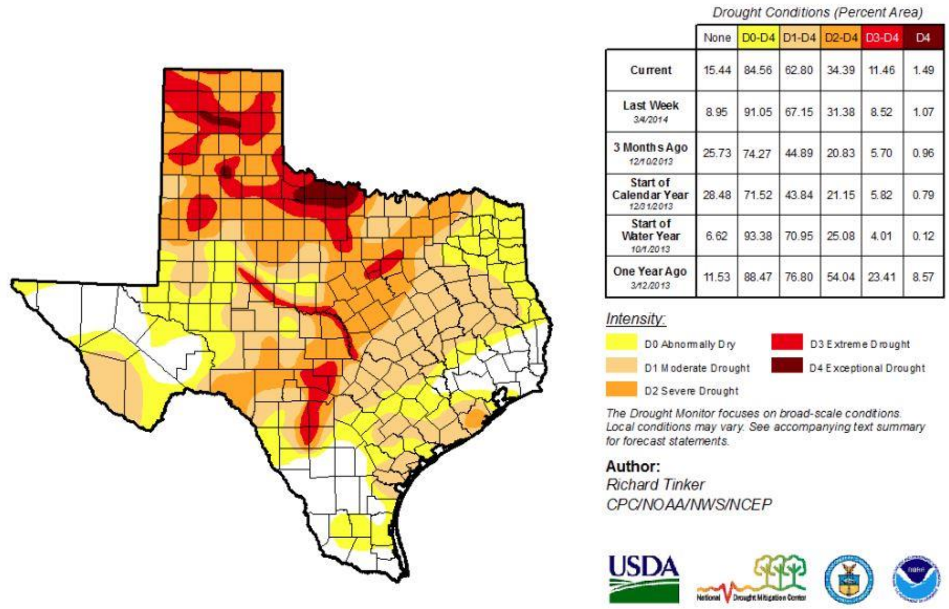
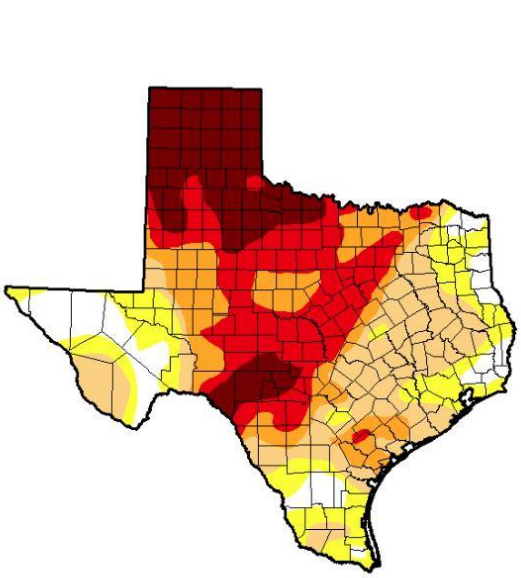


Figure A1-3. Drought areas in Texas during the week of March 15, 2014 (National Drought Mitigation Center, 2019b).



Drought Conditions (Percent Area)

	None	D0-D4	D1-D4	D2-D4	D3-D4	D4
Current	9.88	90.12	74.47	52.91	37.86	17.75
Last Week *4/22/2014*	13.62	86.38	68.68	48.56	32.67	12.54
3 Months Ago *1/28/2014*	19.30	80.70	49.37	22.63	7.14	0.79
Start of Calendar Year *12/31/2013*	28.48	71.52	43.84	21.15	5.82	0.79
Start of Water Year *10/1/2013*	6.62	93.38	70.95	25.08	4.01	0.12
One Year Ago *4/30/2013*	1.45	98.55	91.99	73.73	36.42	10.09

Intensity:

