Methodology to Assess Forest Fire Impacts on Air Quality and Human Health in Washington State: A Case Study on the 2006 Tripod Wildfires

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Abstract

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A Case Study on the 2006 Tripod Wildfires

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Fire is an essential ecological process. However, forest fire burn area in the Pacific Northwest is likely to double or even triple by the end of the 2040s based on projected climate change models and ecosystem evaluations. The projected increase in forest fires has negative health implications because of air quality impacts. This study aims to characterize the linkage between air quality degradation due to wildfires and hospital respiratory and cardiovascular admissions, using the 2006 Tripod wildfires as a case study. The 2006 Tripod wildfires included the Spur Peak and Tripod Complex wildfires and were some of the largest wildfires in the past half-century in Washington State.

Air monitoring and air modeling data were used for different research analyses. Air monitoring data from the U.S. Environmental Protection Agency (EPA) and the U.S. Forest Service (USFS) were analyzed to assess any potential air quality degradation and air monitor availability during the Tripod wildfire event. The USFS smoke plume modeling data containing geospatial estimates of exposure for 33 days were used for analyses that linked air quality data to hospitalization and population data. Using a case-crossover epidemiological study, the relationship between air quality and respiratory and cardiovascular hospitalizations was assessed. The case-crossover analysis was based on resident zip code exposures, and conducted using USFS air quality modeling data and respiratory and cardiovascular hospitalization records from the Washington comprehensive hospital abstract reporting system. Hospital relative rates addressing cardiovascular and respiratory hospitalizations impacts and exposure impacts in zip codes in Okanogan and surrounding counties were also assessed during the 33-day period, using 2010 Census data because the 2010 data had the most spatial coverage for the study area of interest. Lastly, modeled air quality data were compared against monitoring data from the EPA and USFS to assess the model's validity, sensitivity, and specificity.

Air monitoring data from the EPA and USFS showed that there were higher than normal air quality degradation during the 2006 Tripod wildfire event. No significant results were found for modeled air quality data and their impacts on cardiovascular and respiratory hospitalizations in several epidemiological analyses by hospital zip codes and residential zip codes. The research found that current air quality model data systems are not accurate predictors of ground-level air monitor data systems.

For future studies, two scientific recommendations were determined. First, the medians and means of the modeled air quality values prior to the hospitalization date were found to be more meaningful, in comparison to mean modeled air quality value on the hospitalization date. Second, age categories for sensitive and non-sensitive populations (three age categories) were found to be more useful than finer divisions of six age categories. Policy recommendations to improve this type of research include increasing governmental agency coordination, improving the air quality monitoring network and air models, and having further research on the impact of wildfire events on air quality and hospitalizations. Additional suggestions were also made for future research into this subject including focusing on a smaller population and using smartphones to measure air quality and other types of data to address health impacts.

Table of Contents

Table of Contents i

Acknowledgements x

Introduction 1

Motivations 1

Aims 2

Chapter 1: Wildfires, Air Pollution, and Human Health 3

Composition of Wildfire Smoke 3

Air Quality Standards 4

Health Impacts of Wildfires 5

Epidemiology and Exposure Assessment Literature Review: Wildfires and Health Hospitalizations 6

Climate Change and Wildfires 12

Chapter 2: Wildfires in Washington State 15

Top Wildfires of Interest to Public Health (2001 to 2009) 15

2006 Tripod Wildfires 19

Air Monitoring Data for the 2006 Tripod Wildfire 20

Background on Air Monitoring 21

Methods 23

Results 24

Conclusions 25

Air Modeling Data for the 2006 Tripod Wildfires 26

Background on U.S. Forest Service Air Modeling 26

Background on Satellite Data 28

Methods 30

Results 32

Conclusions 33

Chapter 3: Epidemiologic Analysis of Air Pollution Impacts on Hospitalizations...............................35

Introduction..35

Washington State Comprehensive Hospital Abstract Reporting System (CHARS) 35

Census Data..37

Hospital Relative Rates 38

Methods 39

Results 41

Case-Crossover Study Design..42

Methods 45

Table 9: Respiratory and Cardiovascular Categories and ICD-9 CM Codes................................45

Results 49

Public Health Population Analysis..51

Methods 53

Results 53

Conclusions 54

Chapter 4: Evaluation of the U.S. Forest Service Air Pollution Model..56

Introduction..56

Assessing Smoke Impacts on Study Area 56

Methods 57

Results 58

Air Quality Model and Monitor Sensitivity Analysis 60

Methods 61

Results 62

Conclusions 64

Chapter 5: Research Limitations..66

Exposure Errors 66

Hospitalization Data..67

Modeling Data Limitations..67

Study Area..69

Zip Codes and Spatial Limitations 70

Table 42: Descriptive Statistics Values for 98862 and 98856 71

Determining Wildfire Impacts..72

Confounders..73

Chapter 6: Policy Implications, Recommendations, Suggestions for Further Research, and Conclusions..74

Policy Implications 74

Global Climate Change Impacts on Wildfires and Health Costs 74

Projected Public Health Costs from Tripod 2006 Wildfires..75

Recommendations 78

Increase Governmental Agency Coordination..78

Improve Air Quality Monitoring, Modeling, and Satellite Data Systems..80

Further Research Suggestions..81

Conclusion 84

Bibliography..86

Chapter 8: Tables and Figures 91

Chapter 2: Characterization of Air Pollution....91
Table 1: Major Washington Wildfires from 2001-2009 and Available Air Quality Data....91
Figure 1: Historical and Current EPA Air Quality DataMart Monitors Addressing $PM_{2.5}$ Concentrations....92
Figure 2: BlueSky Framework (Pacific Northwest Research Station, 2006)....92
Figure 3: 2005 EPA Air Quality DataMart Data for Okanogan County....93
Figure 4: 2006 EPA Air Quality DataMart Data for Okanogan County....94
Figure 5: 2007 EPA Air Quality DataMart Data for Okanogan County....95
Figure 6: Air Quality Monitoring Data from U.S. Forest Service Pacific Wildland Fire Sciences Laboratory for August and September 2006....96
Figure 7: 2005 EPA Air Quality DataMart Data for Counties Surrounding Okanogan County 97
Figure 8: 2006 EPA Air Quality DataMart Data for Counties Surrounding Okanogan County 98
Figure 9: 2007 EPA Air Quality DataMart Data for Counties Surrounding Okanogan County 99
Figure 10: Spatial Coverage Differences for 2000 and 2010 Census Data and 2006 ESRI Data for Washington Zip Codes.... 100
Chapter 3: Epidemiologic Analysis of Air Pollution Impacts on Hospitalizations.... 101
Figure 11: Hospital Locations and Surrounding Counties Based on Proximity.... 101
Figure 12: Selected Hospitals with Relative Risks Greater than 1 for Respiratory Hospitalizations.... 102
Figure 13: Selected Hospitals with Relative Risks Greater than 1 for Cardiovascular Hospitalizations.... 103
Table 2: Respiratory Hospitalizations from August 14 to September 15, 2006 (Zero $PM_{2.5}$ values and values greater than zero in parentheses if there is a change).... 104

Table 3: Cardiovascular Hospitalizations from August 14 to September 15, 2006 (Zero $PM_{2.5}$ values and values greater than zero in parentheses if there is a change) 105

Table 4: Respiratory Hospitalizations on Non-Zero $PM_{2.5}$ Days 106

Table 5: Cardiovascular Hospitalizations on Non-Zero $PM_{2.5}$ Days... 107

Table 6: Comparison of R's for Hospitalizations (based on hospital zip code) on Non-Zero and Zero Modeled Particulate Matter Days 108

Table 7: Number of Non-Zero/Zero PM Days and Respiratory Hospitalizations on Non-Zero/Zero PM Days.. 109

Table 8: Number of Non-Zero/Zero PM Days and Cardiovascular Hospitalizations on Non-Zero/Zero PM Days.. 110

Table 10: Logistic Regression for All Hospitalizations (non-lag, non-sensitive) 111

Table 11: Logistic Regression for All Hospitalizations (non-lag, sensitive)................................ 112

Table 12: Logistic Regression for All Hospitalizations (interaction terms, non-lag, non-sensitive) 113

Table 13: Logistic Regression for All Hospitalizations (interaction terms, non-lag, sensitive). 114

Table 14: Logistic Regression for Respiratory Hospitalizations (non-lag, non-sensitive) 115

Table 15: Logistic Regression for Respiratory Hospitalizations (non-lag, sensitive)................. 115

Table 16: Logistic Regression for Respiratory Hospitalizations (interaction terms, non-lag, non-sensitive)... 116

Table 17: Logistic Regression for Respiratory Hospitalizations (interaction terms, non-lag, sensitive)... 117

Table 18: Logistic Regression for Cardiovascular Hospitalizations (non-lag, non-sensitive) ... 117

Table 19: Logistic Regression for Cardiovascular Hospitalizations (non-lag, sensitive)............ 118

Table 20: Logistic Regression for Cardiovascular Hospitalizations (interaction terms, non-lag, non-sensitive) 119

Table 21: Logistic Regression for Cardiovascular Hospitalizations (interaction terms, non-lag, sensitive) 120

Table 22: Logistic Regression for All Hospitalizations (interaction terms, non-sensitive, comparison of modeled air quality using mean of 3 days prior against mean on hospitalization day) 121

Table 23: Logistic Regression for All Hospitalizations (interaction terms, non-sensitive, comparison of modeled air quality using median of 3 days prior against mean on hospitalization day) 123

Table 24: Logistic Regression for All Hospitalizations (interaction terms, sensitive, comparison of modeled air quality using mean of 3 days prior against mean on hospitalization day) 125

Table 25: Logistic Regression for All Hospitalizations (interaction terms, sensitive, comparison of modeled air quality using median of 3 days compared against mean on hospitalization day) 126

Table 26: Logistic Regression for Respiratory Hospitalizations (interaction terms, non-sensitive, comparison of modeled air quality using mean of 3 days prior compared against mean on hospitalization day) 127