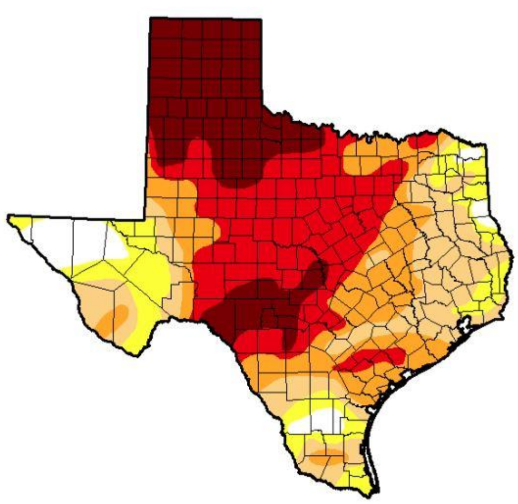
D0 Abnormally Dry
D1 Moderate Drought
D2 Severe Drought
D3 Extreme Drought
D4 Exceptional Drought

The Drought Monitor focuses on broad-scale conditions. Local conditions may vary. See accompanying text summary for forecast statements.

Author:
Richard Heim
NCDC/NOAA

USDA

Figure A1-4. Drought areas in Texas during the week of April 27, 2014 (National Drought Mitigation Center, 2019b).



Drought Conditions (Percent Area)

	None	D0-D4	D1-D4	D2-D4	D3-D4	D4
Current	5.11	94.89	83.35	65.13	46.17	21.28
Last Week *4/29/2014*	9.88	90.12	74.47	52.91	37.86	17.75
3 Months Ago *2/4/2014*	14.95	85.05	51.68	22.34	7.95	0.71
Start of Calendar Year *12/31/2013*	28.48	71.52	43.84	21.15	5.82	0.79
Start of Water Year *10/1/2013*	6.62	93.38	70.95	25.08	4.01	0.12
One Year Ago *5/7/2013*	1.45	98.55	92.13	72.82	40.58	12.88

Intensity:

D0 Abnormally Dry
D1 Moderate Drought
D2 Severe Drought
D3 Extreme Drought
D4 Exceptional Drought

The Drought Monitor focuses on broad-scale conditions. Local conditions may vary. See accompanying text summary for forecast statements.

Author:
Mark Svoboda
National Drought Mitigation Center

USDA

Figure A1-5. Drought areas in Texas during the week of May 3, 2014 (National Drought Mitigation Center, 2019b).

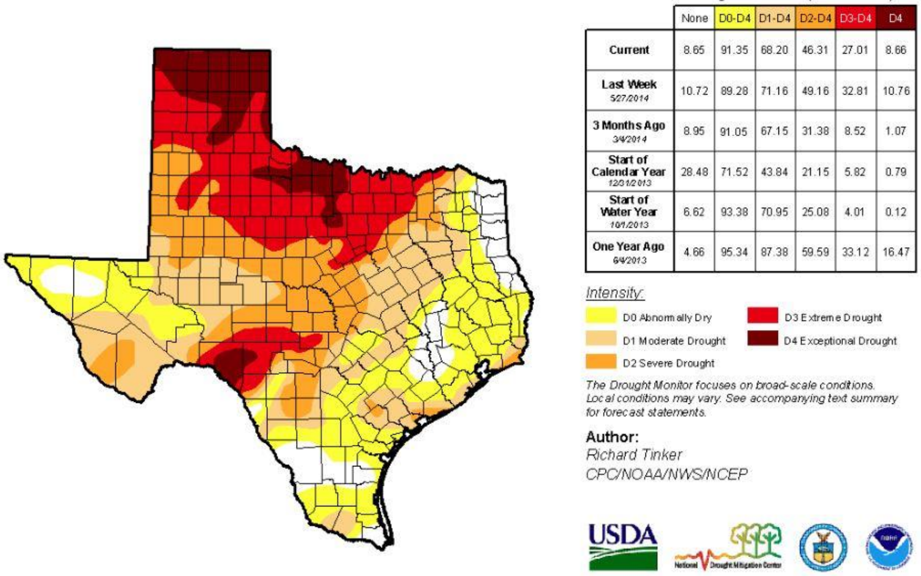


Figure A1-6. Drought areas in Texas during the week of June 5, 2014 (National Drought Mitigation Center, 2019b).