Table 27: Logistic Regression for Respiratory Hospitalizations (interaction terms, non-sensitive, comparison of modeled air quality of median of 3 days prior against mean on hospitalization day) 129

Table 28: Logistic Regression for Respiratory Hospitalizations (interaction terms, sensitive, comparison of modeled air quality using mean of 3 days prior against mean on hospitalization day) 131

Table 29: Logistic Regression for Respiratory Hospitalizations (interaction terms, sensitive, comparison of modeled air quality using median of 3 days prior against mean on hospitalization day)........ 132

Table 30: Logistic Regression for Cardiovascular Hospitalizations (interaction terms, non-sensitive, comparison of modeled air quality using mean of 3 days prior against mean on hospitalization day)........ 133

Table 31: Logistic Regression for Cardiovascular Hospitalizations (interaction terms, non-sensitive, comparison of modeled air quality using median of 3 days prior against mean on hospitalization day)........ 134

Table 32: Logistic Regression for Cardiovascular Hospitalizations (interaction terms, sensitive, comparison of modeled air quality using mean of 3 days prior against mean on hospitalization day)........ 135

Table 33: Logistic Regression for Cardiovascular Hospitalizations (interaction terms, sensitive, comparison of modeled air quality using median of 3 days prior against mean on hospitalization day)........ 136

Chapter 4: Evaluation of the U.S. Forest Service Air Pollution Model........ 137

Table 34: Public Health Population Impacts in Okanogan and Surrounding Counties (Based on proximity)........ 137

Table 35: 2006 Counties of Interest and $PM_{2.5}$ Air Quality Monitors........ 138

Table 36: Cumulative Smoke Impacts in Washington Counties during 33-Day Study Period. 139

Table 37: Smoke Impact Statistics for Washington Zip Codes during 33-Day Study Period... 140

Table 38: Descriptive Statistics for U.S. Forest Service (non-enforceable) and U.S. Environmental Protection Agency (enforceable) Monitor Data Compared Against U.S. Forest Service Model Data........ 141

Table 39: Descriptive Statistics for U.S. Forest Service Monitor Data (non-enforceable) Compared Against U.S. Forest Service Model Data 141

Table 40: Descriptive Statistics for U.S. Environmental Protection Agency Monitor Data (enforceable) Compared Against U.S. Forest Service Model Data 142

Table 41: Public Health Population Impacts in 14 Counties (Based on cumulative smoke impacts) 143

Figure 14: 33-Day Air Quality Sum of Modeled Smoke Impacts 144

Figure 15: Top 14 Counties (75th percentile) Impacted by Cumulative Wildfire Smoke 144

Figure 16: Hospital Locations and 14 Counties of Cumulative Smoke Impacts 145

Figure 17: Modeled $PM_{2.5}$ Values (U.S. Forest Service model) Versus Actual Monitor $PM_{2.5}$ Values (U.S. Forest Service and U.S. EPA from August 14 to September 15, 2006 Daily Averages 146

Figure 18: Modeled $PM_{2.5}$ Values (U.S. Forest Service model) Versus Actual Monitor $PM_{2.5}$ Values (U.S. Forest Service only) from August 14 to September 15, 2006 Daily Averages 147

Figure 19: Modeled $PM_{2.5}$ Values (U.S. Forest Service model) Versus Actual Monitor $PM_{2.5}$ Values (U.S. EPA) from August 14 to September 15, 2006 Daily Averages 148

Figure 20: Model versus Monitor $PM_{2.5}$ Values for Conconully (Okanogan County, USFS) ... 149

Figure 21: Model versus Monitor $PM_{2.5}$ Values for Eight Mile (Okanogan County, USFS) 149

Figure 22: Model versus Monitor $PM_{2.5}$ Values for Nespelem (Okanogan County, USFS) 150

Figure 23: Model versus Monitor $PM_{2.5}$ Values for Omak (Okanogan County, USFS) 150

Figure 24: Model versus Monitor $PM_{2.5}$ Values for Twisp Forest (Okanogan County, EPA) .. 151

Figure 25: Model versus Monitor $PM_{2.5}$ Values for Twisp Third Ave (Okanogan County, EPA) 152

Figure 26: Model versus Monitor $PM_{2.5}$ Values for Winthrop (Okanogan County, EPA) 153

Chapter 5: Research Limitations 154

Figure 27: Monitoring Locations in Washington State against Modeled Smoke Plume on August 14, 2006 154

Figure 28: Monitoring Stations in Zip Codes 98862 and 98856 Within Modeled Smoke Plume on August 14, 2006 155

Chapter 6: Policy Implications 156

Table 43: Per-unit Economic Value Used in U.S. EPA (1999) (Kochi, et al. 2010) 156

Chapter 7: Conclusion 157

Figure 29: NASA MODIS Satellite Image from September 19, 2012 157

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Introduction

Motivations

Research motives began with an interest in possible public health impacts from climate change projections in Washington State. In a future of possible climate change, heat waves and degraded air quality are two estimated public health impacts. The Yost and Fenske lab group have tracked Washington State's previous weather between May and September for the past 26 years and assessed death records, and found excess deaths during heat events.

Forest fire burn area in Washington State is likely to double or even triple by the end of the 2080s based on the best statistical models (Littell, et al. 2010). The projected increase in forest fires has negative health implications because of air quality impacts. Projections from Kovalev, et al (2009) show that there will be an increased frequency and severity of wildfires and a longer fire season in the western United States.

The research began with locating wildfire events of interest to public health impacts, and a list was compiled of top wildfires of interest from 2001 to 2009. The 2006 Tripod wildfires were some of the largest wildfires in the state in the past half-century. A preliminary analysis of the air quality during the Tripod 2006 wildfires was done using air quality data from enforceable air monitors from the U.S. Environmental Protection Agency (EPA) and temporary air monitors from the U.S. Forest Service (USFS). Air quality modeling data from the U.S. Forest Service became available for the Tripod 2006 wildfires. The availability of the air quality modeling data presented a unique opportunity to develop a methodology to assess the impact of the Tripod 2006 wildfires on air quality and respiratory and cardiovascular hospitalizations.

Aims

After assessing wildfire events of interest to public health in Washington State from 2001 to 2009, the 2006 Tripod wildfire event was chosen for further analysis. Methodologies were developed to analyze the impact of the Tripod 2006 wildfire event on air quality and respiratory and cardiovascular hospitalizations. The associated aims of the research in developing the methodologies were as follows:

1. Determine and assess available and necessary data addressing air quality and hospitalizations for the Tripod wildfire event.
2. Use the U.S. Forest Service air quality model to determine:
    - Whether there were increased respiratory and cardiovascular hospitalizations due to the Tripod wildfire.
    - Relative risks by hospital catchment area.
    - Population impacted by the wildfire.
3. Evaluate the performance of the U.S. Forest Service air quality model.

Chapter 1: Wildfires, Air Pollution, and Human Health

Chapter 1 provides the background on wildfires such as wildfire smoke composition, air quality standards, and how wildfires impact human health. Chapter 1 also summarizes the research literature on epidemiology studies during wildfire events, using various forms of air quality data, as well as research literature addressing future estimates of climate change impacts on wildfire events.

Composition of Wildfire Smoke

Carbon dioxide and water are the two primary products of complete combustion and generally make up over 90 percent of the total emissions from a wildfire. In the incomplete combustion that occurs under wildfire conditions, smoke comprises of carbon dioxide, water vapor, carbon monoxide, particulate matter, hydrocarbons and other organic compounds, nitrogen oxides, trace minerals, and several thousand other compounds (Ryan & McMahon, 1976) (Peterson & Ward, 1992). Particulate matter (PM) is the principal pollutant of concern to human health from wildfire smoke for short-term exposures typically experienced by firefighters and the public (Sugihara, 2006). Studies indicate that 90 percent of smoke particles emitted during wildfires are particles less than ten microns in size (PM_{10}) and about 90 percent of these are less than 2.5 microns ($PM_{2.5}$) (Ward & Hardy, 1991). Other pollutants of concern include carbon monoxide, nitrogen oxides and hydrocarbons.

Wildfires are complex and variable, and studying their effects is often complicated. The architecture of the forest as described by species composition and structure, including fuel amounts, size classes, and arrangement, affects the manner in which a fire burns (Agee, 1998). Fire is a chemical reaction, combustion, requiring three components of a "fire triangle" which include fuels, heat sufficient to ignite available fuels, and oxygen to feed the chemical reaction, known as oxidation

(UCAR, 2012). Removing any side of this fire triangle stops a fire (UCAR, 2012). The availability of fuels, heat, and oxygen to a wildfire is strongly influenced by the interplay of climate patterns, recent weather, and the topography of the landscape (UCAR, 2012). Weather is one of the most significant factors in determining the severity of wild land fires. The intensity of fires and the rate at which they spread is directly related to the wind speed, temperature and relative humidity (NWS, 2006). Climatic conditions such as long term drought also play a major role in the number and intensity of wildfires (NWS, 2006).

Wildfire disturbance typically is characterized by a combination of factors: type, frequency, variability, magnitude, extent, and seasonality (Agee, 1998). The amount of smoke produced from a wildfire is dependent on what part of a wildfire flame is burning or the location of the wildfire during the combustion process. There are four major phases of combustion when fuel particles are consumed:

1. Pre-ignition
2. Flaming
3. Smoldering
4. Glowing

During the smoldering phase, the smoke consists mostly of droplets less than a micrometer in size and the amount of particulate emissions generated per mass of fuel consumed during the smoldering phase is more than double that of the flaming phase (NWCG Fire Use Working Team, 2001).

Air Quality Standards

Under the Clean Air Act enforced by the EPA, National Ambient Air Quality Standards (NAAQS) have been established to protect human health and public welfare. For public health protection, primary standards protect the most sensitive members of the population such as asthmatics, children, and the elderly. For public welfare protection, secondary standards protect against decreased visibility and damage to animals, crops, vegetation, and buildings. The pollutants of particular concern from fires are particulate matter. PM_{10} is particulate matter less than 10 microns in diameter and $PM_{2.5}$ is particulate matter less than 2.5 microns in diameter. PM_{10} and $PM_{2.5}$ are the regulated pollutants of concern emitted during a wildfire event. The EPA enforces a 24-hour $PM_{2.5}$ standard of 35 $\mu g/m^3$, and an area meets the standard if the 98^{th} percentile of 24-hour $PM_{2.5}$ concentrations in one year, averaged over three years, is less than or equal to 35 $\mu g/m^3$. As of December 14, 2012, the EPA now enforces an annual primary standard of 12 $\mu g/m^3$, averaged over three years, as it had previously been 15 $\mu g/m^3$ (EPA, 2012). However, these standards are not as relevant to wildfire events, which are typically weeks in duration with high particulate concentration values, and are more difficult to monitor because of their variability.

Health Impacts of Wildfires

There are short-term and long-term health impacts associated with smoke exposure (Hope, 2005). With short-term exposures to general smoke, individuals may experience coughing, difficulty breathing, aggravated asthma and bronchitis, and increased emergency room and hospital visits. With long-term exposures to smoke, there are increased deaths per day and an increased long-term risk of dying. Long-term exposures to smoke are similar to the effects caused by second hand smoke in causing cancer, and have been tentatively linked to systemic and genetic effects in newborns, and adversely affecting the heart through rhythm changes and flow blockage. Sensitive populations include asthmatics, children, pregnant women, elderly (populations that are 65 years and older), smokers, and individuals with pre-existing conditions including cardiopulmonary diseases, chronic obstructive pulmonary disease, and cardiovascular disease.

There is more scientific literature on industrial particulate matter pollutants and their impacts on respiratory and cardiovascular hospitalizations, in comparison to the literature on particulate matter pollutants from wildfire events. Particulate matter from fossil fuel combustion has been conclusively associated with respiratory and cardiovascular morbidity and mortality (Henderson, 2009). It has also been suggested that particulates derived from wood smoke may be more detrimental to human health than particulates from other sources known to cause ill health (Bowman & Johnston, 2005). Health effects from wildfire-related particulate matter and smoke have not been thoroughly examined in the scientific literature, in comparison to health effects from particulate matter from industrial sources. The majority of smoke effects on health in the scientific literature are based on residential wood burning studies.

Epidemiology and Exposure Assessment Literature Review: Wildfires and Health Hospitalizations

Some of the many challenges with studying health effects from wildfires include the variability and infrequency of wildfires and the large number of potential confounders that make it difficult to distinguish the epidemiologic "signal" from the background "noise" (Bowman & Johnston, 2005). Studies that have evaluated the impacts of wildfire PM on hospital admissions, emergency department visits or clinic visits have found associations with respiratory outcomes (Delfino, et al., 2009). There has been little research on the impact of wildfire smoke on cardiovascular outcomes and there have been conflicting reports on wildfire smoke and mortality (Delfino, et al., 2009). The most recent epidemiological studies addressing wildfire and health hospitalizations are summarized below.

Naeher, et al. (2007) conducted a review of the existing literature on wildfire-induced morbidity studies, with the many of the studies from areas outside North America such as Thailand, Singapore, Brazil, Australia, and Malaysia. In comparison to conventional PM studies, these studies have found that wildfires are less likely to find a significant positive mortality effect despite very large increases in particulate matter levels during the wildfire events. These studies found that wildfire events have been associated with increases of general respiratory-related and asthma-related admissions, but no demonstrated effects on cardiovascular-related admissions during wildfire events. However, the papers in the literature review conducted by Naeher, et al. (2007) used data from a limited number of air monitors rather than air modeling data covering a larger spatial area. Also, some of the studies in the review analyzed PM_{10} and bushfires, so some of the findings do not directly apply to forest fire conditions or assessing $PM_{2.5}$. It is possible that there is less respiratory toxicity from bushfire smoke than from forest fire smoke due to chemical and physical differences between the two (Naeher, et al. 2007).

Within the scientific literature, there has been the most public health research addressing particulate matter and wildfires for the 2003 southern California wildfires. The southern California fires of late October 2003 were cumulatively, the single largest event in California's recent history. In one week, the wildfires burned over 742,000 acres and a total of 3,361 homes and 26 lives lost (Keeley, et al. 2004).

Delfino, et al. (2009) analyzed the 2003 southern California wildfires and its relationship to cardiorespiratory hospital admissions (n = 40,856), which has been the largest study to date analyzing wildfires on cardiorespiratory outcomes. This group was one of the first to analyze modeled air quality data for wildfires and link the data to health admissions. They built a prediction model based on temporal profiles of continuous hourly PM data at co-located or closely located sites and light extinction from visibility data, from MODIS satellite images at a 250 meter resolution. In their research, multiple lag models were considered to investigate associations between $PM_{2.5}$ and hospital admission rates, including a 7-day polynomial distributed lag, and stratified analyses considering different lag associations. Delfino, et al. (2009) found the two-day moving average of $PM_{2.5}$ (average of today and yesterday) provided the best fitting model that adequately captured the association between $PM_{2.5}$ and admissions.

For $PM_{2.5}$ associations and interactions with the wildfire period, Delfino, et al. (2009) found that wildfire-related $PM_{2.5}$ led to increased respiratory hospital admissions, especially asthma. Their results found that there were stronger associations of 2-day average $PM_{2.5}$ with respiratory admissions during the fires compared to before or after the fires. The strongest wildfire-related $PM_{2.5}$ associations were for people ages 65 to 99 years (10.1% increase per 10 $\mu g/m^3$ $PM_{2.5}$, 95% confidence interval (CI)—3.0 to 17.8%) and ages 0 to 4 years (8.3%, 95 percent CI—2.2 to 14.9%). For every increase in 10 $\mu g/m^3$ of wildfire-related $PM_{2.5}$, acute bronchitis admissions across all ages increased by 9.6 percent (95% CI—1.8 to 17.9%), chronic obstructive pulmonary disease admissions for ages 20 to 64 years by 6.9 percent (95% CI—0.9 to 13.1%), and pneumonia admissions for ages 5 to 18 years by 6.4 percent (95% CI—1.0 to 14.2%). The number of acute bronchitis and pneumonia admissions also increased after the fires. There was limited evidence of a small impact of wildfire-related $PM_{2.5}$ on cardiovascular admissions. (Delfino, et al., 2009)

Delfino, et al. (2009) found significantly increased risks for all respiratory hospital admissions after the wildfires compared with the pre-fire period. Admissions increased for all ages by 17 percent ($p<0.001$), and in age groups 5 to 19 years (25%), and 20 to 64 years (27%), but associations for both groups were stronger after the fires (56% and 36% respectively). For all ages, admissions increased greatly for asthma (26%), acute bronchitis and bronchiolitis (48%), and pneumonia. The rates increased even more within specific age groups—for ages 0 to 4, association for acute bronchitis and bronchiolitis by 51% and pneumonia by 46%; ages 5 to 19, asthma increased 56%; for ages 20-64, asthma increased 36%, acute bronchitis and bronchiolitis by 137% and pneumonia by 30%. For the period after the fires, there was a 6.1% increased risk of combined cardiovascular admissions ($p<0.05$) and an 11.3% increased risk of congestive heart failure admissions ($p<0.06$). (Delfino, et al., 2009)

The results from Delfino, et al. (2009) show a significantly increased risk of admissions for total cardiovascular outcomes and congestive heart failure after the wildfire event. Their results confirm that the impacts of wildfires on human health are challenging regarding time in relation to the wildfire and particulate matter pollutants. They concluded that the increased cardiorespiratory admissions after the wildfire may be attributed to the following reasons:

1. People may delay deciding to go to the hospital until symptoms become too severe.
2. Cumulative biological effects of wildfire PM may culminate in severe symptoms many days after the initial cardiorespiratory impact.
3. Sustained effects of wildfire PM may lead to susceptibility to, or increased severity of, later respiratory infections, possibly through alterations in immune function or respiratory clearance mechanisms.

Although this thesis addresses the linkage of air quality data with hospitalization data, the data on air quality during wildfire events at fine spatial resolutions is still limited. Air quality monitoring is sparse in many fire-affected areas, so it is challenging to apply epidemiologic methods that require individual-level exposure assessment. Data from dispersion models and remote sensors are spatially extensive and may provide viable exposure estimation alternatives. The studies presented below give some insight to a new area of research that uses modeling and remote sensing data to assess air quality impacts from wildfires.

Wu, et al. (2006) were the first to systematically examine and estimate daily particulate matter (PM_{10} and $PM_{2.5}$) concentrations at a fine spatial resolution over a relatively large study domain. More specifically, they examined PM concentrations at a zip code level in southern California before, during, and after the 2003 southern California wildfires. Wu, et al. (2006) used satellite, visibility, and air quality data to conclude that heavy smoke increased PM_{10} and $PM_{2.5}$ concentrations by 160 and 100 $\mu g/m^3$, respectively. Wu, et al. (2006) were able to fill missing data (due to failure or intermittence) from 37 particulate matter samplers. Wu, et al. (2006) also concluded that fine temporal-spatial resolution of the PM data generated from satellite, visibility, and air quality data are suitable for linkage to the residential zip code of subjects admitted to hospital for cardiorespiratory illnesses. Henderson, et al. (2008) briefly critiqued Wu, et al. (2006)'s article and explain that although their results were favorable, their use of moderate resolution imaging spectroradiometer (MODIS) remains qualitative and that their method is limited to areas with relatively dense monitoring networks. The definition and application of MODIS will be explained later in this chapter.

Henderson, et al. (2008) show that all studies to-date report considerable error between observed and output data under some conditions and that dispersion models of fire smoke are challenging to simulate and model output needs rigorous evaluation. Henderson, et al. (2008) suggest the use of the measurement, spatial and temporal strengths of different data to allow for a straightforward and holistic evaluation of model performance.