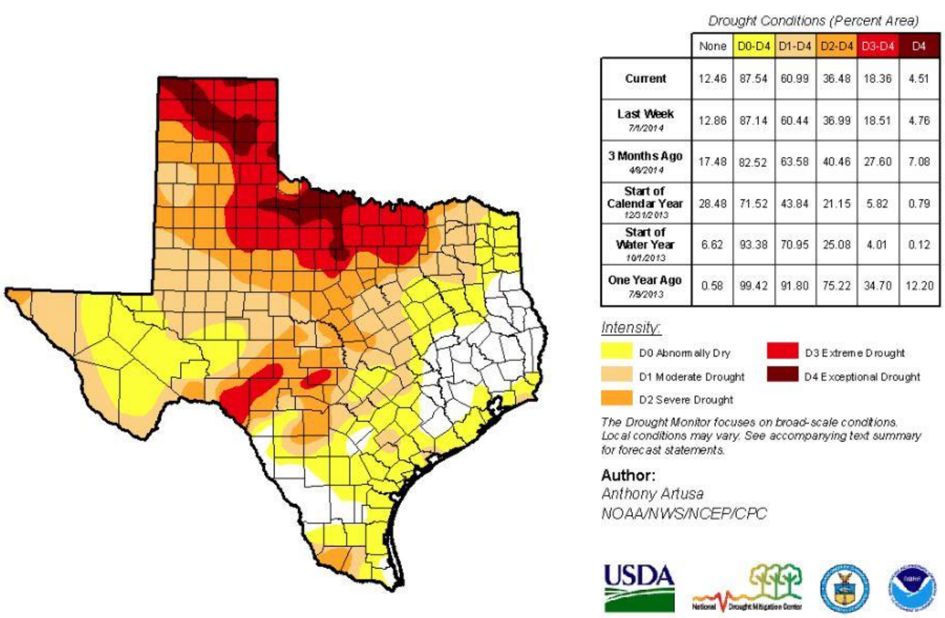


Figure A1-7. Drought areas in Texas during the week of July 7, 2014 (National Drought Mitigation Center, 2019b).

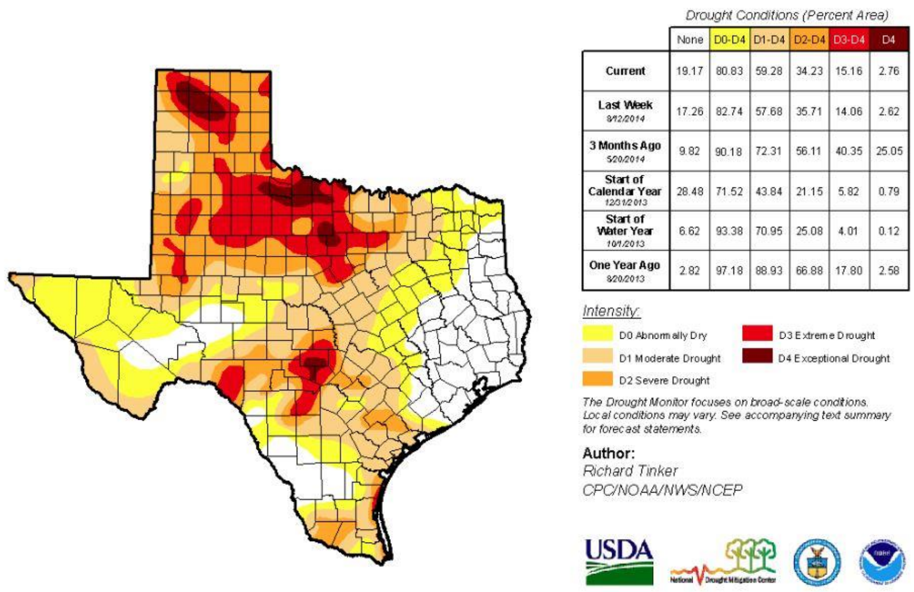


Figure A1-8. Drought areas in Texas during the week of August 23, 2014 (National Drought Mitigation Center, 2019b).

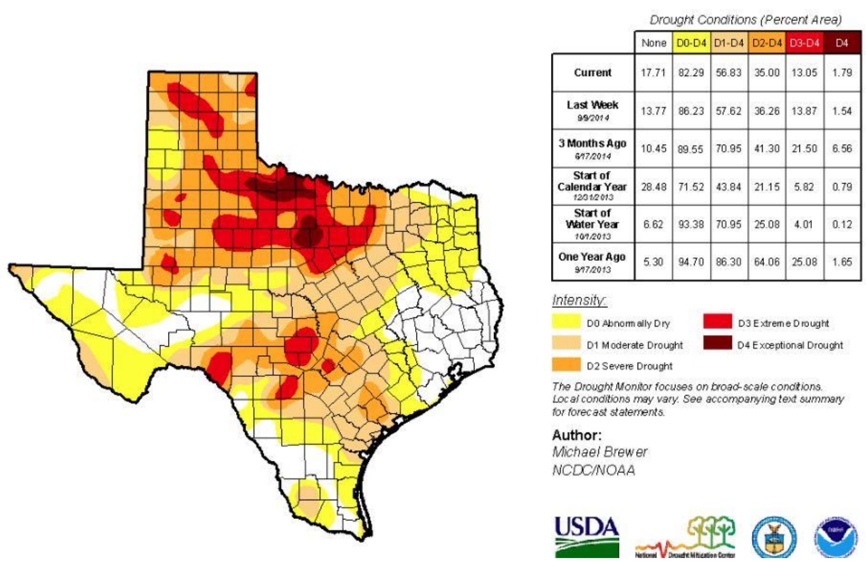


Figure A1-9. Drought areas in Texas during the week of September 17, 2014 (National Drought Mitigation Center, 2019b).

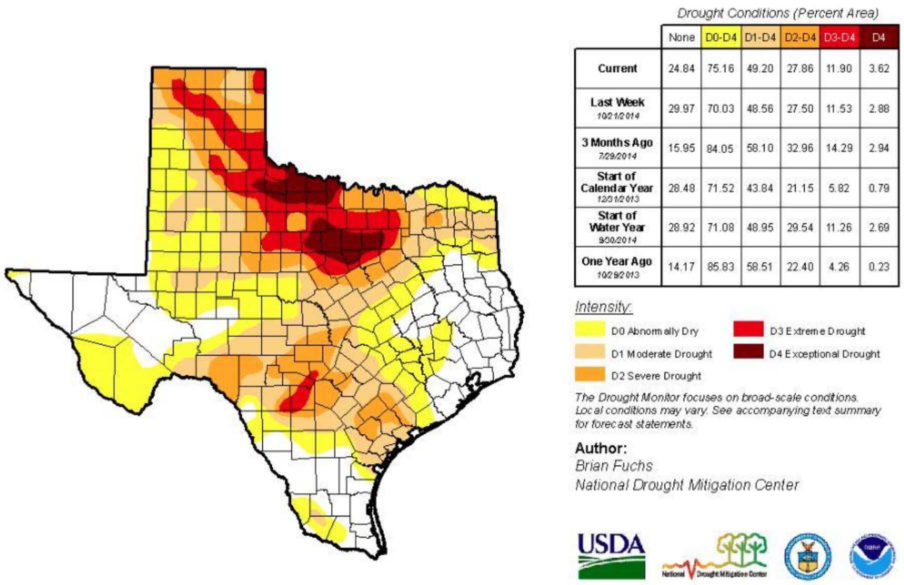


Figure A1-10. Drought areas in Texas during the week of October 29, 2014 (National Drought Mitigation Center, 2019b).