Henderson, et al. (2011) performed the first cohort study for a wildfire event through their research on the 2003 British Columbia wildfires. During the 2003 wildfire season in British

Columbia, more than 2,600 km^2 of forest were consumed in the southern interior and 343 homes were destroyed (Henderson, et al., 2011). The cohort for the study included all 640,000 British Columbia residents. From administrative health data, 280,000 subjects were identified for their population-based cohort. Three daily smoke exposure estimates were assigned for each individual according to residential location. These daily smoke exposure estimates included the following: total measurements of PM_{10} from six air quality monitors that meet U.S. and international particulate monitoring regulations using tapered element oscillating microbalance (TEOM), smoke-related PM_{10} from a CALPUFF dispersion model run for the study, and an exposure metric for the presence or absence of exposure to a fire smoke plume (SMOKE) for plumes visible in satellite images. CALPUFF is a non-steady-state puff dispersion model that simulates the effects of time- and space-varying meteorological conditions on pollution transport, transformation, and removal. CALPUFF can be applied for long-range transport and for complex terrain.

Henderson, et al. (2011) used a longitudinal logistic regression to examine the independent effects of each exposure over the 92-day study period. Through their statistical analyses, the researchers found that increases in smoke particulates, PM_{10}, were associated with increased odds of respiratory physician visits and hospital admissions, but not with cardiovascular health outcomes. Residents in Kelowna experienced an increase of 100 micrograms of particulate per cubic meter of air, which resulted in an 80 percent increase in respiratory hospital admissions and a six percent increase in the odds of an asthma-specific physician visit. While odds ratios for the particulate monitoring metric using TEOM were consistent with other reports, those for the CALPUFF metric were biased towards the null. Results for SMOKE tracked with those for TEOM, but with much wider confidence intervals. Their results show that additional work is needed with air quality smoke modeling and satellite data. Their research was unable to show that air quality modeling is an improvement over monitoring.

In conclusion, the study from Henderson (2009):

1. Highlights the potential of new smoke exposure assessment methods
2. Demonstrates that plume dispersion models can be simplified with remote sensing data
3. Confirms the respiratory health effects of forest fire smoke. (Henderson, 2009)

With the exception of the studies presented in this literature review, the relationship between hospitalizations and wildfires has been examined mostly via time-series analyses without linking health data to air monitoring or modeling data. There have been more recent studies that used stationary air quality monitor data. Additional research is needed to address higher spatial air quality modeling and satellite data in epidemiologic analyses. Further work is also needed for air quality exposure assessments at higher spatial levels.

Climate Change and Wildfires

It is possible that a warmer climate will lead to more frequent fires, possibly more severe fires, and a longer fire season in the western United States (Westerling, et al., 2006). Recent decades have already witnessed an increase in the frequency, duration, and severity of wildfires in the western United States (Kovalev, et al. 2009). Since warming temperatures will increase the likelihood of drought, it will be easier for forests to burn, and burns will be more severe (Joint Fire Science Program, 2008). Fuel levels may have elevated the average fire risk to a point where thresholds will once again be sensitive to the influence of climatic variability in coming decades, regardless of fire suppression activities (Joint Fire Science Program, 2008).

Regional fire models suggest that summer precipitation and temperature historically played a large role in the area burned by fire (Littell, et al., 2010). For Washington State, the future area burned projections from the best statistical model suggest a doubling or tripling by the 2080s (Littell, et al., 2010). Littell, et al. (2010) determined that future median regional area burned, averaged over two global climate models, is projected to increase from about 0.2 million hectare acres (ha) to 0.3 million hectares in the 2020s, 0.5 million ha in the 2040s (about 2.5 times), and 0.8 million ha in the 2080s (about 4 times). Littell, et al. (2010) determined that the probability of exceeding the 95% quantile area burned for the time period, 1916 to 2006, increases from 0.05 to 0.48 by the 2080s.

Heat waves are projected to increase in the future due to global climate change impacts. Heat waves also build an environment for wildfires. According to a study by Jackson, et al., (2010), projected warming would likely result in 101 additional deaths among persons aged 45 and above during heat events in 2025 and 156 additional deaths in 2045 in the greater Seattle area alone (relative to 1980-2006). By mid-century, King County will likely experience 132 additional deaths between May and September annually due to worsened air quality caused by climate change.

The global impact of wildfires is an enormous issue. A recent study from Johnston, et al. (2012) is the first to estimate a death toll for landscape fires, and estimated that wildfires, peat fires, and controlled burns on farming lands kill 339,000 people worldwide each year. Most of these deaths are concentrated in sub-Saharan Africa, where an estimated 157,000 people die as a result of being exposed to such fires annually, with Southeast Asia ranking second with 110,000 deaths. Johnston, et al. (2012) looked at the number of deaths from all causes in areas that were exposed to heavy smoke and landscape fire between 1997 and 2006 using satellite data and chemical transport models to assess the health impacts of $PM_{2.5}$. In comparison, the number of wildfires come in far below the previously estimated global tolls for indoor air pollution (2 million people per year) and urban air pollution (800,000 people per year). The research from Johnston, et al. (2012) also suggests a significant link between climate and fire mortality with their finding that about twice as many people died during El Niño years when the surface ocean temperature rises in the tropical eastern Pacific Ocean (averaging 532,000) as during cooler La Niña years (averaging 262,000).

In a future of possible climate change, wildfires are projected to increase in severity and frequency in Washington State and globally. These studies show a demonstrated need to look more closely at the impact of wildfires on health effects.

Chapter 2: Wildfires in Washington State

The 2006 Tripod wildfire event was chosen for this analysis as it was one of the largest wildfire events in the past half-century in Washington State and also for the availability of air modeling data from the U.S. Forest Service. Chapter 2 explains the following topics:

- Identifies large, naturally occurring wildfire events in Washington State in the past ten years that could have had potential health impacts and available air monitoring data to assess their public health impacts (Top Wildfires of Interest to Public Health (2001 to 2009))
- Provides background on the 2006 Tripod wildfires. (2006 Tripod Wildfires)
- Addresses the available air monitoring and modeling data systems associated with the Tripod 2006 wildfires. (Air Monitoring Data for the 2006 Tripod Wildfires)
- Explains the benefits and limitations of the monitoring and modeling data systems from the EPA and the U.S. Forest Service. (Air Monitoring Data for the 2006 Tripod Wildfires, Air Modeling Data for the 2006 Tripod Wildfires, Satellite Data)

This chapter also provides the preliminary analysis of available air monitoring and modeling data systems. Air quality modeling data from the U.S. Forest Service were later linked to Washington State health hospitalization data and Census 2010 data for further epidemiological and population level analyses.

Top Wildfires of Interest to Public Health (2001 to 2009)

The goal of the original data scoping and analysis was to identify naturally occurring wildfire events of “large impact” to public health in Washington State from the past ten years. Washington

State health hospitalization data also known as the Comprehensive Hospital Abstract Reporting System data (CHARS) were available through 2009. Therefore, the search for wildfire event data was focused for the years 2001 to 2009.

Forest science professionals define "large wildfire events" in terms of acreage of forest impacted and forest ecosystem impacts. The National Wildland Coordinating Group defines "large wildfire events" as those larger than 100 acres in timber or greater than 300 acres in grasslands or rangelands or has an Incident Management Team assigned to the wildfire event (Northwest Interagency Coordination Center, 2012). Many wildfires occur in more remote areas located many hours away from more populated areas. Wildfires may have a concentrated ecological impact in terms of acreage of forests burned. However, determining air quality impacts to population centers further away is more complicated, since impacts depend on how smoke plumes travel. Each wildfire burns differently, which also means that smoke plume travel changes with each wildfire. Because of the complexity of smoke plume travel, it is difficult to define these "large wildfire events" without a more thorough analysis. Understanding the exposure implications would require additional research on smoke travel for each wildfire event. One would have to look at satellite and modeled projections to estimate whether the plume had a large impact to population centers further away.

The lists for wildfire events in Washington State were extensive and scattered across various governmental sources. The lists designated whether a wildfire was naturally occurring or human-induced. Much effort was made to research the large wildfires and eliminate those that were human-induced. The located lists came from the following sources:

- Wildfire event on non-national forest lands from 1970-2009 (Stanger, Brant, USFS, personal communication, February 17, 2011)

- Wildfire event on state and private forest land from 2004-2009 (Kassel, Albert, Washington State Department of Natural Resources, personal communication, February 23, 2011)
- Wildfire event on national forest lands in Eastern Washington, 2000-2004, Okanogan-Wenatchee 2003-2009 (Ohlson, Pete, USFS, personal communication, March 16, 2011)
- Additional details from National Wildfire Coordinating Group's Incident Status Summaries (http://www.nwcg.gov) and Incident Management Team (http://www.imtcenter.net/main/default.aspx)

The original ranking system of large wildfires question was focused to natural wildfires that were large in terms of acres impacted and their location to larger population centers in the state within the past ten years. Wildfires can arise from natural or a variety of human-induced causes. Since wildfires are projected to increase in the future due to climate change, this research analysis focused on naturally occurring wildfires. The definition of "large wildfires" in terms of acres impacted included wildfire events where the estimated acreage impact was over 1,000 acres. The definition of what constitutes a "large wildfire" in terms of their location to larger population centers in the state is a more difficult to determine. Since smoke from wildfires is variable, it is difficult to estimate the wider extent of wildfires on possible population impacts. When assessing the larger extent of wildfires, it is necessary to perform a more thorough analysis for each wildfire event using satellite and other available smoke plume modeling data. Another deciding factor of whether a wildfire event was listed was whether there were any associated EPA DataMart air quality monitors for the same county. There could have been wildfires in areas closer to more populated areas, but they were not included if there was no associated EPA DataMart data.

Therefore, the final ranking system was based on the following criteria:

- The cause of the wildfire event was natural. (For example, due to lightning.)

- The wildfire event's total acreage impact was greater than 10,000 acres.
- There was available air quality data for the county of wildfire occurrence in the EPA Air Quality DataMart.