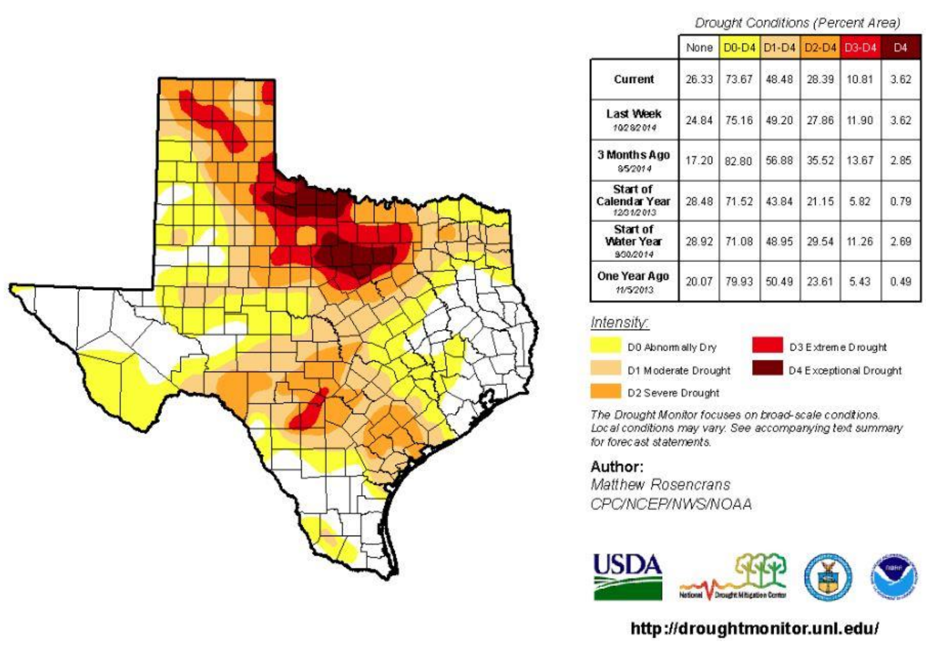


Figure A1-11. Drought areas in Texas during the week of November 5, 2014 (National Drought Mitigation Center, 2019b).

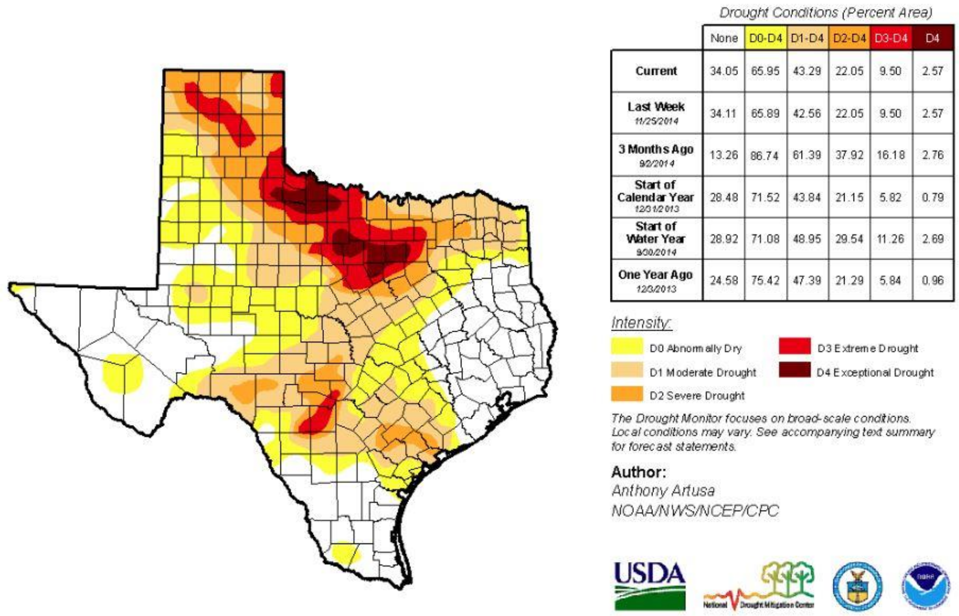


Figure A1-12. Drought areas in Texas during the week of December 3, 2014 (National Drought Mitigation Center, 2019b).

Appendix 2: RBF Procedures

This appendix shows the in-depth procedures for creating and using the RBF neural network. The first portion of using an RBF neural network involves creation of the network. The first step in creating an RBF network is to define the input. In Matlab, this is done by using the code *P* = *u*, with *u* being either the matrix or the set of values which will be used as the input. Next, one must define the targets. The code for that is *T* = *v*, with *v* being either the matrix or the set of values which will be the targets. After that, the input and target values must be normalized using the formulas *[PN,PS] = mapminmax(P)* and *[TN,TS] = mapminmax(T)*, where *PN* is equal to the normalized input, *P*, and *TN* is equal to the normalized targets, *T*. Lastly, the training for the network is run, using *net = newrb(PN,TN,g,s,MN,DF)*. In that formula, *g* is the goal (the default is 0), *s* is the spread (the default is 1), *MN* is the maximum number of neurons, and *DF* is the number of neurons to add between displays.

The second portion of the process involves testing the performance of the RBF network by generating a regression output. First, the RBF network must be run using *[Y,Xf,Af] = sim(net,PN)*. Then, the output must be transformed using *[a] = postmnmx(Y,mint,maxt)*, where *Y* is the output from the previous step and *a* is the transformed output. Finally, a regression of output versus targets is to be plotted using [*m,b,r] = postreg(a,T)*, where *T* is target values.

When satisfied with the RBF neural network performance, the steps for using the RBF network for a new dataset are the following. First, define the input, *k*. This is done by using *k* = *u*, just like defining the input in the creation of the RBF network (described above). Next, normalize the inputs using *[kn] = tramnmx(k,minp,maxp)*. Note that the minimum and maximum are the same as the within the creation of the RBF neural network. Then run the network using *[Y,Xf,Af] = sim(net,kn)*. Lastly, transform the output using *[a] = postmnmx(Y,mint,maxt)*.

Appendix 3: Sample $PM_{2.5}$ Estimations

Once the RBF network was created, tested, and run, the output was the estimated $PM_{2.5}$ concentrations for the locations of the asthma case points within the study area. A sample of the output of the RBF network (the estimated $PM_{2.5}$ concentrations) is shown in the tables below—Tables A3-1, A3-2, and A3-3. The tables also include the input material—the weather, road, and land use variables. Please refer to the section entitled *Procedure* in Chapter 3 to define the land use and road class values.

Admit Date	Maximum Temperature (degrees C)	Average Station Pressure (HPa)	Total Precipitation (mm)	Average Relative Humidity (%)	Average Wind Speed (km/h)	Sustained Wind Speed (km/h)	Road ADT	Road Class	Dominant Land Use Class	$PM_{2.5}$
2/7/2014 0:00	0	966.149	0.046	74	5.655	15.451	340	1	5	7.580
2/7/2014 0:00	0	965.997	0.005	73	7.740	14.838	330	1	5	8.091
2/7/2014 0:00	0	965.606	0.020	74	6.033	15.794	1800	1	5	8.065
2/7/2014 0:00	0	966.032	0.013	73	7.671	15.118	1026	1	4	8.447
2/7/2014 0:00	0	965.913	0.012	73	7.770	15.280	22028	3	5	8.235
2/7/2014 0:00	0	965.766	0.014	73	7.762	15.351	330	1	5	8.238
2/7/2014 0:00	1	968.585	0.224	75	6.083	16.208	1076	1	5	8.829
2/7/2014 0:00	0	968.193	0.157	74	6.240	16.476	11362	2	5	8.395
2/7/2014 0:00	0	965.526	0.016	73	7.770	15.484	1055	1	5	8.237
2/7/2014 0:00	0	965.471	0.016	73	7.761	15.520	13049	2	5	8.237
2/7/2014 0:00	0	965.868	0.017	73	7.733	15.672	101544	5	5	8.230
2/7/2014 0:00	0	966.540	0.025	73	7.708	15.942	330	1	5	8.081
2/7/2014 0:00	0	967.890	0.051	74	7.718	16.742	32094	4	5	7.777
2/7/2014 0:00	0	968.147	0.060	74	7.765	16.847	340	1	5	7.561
2/7/2014 0:00	0	965.820	0.017	73	7.775	16.152	330	1	5	8.139
2/7/2014 0:00	0	966.911	0.022	73	8.130	16.705	1548	1	5	8.080
2/7/2014 0:00	0	968.354	0.062	74	8.153	17.129	15142	3	5	7.967
2/7/2014 0:00	0	970.709	0.289	75	6.666	16.603	340	1	5	8.572
2/7/2014 0:00	0	970.677	0.333	76	6.678	16.256	6327	2	5	8.833
2/7/2014 0:00	0	970.658	0.315	76	6.766	16.266	20932	3	5	8.693
2/7/2014 0:00	0	966.707	0.015	74	8.155	16.881	330	1	5	8.079
2/7/2014 0:00	0	971.205	0.218	75	7.096	17.163	13774	2	5	7.891
2/7/2014 0:00	0	967.349	0.024	74	8.248	17.104	330	1	5	8.036
2/7/2014 0:00	0	970.248	0.236	76	7.043	16.125	1765	1	5	9.259
2/7/2014 0:00	0	968.490	0.058	74	8.115	17.238	280	1	5	7.871
2/7/2014 0:00	0	970.106	0.160	75	7.384	16.803	25600	4	5	7.733
2/7/2014 0:00	0	968.865	0.060	76	7.562	16.170	7230	2	5	6.944
2/7/2014 0:00	0	968.513	0.027	76	7.565	15.835	571	1	3	6.904