The analysis of wildfire events in Washington for the past ten years showed that there were events of varying sizes, and in some cases, in closer proximity to more populated counties in Washington. There also were gaps and inconsistencies in the availability of air quality monitoring and related event characterization data from governmental agencies. An end product of the analysis is a list (see Table 1, Appendices in Chapter 8) of wildfire events in the past ten years that could have had air quality impacts due to the wildfire's acreage impacts and potential spread of smoke impacts.

Examples of the differences in data across years and counties are also documented in Table 1. After assessing wildfire events in Washington State from 2001 to 2009, it was also found there were limited enforceable monitors from the EPA Air Quality DataMart data with many counties having only one or two air quality monitors. Some wildfire events did not have any associated air monitoring data at all, and were excluded from the final tables.

For many counties, there are only a few monitors available for the entire county, and no monitors in some more rural counties. One or several monitors do not adequately represent the air quality for an entire county. The air quality monitors are only representative for the air quality at the monitor's location. For many of the wildfires, there is not adequate air monitoring data to analyze estimated health effects.

2006 Tripod Wildfires

The Tripod Complex 2006 wildfires included the Spur Peak and Tripod fires were some of the largest wildfires in the past half-century in the state, generating increased ambient concentrations of inhalable particulate matter (NSF, 2008). The Spur Peak fire began on July 3, 2006. The Spur Peak fire was fairly active at first, but then some rains came through and it was slowed down, but was not completely out. On July 24, the Tripod fire started about 10 to 12 miles south of Spur Peak and quickly grew and merged with the Spur Peak fire. After this point, the Tripod wildfire became known as the Tripod Complex Fire. The Tripod Complex wildfire did not end until November 9, 2006. The acreage impacted by the Tripod wildfires was as follows: Spur Peak with 62,173 acres and Tripod Complex with 113,011 acres. (Ohlson, Pete, personal communication, May 14, 2012)

On August 22, 2006, the Tatoosh Buttes fire began in the Pasayten Wilderness, about 25 miles to the northwest of the Tripod Complex at the time (Ohlson, Pete, personal communication, May 14, 2012). The Tripod and Tatoosh Buttes fires never burned near one another and were considered separate fires. The Tatoosh Buttes fire did not end until November 9, 2006 and burned 51,671 acres. In addition to the Tatoosh Buttes fire, there were other wildfires that occurred in Washington in 2006, which are listed below. The thorough analysis of wildfire events in Washington State also allowed us to locate 2006 wildfires that were occurring at the same time as the Tripod wildfires, which may have further increased possible smoke impacts and degraded air quality.

1. Columbia Complex (Southeastern Washington, Columbia/Garfield, Walla Walla): 109,402 acres: 8/21 to 12/1
2. Tatoosh Buttes (Methow, Okanogan County): 51,671 acres (8/22 to 12/1)
3. Tinpan (Entiat, Chelan County): 9,252 acres (7/6 to 11/25)
4. Flick Creek (Chelan, Chelan County): 7,879 acres (7/26 to 10/3)

5. Cedar Creek (Methow, Okanogan County): 1,661 acres (8/22 to 12/1)

6. Van Peak (Methow, Okanogan County): 1,813 acres (9/5 to 11/9 or as late as 12/1)

The 2006 Tripod wildfires consumed over 175,000 acres of mostly USFS and state managed forestland in Okanogan County (Okanogan County Community Wildfire Protection Plan Planning Commitee and Northwest Management, Inc., 2006). Suppression costs of the fire were reported to be $74 million with an additional $28.3 million requested for rehabilitation (Okanogan County Community Wildfire Protection Plan Planning Commitee and Northwest Management, Inc., 2006). However, this amount does not include economic losses, health costs, or other costs associated with the Tripod wildfires. In 2006, nearly 250,000 total acres burned in Okanogan County alone (175,000 from Tripod). In comparison, 275,000 total acres burned in Okanogan County between 2001 and 2005 (Okanogan County Community Wildfire Protection Plan Planning Commitee and Northwest Management, Inc., 2006). From 2001 to 2005, $65 million was spent on fire suppression, which drastically compares to the $74 million spent on the Tripod wildfires (Okanogan County Community Wildfire Protection Plan Planning Commitee and Northwest Management, Inc., 2006).

Air Monitoring Data for the 2006 Tripod Wildfire

In analyzing the Tripod 2006 wildfire event, the first goal was to characterize the event properly in terms of intensity (number of acres burned) and duration (number of days), and then link this information to air quality data in relevant communities. By researching this information, one can then answer the question of whether a forest fire degrades the air quality in nearby communities, and, by how much is the air quality was degraded.

Background on Air Monitoring

Air quality monitoring data is extracted from either gravimetric or optical particle concentration measurement techniques. Gravimetric or filter-based instruments collect particulates on ventilated filters. Optical instruments measure light-absorbing characteristics of the atmosphere, which can then be converted to obtain an estimate of the concentration of airborne particulates (National Wildfire Coordinating Group, 2001). For their state, local, and tribal air quality monitoring stations and the Interagency Monitoring of Protected Visual Environments (IMPROVE), the EPA uses both gravimetric and optical particle concentration measurement techniques. The EPA's gravimetric sources include the following instruments: $PM_{2.5}$ SCC with Correction Factor-TEOM Gravimetric 50 degrees Celsius, $PM_{2.5}$ SSI with Correction Factor-TEOM Gravimetric 50 degrees Celsius, and the Andersen RAAS Teflon. The EPA's nephelometer source is the correlated radiance research M903 with heated inlet-nephelometry. For the temporary monitors to assess the Tripod 2006 wildfires, the instrument used by the USFS was the MIE DataRam, a compact, self-contained instrument that internally estimates mass concentration from the measured scattering of light (USFS, 2006). The MIE DataRam measures particulate concentrations from 0.1 to 400,000 $\mu g/m^3$ and continuously displays the current and time-weighted average mass concentration while logging up to 10,000 data points.

The Washington Department of Ecology is responsible for monitoring public exposure to pollutants. The EPA maintains a database of monitored air quality data via the Air Quality DataMart (EPA, 2008). The monitors in the Air Quality DataMart are permanent monitors that are enforceable by EPA pollutant standards under the Clean Air Act. Air quality monitors in the EPA Air Quality DataMart are managed by federal, state, and local agencies that manage air program air quality data (in the case of this research, Washington State Department of Health and EPA) and

Native American tribes. The DataMart database is not conclusive of all available air quality monitoring data, as the database does not include non-EPA enforceable monitors such as temporary monitor data from other governmental agencies such as the U.S. Forest Service.

Hourly air monitoring data from the Air Quality DataMart are limited and there are often only a few monitors available for an entire county. An analysis of the EPA DataMart database system was done and found that the EPA DataMart database system does not include data for seven counties in Washington State, Douglas, Ferry, Garfield, King, Lincoln, San Juan, and Wahkiakum counties. The EPA DataMart database does have data for the other 32 counties in Washington State. For earlier years, there may not be any monitoring data for various counties or only one monitor for an entire county. The USFS has additional temporary monitors (hourly measurements) for analyzing and tracking wildfire events of interest. To obtain temporary monitor data from the USFS, the data must be requested and is limited for certain wildfire events being assessed by the USFS. For this analysis, the seven monitors of data from the Pacific Wildland Fire Sciences Laboratory team are not considered "air quality monitor data" because the monitors were recording $PM_{2.5}$ concentrations and were not used to give exceedance reports (Strand, Tara, personal communication, April 27, 2012). Therefore, the USFS refers to this data as "observation data" instead of "air quality data". "Air quality monitor data" would refer to data collected and sent to EPA to assess whether monitors were in compliance with EPA enforcement standards.

There are limited air quality monitoring data to address $PM_{2.5}$ concentrations. Figure 1 shows a map of Washington State and the locations of all EPA air quality DataMart monitors that are currently active as well as historical monitors. Some of the monitors are no longer active, but by looking at the map, one can see the inadequacies of available air quality monitoring data, especially in more rural areas where wildfires are more prone to occur. During the time of the Tripod 2006 wildfire, there were even fewer monitors in place. Air quality monitor measurements represent $PM_{2.5}$ concentrations at a specific fixed location in time. Therefore, it would not be accurate to use air quality monitoring data from a specific monitor to represent nearby zip codes, counties, or other spatial entities. Also, smoke conditions change greatly across locations. For example, smoke levels may be high at a monitor location but the air could be clear in a distance one-mile away. Each wildfire event produces varying air quality conditions. Monitors are placed often in more centrally located areas and particulate matter values may come from a variety of sources including pollution from cars, smoke, or industry. It is not completely accurate to use monitor data exclusively for wildfire events since there are other contributing sources to the particulate matter values.

Methods

For the Tripod 2006 wildfires, there were two types of air monitoring data available, as listed below. For the USFS temporary non-enforceable monitors, there were originally twelve instruments but five of them shutdown due to power failure. Seven of the twelve monitors ran for a month or longer, and those seven monitors are included in this analysis (Larkin, et al. 2009). The following monitor data was used for the analysis:

1. Permanent enforceable $PM_{2.5}$ data from the EPA Air Quality DataMart database and enforced locally by the Department of Ecology (Washington State Department of Ecology, 2012)
2. Temporary non-enforceable $PM_{2.5}$ data from the USFS Pacific Wildland Fire Sciences Laboratory (PWFSL) (August and September, 7 monitors)

For both sets of 2006 monitor data, hourly data were averaged for daily means and compared against the EPA's 24-hour $PM_{2.5}$ standard of 35 μg/m³. Using the EPA Air Quality DataMart, air quality monitoring data for 2005 and 2007 (Figures 3 and 5) was also analyzed to determine if the $PM_{2.5}$ values observed in 2006 were typical or abnormal values. The purpose of the analysis is to characterize the intensity and duration of the 2006 Tripod wildfire event. The analysis of the year prior and the year after the wildfire event is helpful to understand what may be considered typical air quality levels. Also, the comparison across the years allows us to understand whether there was demonstrable air quality degradation during the wildfire event and estimating the potential impact within Okanogan and surrounding counties. The comparison analysis of the EPA DataMart monitors was done for Okanogan County and adjacent counties for 2005 to 2007.