Table A3-1. Sample of variable input and $PM_{2.5}$ output.

Admit Date	Maximum Temperature (degrees C)	Average Station Pressure (HPa)	Total Precipitation (mm)	Average Relative Humidity (%)	Average Wind Speed (km/h)	Sustained Wind Speed (km/h)	Road ADT	Road Class	Dominant Land Use Class	$PM_{2.5}$
3/15/2014 0:00	19	985.597	17.897	88	11.191	23.978	340	1	5	7.683
3/15/2014 0:00	19	986.664	17.341	88	12.308	27.336	340	1	5	7.658
3/15/2014 0:00	19	985.721	18.484	88	13.555	30.994	330	1	5	7.672
3/15/2014 0:00	19	985.643	21.722	88	11.579	27.984	340	1	5	7.676
3/15/2014 0:00	19	986.196	22.386	88	11.677	28.180	340	1	5	7.687
3/15/2014 0:00	19	987.536	22.728	87	11.942	29.018	4594	1	5	7.660
3/15/2014 0:00	19	985.787	20.656	88	11.691	27.683	13030	2	5	7.716
3/15/2014 0:00	19	986.077	22.625	88	11.814	28.818	1780	1	5	7.699
3/15/2014 0:00	19	987.119	17.682	88	12.779	29.725	929	1	5	7.543
3/15/2014 0:00	19	986.226	19.262	88	13.384	32.047	330	1	5	7.644
3/15/2014 0:00	19	985.959	22.670	88	11.884	29.317	105	1	5	7.698
3/15/2014 0:00	19	990.070	25.245	88	12.753	33.805	434	1	4	7.618
3/15/2014 0:00	19	986.832	23.457	88	12.134	29.411	11192	2	5	7.758
3/15/2014 0:00	20	986.298	21.942	88	13.264	34.440	330	1	5	7.846
3/15/2014 0:00	19	986.427	19.944	88	13.352	32.965	4952	1	5	7.648
3/15/2014 0:00	19	988.094	24.771	88	12.507	30.563	7248	2	5	7.788
3/15/2014 0:00	20	985.632	23.075	88	13.774	35.363	1690	1	5	7.909
3/15/2014 0:00	19	987.275	21.294	88	12.851	31.929	17551	3	5	7.681
3/15/2014 0:00	19	989.363	25.922	87	12.860	33.472	340	1	5	7.663
3/15/2014 0:00	20	985.579	23.638	88	13.787	35.824	330	1	5	7.908
3/15/2014 0:00	20	986.130	24.039	88	12.779	35.290	330	1	5	8.070
3/15/2014 0:00	19	989.505	25.864	87	13.092	33.245	8926	2	5	7.659
3/15/2014 0:00	20	986.133	23.493	88	13.598	36.335	8712	2	4	7.737
3/15/2014 0:00	19	989.422	25.708	88	13.329	32.063	31358	4	5	7.721
3/15/2014 0:00	19	990.300	26.673	87	13.458	36.316	20605	3	5	7.694
3/15/2014 0:00	19	990.416	26.533	87	13.583	34.418	11225	2	5	7.661
3/15/2014 0:00	19	990.381	26.775	87	13.547	36.915	20186	3	5	7.694
3/15/2014 0:00	19	986.802	25.452	88	13.540	38.270	9075	2	5	7.746
3/15/2014 0:00	19	986.614	26.661	88	13.632	39.136	330	1	5	7.828