Results

From both sets of air monitoring data from the EPA and the USFS, it was determined that only monitors from Okanogan County showed air quality impacts above the EPA 24-hour $PM_{2.5}$ standard. From the EPA enforceable air quality monitoring data in Okanogan County and its surrounding counties, air quality degradation (in terms of $PM_{2.5}$) was found in Okanogan County in the communities of Twisp and Winthrop (Figure 4). In Twisp, concentrations of $PM_{2.5}$ ranged from 1 to 15 μg/m³ in June 2006, but during the peak points of the wildfires in July and August concentrations ranged from 98-160 μg/m³. For Winthrop, $PM_{2.5}$ concentrations averaged around 160 μg/m³. EPA Air Quality DataMart data were unavailable for monitors in Ferry and Lincoln counties. No large differences in air quality were observed for Skagit, Whatcom, Chelan, and Grant counties compared to the normal ambient levels in the winter months. Hourly measurements peaked several times above the 24-hr standard; At Twisp, 398 and at Winthrop, 439 points. In comparison to 2005 and 2007 air quality data from the EPA DataMart (Figures 3 and 5), there was degraded air quality for 2006, most likely due to the Tripod wildfires. Monitors from surrounding counties were also analyzed for air quality data in 2005, 2006, and 2007 (Figures 7, 8, and 9), and no major changes were found for 2006 due to the Tripod wildfires, nor any major discernible differences between the two years.

From the USFS $PM_{2.5}$ (non-enforceable) data, Conconully had 536 hourly measurements exceeding 35 $\mu g/m^3$, Eight Mile with 469, Omak with 217, Fruitland with 59, Nespelem with 50, Oroville with 39, and Kettle Falls with 11. The Eight Mile monitor was located closest to the fire. The Conconully and Omak monitors were located downwind from the Eight Mile monitor and the wildfire, and the Fruitland, Nespelem, Oroville, and Kettle Falls monitors show further downwind trends (Strand, Tara, personal communication, May 24, 2011). Figure 6 shows the $PM_{2.5}$ data collected at the USFS's seven monitors for the Tripod wildfires (Strand, et al., 2011) and gives the idea of the impact to the east, which shows that the smoke was minimal past Nespelem, WA. The USFS did not deploy air monitors to the south because observations showed that most of the smoke was not traveling in that direction (Strand, Tara, personal communication, April 7, 2012).

Conclusions

The results from analyzing air monitor data from the EPA and the USFS demonstrated that there was degraded air quality for Okanogan County during the Tripod wildfire event. As addressed in the Background in Chapter 2, limited monitors exist across counties. Monitors in Washington counties may range from having no monitors to up to three monitors. The limited number of monitors presents a challenge when assigning air quality values to hospitalizations. The next step was to examine the potential of using air quality modeling data for this research analysis.

Air Modeling Data for the 2006 Tripod Wildfires

Although there were measurements from a limited number of air quality monitors from the EPA and the USFS, those measurements only capture air quality at a specific location, and do not accurately reflect the spatial air quality. Therefore, the hypothesis was that modeled air quality data incorporating wind and fire patterns would be a better measurement for this analysis.

Background on U.S. Forest Service Air Modeling

The AirFire team at the Pacific Northwest Research Station of the USFS used a smoke prediction framework known as BlueSky to build the air quality model data for the 2006 Tripod wildfires. The original BlueSky Framework was developed to provide smoke impacts information to forest managers investigating the possibility of a prescribed burn (Larkin, et al. 2009). Figure 2 shows the input components of the BlueSky framework, and the framework is described in more detail below.

> The BlueSky framework pulls data on fire locations and sizes from prescribed burn and wildfire reporting systems. Fuel load data are also essential inputs for BlueSky, with the amount of fuel dependent on fuel moisture, humidity, wind speed, and slope, among other factors. BlueSky uses an emission production model that takes data on fuel load, fuel moisture, burn area, and wind speed, and predicts the amount of fuel consumption and emissions that will occur. The emissions model produces estimates of the total particulate matter, carbon monoxide, carbon dioxide, methane and heat generated from the fires. The next step is calculating the long-range transport of the smoke plume and its gradual

> dispersion. BlueSky uses CALPUFF and Hysplit, a smoke trajectory model developed by the National Oceanic and Atmospheric Administration (NOAA). Every night, BlueSky obtains regional weather forecasts produced by the MM5 model, which is a midscale weather forecasting model, and burn information from state and federal agency reporting systems. Twelve-hour smoke trajectories are computed from each burn location and CALPUFF is run using the emission estimates from the emissions production model and the weather forecast from MM5. (Pacific Northwest Research Station, 2006)

BlueSky addresses climate change in its wildfire predictions through the Fire Scenario Builder function. The Fire Scenario Builder function accounts for variables including climate and vegetation changes. The Fire Scenario Builder is linked to future climate meteorological runs and a statistically based algorithm is used to determine probable start of fire and size (Strand, Tara, personal communication, June 9, 2011). The researchers at the Pacific Northwest Research Station of the USFS modeled the expected $PM_{2.5}$ air quality concentration increases for the 2006 Tripod wildfires. Air quality modeling data were available during 33 days of the Tripod 2006 wildfire time period from August 14 to September 15, 2006. There was no target population with the Tripod air model data system. The monitoring data were collected to obtain observations and gain an understanding of $PM_{2.5}$ concentrations downwind from the Tripod 2006 wildfire event (Strand, Tara, personal communication, July 29, 2012). This dataset from the USFS is unique for being one of the first data systems on $PM_{2.5}$ data during a large wildfire event (Strand, Tara, personal communication, July 29, 2012).

The modeling data were from CALPUFF, a smoke dispersion model developed and distributed by Earth Tech, Inc., which has now been adopted by EPA for national use. For the model data, there were three components used for smoke prediction (a) known fire information at the time through ICS-209 ground reports and satellite detects; (b) forecasted meteorology such as wind pattern estimates; and (c) fuel layers given to the team by the local foresters in the area (Strand, Tara, personal communication, April 27, 2012). The model does not include or adjust for variation from air monitoring instruments.

The air quality modeling data from the USFS were specific to the 2006 Tripod wildfires, but also factored in other Pacific Northwest fires, including one north of the Canadian border (Strand, Tara, personal communication, May 28, 2012). Each pixel value represents the estimated increase in $PM_{2.5}$ due to the Tripod wildfire. The impacts from other wildfires were determined to be minimal over the duration of the observation data collection based on the primary wind direction (Strand, Tara, personal communication, May 28, 2012). The estimated $PM_{2.5}$ values did not include other types of air pollution, such as traffic, and the first layer of the model data has a depth of about 50 meters (Strand, Tara, personal communication, May 28, 2012).

Background on Satellite Data

It is possible to build a smoke exposure model of an exposure shadow from various data sources. Such data may include weather observations with latitude, longitude, elevation, wind speed and direction and data from wildfire reports that address distance, frequency, severity, and burn area during the wildfire event. The U.S. Department of Agriculture and the U.S. Department of Forest Service have an active fire-mapping program that allows users to detect wildfires in real-time (USFS, 2012). Satellite data systems such as Moderate Resolution Imaging Spectroradiometer (MODIS) are also useful. Satellite data, as well as modeled data can often be difficult to relate to ground concentration data due to their focus on higher atmosphere levels, and the tendency to under-predict ground concentration levels. As explained by the National Aeronautics and Space Administration (NASA 2012):

> MODIS is a key instrument aboard the Terra (formally known as the Earth Observing System (EOS)-AM (morning)-1) and Aqua (formerly known as the EOS PM (evening)) satellites. Terra's orbit around the Earth is timed so that it passes from north to south across the equator in the morning, while Aqua passes south to north over the equator in the afternoon. Terra MODIS and Aqua MODIS satellites scan the entire Earth's surface every 1 to 2 days, acquiring data in 36 groups of wavelengths. MODIS data will improve our understanding of global dynamics and processes occurring on the land, in the oceans, and in the lower atmosphere. MODIS is playing a vital role in the development of validated, global, interactive Earth system models able to predict global change accurately enough to assist policy makers in making sound decisions regarding environmental protection.

Satellite data, such as those from NASA, show the extent of the smoke for a specific point in time. Meteorological forecasts adjusted with the observations can be obtained from NOAA and one can use these observations to determine where the smoke may have drifted. It is also possible to look at smoke plume footprints recorded by the satellite versus model predictions, and this type of analysis is called a footprint analysis (Strand, Tara, personal communication, April 27, 2012). There are many errors associated with satellite footprints but this technique gives a general trend of wildfire impacts (Strand, Tara, personal communication, April 27, 2012). Smoke plume footprints only show information at a snapshot level and at a particular time, since the satellites move across the sky.

Satellite data were not readily available from the USFS or NASA and were not used in this research. Smoke impacts were assessed using the modeled air quality data from the Pacific Wildland Fire Sciences Laboratory at the USFS.

Methods

The USFS air quality modeling data were used in the epidemiologic analyses addressing hospitalizations and population impacts that are described in Chapter 3. The study area consisted of Okanogan and adjacent counties. Smoke impacts were not factored in the selection of the study area. Rather, the focus was on where the nearest hospitals were to the Tripod wildfires in Okanogan County. Zip codes were used as the spatial level of exposure assessment. The methodology below describes how air modeling data from the USFS were converted to a usable form to be later linked with hospitalization data, based on hospitalization and residential zip codes.

For the Tripod 2006 wildfire, USFS air quality modeling data were available for a 33-day period from August 14 to September 15, 2006. Air quality modeling data were in the form of MM5 data and needed to be converted into a usable form for further analysis with hospitalization and zip code data. In ESRI's ArcMap Version 10.0, the air quality modeling data were converted from a common data format (CDF) into a TIFF image file. With the data being 4 x 4 km data, MM5 grid extent data from the Northwest Modeling Consortium were added to all 33 TIFF images so that the images were no longer floating in space. Next, the TIFF image was converted from a raster file to a vector format since the data were needed by zip code. Raster files are images made up of grids of rectangles and squares where each one can have its own associated values, whereas vector images are made of polygons, points and/or lines. Spatial reference information and coordinate system data were added before the data were able to overlay in ArcMap.

Hospitalization data included the patient's zip code and the hospital's zip code. Either the patient or hospital zip codes needed to be aligned with the air quality modeling data. The options with zip code data with summarized pros and cons of each data source are highlighted below. ESRI does not provide the formula to their algorithm. However, their method is most likely an aggregation from centroids of blocks with 100% population counts for 2000. Figure 10 shows visually the high spatial variability that exists across the three sources of data. After reassessing the pros and cons as outlined below, 2010 Census zip code shape files were decided to be the best zip code shape file, and its associated population data. U.S. Census Tigerline data are considered the optimal choice, given the uncertainties associated with the ESRI data.

1. ESRI zip code shape file data (2006) with ESRI population adjusted counts (2005)
   - Perfect coverage by zip (Census + unknown algorithm)
   - Population estimated for 2005 in an unknown method from 2000 Census data

2. Tigerline Census zip code shape file data (2000, updated in 2002) with Census population (2000) = Census data used prior to 2010
   - Less coverage (by ZCTA, not zip)
   - Perfect 100% count of population for 2000

3. Tigerline Census zip code shape files data (2010) with Census population (2010)
   - Moderate coverage (by ZCTA, not zip)
   - Perfect 100% count of population for 2010

Each pixel of data in the TIFF image file indicates the increase in $PM_{2.5}$ that was only due to the Tripod wildfire. In ArcMap, 2010 ZCTA and county data were overlaid so that ZCTAs in Okanogan and its surrounding counties were selected. The selection criteria of the zip codes included selecting for zip codes within counties and if any part of zip codes were within boundaries, but not if borders were shared. Using ArcMap, all 33 TIFF images were georeferenced with 1983 State Plane South coordinates. Pixel values were averaged within zip code boundaries. To obtain one $PM_{2.5}$ modeled value per zip code per day, the ArcMap feature, "Zonal Statistics as Table", was used to connect TIFF images to zip code data. There were many pixels that could have been a part of one zip code. Therefore, the aforementioned step calculated the average of the pixel values within each zip code so that every zip code had a unique value of the air pollution for each of the 30 days. Statistical Package for the Social Sciences (SPSS) Version 20 was the software version used for the statistical analyses in this research, and was then used to compile the 33 days of modeled air quality values based on 2010 zip codes.

Results

In using the U.S. Census 2010 data, zip codes in Okanogan and its surrounding counties were selected if any part of the zip codes were contained within the county boundaries. Since hospitalization data were analyzed for Okanogan and its adjacent counties, a preliminary analysis was done for the aggregate modeled air quality data. The 75th percentile of modeled air quality for all zip codes in Okanogan and its adjacent counties across the 33-days daily was determined to be 0.504 $\mu g/m^3$ based on 867 data points. For Okanogan and its adjacent counties, each zip code had a daily-averaged associated $PM_{2.5}$ value, which allowed for the data to be later linked to hospitalization data at the zip code level.

In using the 75th percentile of all of the modeled air quality values in the zip codes of Okanogan and its surrounding counties in residential zip codes, the majority of the exposures were zero values. There were very few values above the 75th percentile. In addition, the 75th percentile value comprised a large area, much of which may not have been impacted by the Tripod wildfire. The prevalence of the zero values also, even in Okanogan County hospitals, first raised the question of whether the modeled data had "ground truth". "Ground truth" would refer to whether the air modeling data was representative of smoke particulate matter at ground concentration levels. A threshold, whether zero and non-zero values or 75th and 25th percentiles needed to be used because there were different daily $PM_{2.5}$ values associated for the same zip code. On one day, a zip code could have been a "high PM/exposed" exposure, but on another day, it could have been a "low PM/non-exposed exposure".

Because the modeled air quality pollution increases were such small values, the previous consideration of creating air quality buffer zones was not used. Otherwise, one could analyze the data based on air quality $PM_{2.5}$ categories: 0 to 0.5, 0.5 to 3, 3-35, or above 35 μg/m³, since 35 μg/m³ is the EPA 24-hour standard for $PM_{2.5}$. For further analysis, the modeled air quality data were linked to hospitalization and Census 2010 data with the methodology and results are shown in Chapters 3 and 4.

Conclusions

Given the limited spatial data available for monitor data and the link being established for the air quality monitors in Okanogan County, it was hypothesized that air quality modeling data from the USFS could be linked to hospital admission data. In analyzing the data by hospitals, exposure characterization was done for the modeled air quality data. The preliminary statistical analysis in the chapter hints that the modeled estimates in air pollution due to the Tripod wildfire were under 0 μg/m³. In translating to air monitoring terminology, zero values would mean values below the detectable limits. With modeling data, it is possible that these zero values could be inaccurate and underpredicted values. However, the availability of the air modeling data presented a unique opportunity to develop the methodology to assess wildfire impacts on air quality and human health, which will be addressed in Chapter 3.

Chapter 3: Epidemiologic Analysis of Air Pollution Impacts on Hospitalizations

Introduction

Chapter 3 describes the methodology and results of epidemiologic analyses to address air pollution impacts from the Tripod 2006 wildfires on cardiovascular and respiratory hospitalizations. Three epidemiologic analyses were conducted:

1. Hospital relative rates
2. Case-crossover study design
3. Public health population analysis

Washington State Comprehensive Hospital Abstract Reporting System (CHARS)

In Washington State, the hospitalization data system is referred to as CHARS (Comprehensive Hospital Abstract Reporting System) and is managed by the Washington State Department of Health. For the time period of the Tripod wildfires, cause-specific morbidity CHARS data were available for May to September 2006. This analysis focuses on non-traumatic respiratory and cardiovascular hospitalizations. Available variables are as follows and those used in this analysis are denoted with an asterisk (*):

1. Date of admission*
2. Date of discharge
3. Source of admission
4. Total charges
5. ICD-9 diagnosis codes* (principal, and up to 5 other codes) (organized into whether the hospital admission was a cardiovascular or respiratory admission)
6. Hospital of admission (and associated address and zip)*

7. Zip code of patient's residence*
8. Patient's gender*
9. Patient's age* (organized into age categories)
10. Length of stay
11. Primary payer ID codes

The CHARS database contains data for all non-traumatic hospitalizations, which contains information on hospital discharges. The non-traumatic hospitalizations include circulatory and respiratory admissions, based on primary diagnosis code. Secondary and tertiary diagnoses were unavailable in the dataset. For 2006, there is only data on hospitalizations that occurred from May to September. Hospitalization data were requested for Okanogan and its surrounding counties. The wildfire occurred in Okanogan County, but impacted residents in nearby counties may have gone to the hospital closest to their residence. Figure 11 shows all of the hospitals in Okanogan and its surrounding counties of Chelan, Ferry, Grant, Lincoln, Skagit and Whatcom that will be used for this analysis. As one can see in Figure 11, the number of hospital locations in Okanogan and its surrounding counties is small compared to more populated areas in Washington State.

Hospitalization data were available from May to September 2006. However, since air quality modeling data were only available for 33 days, the same period was used for the hospitalization data. Air quality modeling data were aligned with hospitalization data, which limited the number of cases that could actually be analyzed, since many of the hospitalizations occurred on days where there were zero $PM_{2.5}$ values. Prior to limiting cases with no observable air quality values, during the time period of August 14 to September 15, 2006, a total of 268 people were hospitalized for a respiratory hospitalization, and 445 people for a cardiovascular hospitalization in hospitals located in Okanogan and its surrounding counties. However, some of those cases had no associated modeled air quality value (not even a zero predicted $PM_{2.5}$ value) and were taken out of the analysis, leaving 252 respiratory hospitalizations and 381 cardiovascular hospitalizations. Tables 2 and 3 provide detail on respiratory and cardiovascular hospitalizations by hospital and county. The numbers in parentheses indicate the non-zero $PM_{2.5}$ values used in this analysis. The numbers that are not in parentheses include all hospitalizations; including those with associated zero PM values.

Census Data

On a yearly basis, the U.S. Census Bureau provides population estimates by state, city, towns, county for the United States as well as for the Commonwealth of Puerto Rico and its municipalities. The Census data also has data on demographic components of population change (births, deaths, migration) at the national, state, and county levels of geography. Housing unit estimates are also produced for the nation, states, and counties. However, yearly data are not available for population estimates by zip code. The most recent Census data with population estimates by zip code are from 2000 and 2010. U.S. Census Tigerline data contains Census data with the most recent updates. The U.S. Census provides updated geographical spatial data and age-specific population data for every ten years, and provides additional updates for any changes in the data via Tigerline data. Any estimates for specific years of data by zip code are from third parties and therefore, the algorithms to their calculations are unknown. For 2006 estimates, there was geographical spatial data from ESRI (Environmental Systems Research Institute). ESRI is a software development and services company providing Geographic Information System (GIS) software and geodatabase management applications, such as ArcMap, which was used for this research. However, the 2006 ESRI data only contained total population information, and did not have age-specific population information.

ESRI is a third party vendor that develops formulas and algorithms and purchases additional spatial information to update their data, so that they have yearly updated Census. Their extra-developed data include information on yearly population estimates and spatial boundaries. However, the methodology that ESRI uses to update the Census data is unavailable to the user. For the best data integrity, this research was done using U.S. Census data directly from the source. However, there are zip code limitations with the Census data. The Census data comprises of zip code tabulation areas (ZCTAs) for their zip codes. There is not spatial data associated with U.S. Postal Service (USPS) zip codes, but only ZCTAs. As explained by the U.S. Census Bureau (2012):

> ZCTAs are a statistical geographic entities produced by the U.S. Census Bureau for tabulating summary statistics, first developed for Census 2000. This entity was developed to overcome the difficulties in precisely defining the land area covered by each zip code, which is necessary in order to accurately tabulate census data for that area. ZCTAs are generalized area representations of USPS Code service areas and represent the most frequently occurring five-digit zip code found in a given area. Each ZCTA is built by aggregating 2010 Census blocks, whose addresses use a given zip code. Each resulting ZCTA is then assigned the most frequently occurring zip Code as its ZCTA code.