Table A3-2. Sample of variable input

and $PM_{2.5}$ output.

Admit Date	Maximum Temperature (degrees C)	Average Station Pressure (HPa)	Total Precipitation (mm)	Average Relative Humidity (%)	Average Wind Speed (km/h)	Sustained Wind Speed (km/h)	Road ADT	Road Class	Dominant Land Use Class	$PM_{2.5}$
7/7/2014 0:00	37	954.949	0.043	55	14.886	27.958	7342	2	5	17.079
7/7/2014 0:00	37	956.039	0.025	55	14.886	28.209	26388	4	5	17.035
7/7/2014 0:00	37	957.101	0.001	54	14.886	28.499	15142	3	5	16.737
7/7/2014 0:00	37	953.172	0.012	55	14.283	27.916	29763	4	5	17.271
7/7/2014 0:00	37	957.195	0.001	54	14.886	28.525	340	1	5	15.771
7/7/2014 0:00	37	953.134	0.016	53	14.162	27.869	330	1	4	18.471
7/7/2014 0:00	37	952.776	0.012	54	14.162	27.914	330	1	5	16.555
7/7/2014 0:00	37	957.413	0.080	55	14.886	29.212	35620	4	5	17.033
7/7/2014 0:00	36	947.834	0.708	57	14.511	28.008	459	1	5	17.227
7/7/2014 0:00	36	955.478	0.048	59	14.350	28.977	13989	2	5	15.936
7/7/2014 0:00	35	943.505	1.449	58	14.511	27.956	5564	2	5	17.231
9/17/2014 0:00	34	960.602	0.955	72	7.577	25.448	190	1	5	6.926
9/17/2014 0:00	34	955.167	2.679	72	7.550	24.709	762	1	5	9.781
9/17/2014 0:00	34	954.972	2.710	72	7.550	24.665	1620	1	5	9.896
9/17/2014 0:00	35	955.161	3.437	72	7.550	26.884	3774	1	5	10.491
9/17/2014 0:00	35	953.965	3.368	72	7.403	27.008	340	1	5	11.021
9/17/2014 0:00	34	953.262	2.172	70	7.135	23.777	330	1	5	6.292
9/17/2014 0:00	34	953.771	1.921	69	7.135	25.031	330	1	5	5.426
9/17/2014 0:00	33	954.619	1.998	70	7.135	27.353	330	1	5	5.935
9/17/2014 0:00	34	954.194	1.775	69	7.135	26.444	330	1	5	5.009
9/17/2014 0:00	34	954.079	1.760	69	7.135	26.051	330	1	5	5.021
9/17/2014 0:00	34	954.034	1.741	68	7.135	25.344	330	1	5	5.956
9/17/2014 0:00	35	955.369	3.966	71	7.403	29.821	340	1	5	9.348
9/17/2014 0:00	34	954.039	1.674	68	7.135	25.754	1215	1	5	5.583
9/17/2014 0:00	35	955.889	3.804	71	7.403	29.867	340	1	5	9.275
9/17/2014 0:00	35	955.959	3.811	71	7.403	30.207	340	1	5	9.101
9/17/2014 0:00	35	955.394	3.986	71	7.403	30.408	340	1	5	9.074
9/17/2014 0:00	35	957.437	3.188	71	7.215	29.357	9994	2	5	8.316
9/17/2014 0:00	35	956.567	3.627	70	7.403	30.582	11362	2	5	8.690

Table A3-3. Sample of variable input

and $PM_{2.5}$ output.

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