Hospital Relative Rates

Hospitalization zip codes were used to link hospitalization data with modeled air quality data, rather than residence zip codes. This analysis by hospital allows us to analyze hospitals as catchment areas and to understand if any observed effects are because certain hospitals have increased population, and generally have more patients.

Methods

Hospitals used in this analysis included hospitals located in Okanogan and its adjacent counties (Figure 11). CHARS hospitalization data were linked with modeled air quality data (August 14 to September 15), based on the zip code of the hospital. The analysis by hospital zip codes, rather than residential zip codes, allows us to understand whether any increases in health outcomes may be due to a hospital having more patients, and which hospitals were associated with non-zero $PM_{2.5}$ values. There are some disadvantages to analyzing the air quality modeling data system and hospital data system based on hospital zip codes and not residential zip codes. The use of hospital zip codes assumes that all patients were impacted by the wildfire. However, there may be patients from zip codes from farther locations in the state or other states, and these patients may not have been in areas close to the Tripod wildfire.

Using ArcMap, air quality modeling data were first merged with Census 2010 shapefiles addressing zip code locations. For each day in the air quality model, averaged $PM_{2.5}$ values were noted for each U.S. Census zip code so that an averaged $PM_{2.5}$ value would be available for every U.S. 2010 Census zip code of interest per day. Next, using SPSS, air quality modeling data were then matched to hospitalization data, based on the hospital zip code and hospitalization date of the patient. Hospital zip codes that did not match with Census 2010 zip codes were not included in the analysis, since air quality modeled data were based on Census 2010 zip code locations. With CHARS hospitalization data, the only spatial data associated with a patient is the zip code of the patient and the zip code of the hospital. Each hospital serves as a stand-in for the catchment area for air pollution exposures, by serving as a hospital located in Okanogan County or a surrounding county.

There were many $PM_{2.5}$ values with zero values. With monitor measurements, measurements that are zero are those which we do not have a number because they are less than the limit of detection. However, since these are modeled air quality values, these zero values are a prediction value, and are not necessarily values which would have been beyond the limit of detection. Given the limited number of $PM_{2.5}$ values above zero, this analysis distinguishes between zero and non-zero $PM_{2.5}$ values.

Relative risks (R values) were calculated using the following formula for each hospital, with separate calculations for respiratory and cardiovascular hospitalizations:

$$\mathbf{RR = HR_{PM2.5} / HR_{noPM2.5}}$$

Where RR = relative risk

HR = hospitalization rate

$HR_{PM2.5}$ = number of hospitalizations on non-zero $PM_{2.5}$ days divided by number of non-zero $PM_{2.5}$ days

$HR_{noPM2.5}$ = number of hospitalizations on days with $PM_{2.5}$ less than the limit of detection divided by number of days with $PM_{2.5}$ less than the limit of detection

Exposure characterization was needed to determine what constitutes an "exposed" and "unexposed" population. In this case, non-zero value $PM_{2.5}$ events were "high exposure events", or the total number of hospitalizations where there was a $PM_{2.5}$ value associated with the day. Zero value $PM_{2.5}$ events were "low exposure events", or the total number of hospitalizations where there was a $PM_{2.5}$ with a "0" value associated with the day. The non-zero and zero $PM_{2.5}$ days were the cumulative number of days of whether the modeled air quality value had an associated non-zero or zero value. Since this analysis assessed the modeled air quality data, there were 33 days for which the

USFS modeling data were available. In total, there were 3,207 unique $PM_{2.5}$ events, with 2,473 of them being a zero $PM_{2.5}$ events.

Results

Tables 4 and 5 show all of the respiratory and cardiovascular hospitalizations where there were non-zero $PM_{2.5}$ values listed in descending order of values. For the data displayed in Table 6, relative risks (R values) were calculated for hospital locations based on the number of non-zero and zero PM days in the modeled merged air quality and hospitalization dataset. Table 7 shows the number of non-zero $PM_{2.5}$ and zero $PM_{2.5}$ days and the number of respiratory hospitalizations on both categories; Table 8 does the same but for cardiovascular hospitalizations. The two maps (Figures 12 and 13) show hospitals with R values greater than 1 for respiratory and cardiovascular hospitalizations. The R values greater than 1 (2 significant digits) are also highlighted below with the number of respiratory or cardiovascular hospitalizations on non-zero PM days in parentheses. Since these calculations were done with the formula described in the methods, there is no associated relative risk calculation.

Respiratory R (map shown in Figure 12)

- Central Washington Hospital: 1.22 (10)
- Coulee Community Hospital: 2.80 (1)
- Lincoln Hospital: 2.82 (2)
- Quincy Valley Medical Center: 5.60 (1)
- United General Hospital: 3.11 (3)

Cardiovascular R (map shown in Figure 13)

- Island Hospital: 1.87 (4)
- Lincoln Hospital: 3.10 (1)

- North Valley Hospital: 1.71 (3)
- Peace Health Saint Joseph: 1.31 (42)
- Skagit Valley Hospital: 1.50 (11)
- United General Hospital: 3.62 (2)

Overall, there were not many relative risks above 1 for respiratory and cardiovascular hospitalizations. Within the hospitals with relative risks above 1, there were a limited number of respiratory and cardiovascular hospitalizations for non-zero $PM_{2.5}$ days. The exception was Peace Health Saint Joseph Hospital, where there were 42 cardiovascular hospitalizations during non-zero PM days.

Case-Crossover Study Design

In the case-crossover study design, each case serves as his or her control by comparing exposures near the time of the incident health event with exposures to the same person at another time—either before or after the incident even (Baker & Nieuwenhuijsen, 2008). The analysis compares the difference between exposures during the event and control time periods for the same individual, so it is a 'matched' case-control analysis (Baker & Nieuwenhuijsen, 2008). The rationale for this design is that if precipitating events exist, they should occur more frequently immediately prior to the onset of disease rather than during a period more distant from the onset of disease (Merrill, 2010). The case-crossover study design is especially appropriate when individual exposures are intermittent wherein the disease occurs abruptly and the incubation period for detection and the induction period are short (Merrill, 2010).

The lag effect is important to case-crossover analyses. Some studies assign case events to the calendar date on which the patient presented to hospital or died, and exposure is based on the daily level of particulate matter (Mittleman, 2005). However, these studies do not take into account that the event might have begun any time between 0:00 and 23:59 hours (Mittleman, 2005). These studies may be misclassifying exposure by a half-day on average (Mittleman, 2005).

The size of the population at risk is not an issue with the case-crossover design (Neas, et al. 1999). The case-crossover design controls many time-varying confounders by design because the case and control periods in each risk set are separated by a relatively small interval of time (Neas, et al. 1999). This time interval may be only a few hours in some cardiovascular research or several days in air pollution research (Neas, et al. 1999). The case-crossover study design controls for confounding by month and season by design. The case-crossover study design with time-stratified sampling is appealing since it affords control for confounding by day of week, month, and season of year by design (Buckley and Richardson, 2012). It is important to control for season and day-of-week effects (or at least weekend/week-day contrasts) for several reasons. Because air pollution has seasonal variability, there is the potential to confound the pollution associations if not controlled (Neas, et al. 1999). In addition, seasonality may modify the relationship between ambient concentrations of particles and personal exposure to particles of ambient origin, for example, the amount of time spent outdoors or window opening. In addition to this 365 day cycle, behavior and exposure change substantially between weekdays and weekends (Neas, et al. 1999). Factors that vary slowly over a longer time scale, such as trend, season, and smoking status, are essentially the same in both periods and therefore do not confound the health effects of more rapidly varying factors such as air pollution.

The case-crossover study design has been especially used for research on the effects of air pollution on cardiovascular disease events, such as deaths, hospitalizations, ventricular arrhythmias, and intracerebral hemorrhage (Baker & Nieuwenhuijsen, 2008). In case-cross-over studies addressing the impacts of air pollution, the air pollution concentration that corresponded in time with a person's adverse event is compared with a "control" time when the event did not occur (Vedal, 2002). In comparison, in a time-series study, the association between parallel time-series of varying air pollution concentrations and daily mortality or morbidity counts is assessed over a period of time (Vedal, 2002).

The case-crossover design does not address the issue of exposure measurement error or the discrepancy of ambient and personal exposures (both challenges are addressed in Chapter 5), but does represent a unique approach to control for confounding. For example, by making within-subject comparisons, time-independent confounders are controlled by design (Janes, et al. 2005). Also, if the referent times are matched to the index time with respect to time-dependent confounders, these confounding effects are controlled by design (Janes, et al. 2005).

Studies of acute effects face many challenges, including exposure measurement error, the discrepancy between ambient and personal exposures, and confounding (Janes, et al. 2005). Only a limited number of research topics are amenable to the case-crossover design. The exposure must vary over time within individuals rather than stay constant (Rothman, et al. 2008). The exposure must also have a short induction time and a transient effect; otherwise, exposures in the distant past could be the cause of a recent disease onset (a carryover effect) (Rothman, et al. 2008). Control of time-varying confounders, such as daily variation in ambient temperature, may be achieved through regression modeling (Buckley and Richardson, 2012). Case-crossover studies suffer from confounding when the baseline risk of the outcome is not constant within the referent window (Buckley and Richardson, 2012). The time-stratified, bi-directional approach to control period sampling within a one-month referent window constrains variation in potential time-varying confounders but does not eliminate it (Buckley and Richardson, 2012). Despite any limitations, studies have demonstrated that the case-crossover gives unbiased estimates in the presence of strong seasonal confounding (Guo, et al. 2010). With the rare exception, recent findings show that case-crossover studies are generally consistent with findings from time-series studies. (Vedal, 2002)

Methods

Dependent Variables

The dependent variables in this case-crossover analysis were whether one was either any type of hospitalization case, a respiratory or a cardiovascular hospitalization case, as there were multiple analyses. From the CHARS data, patients that had a respiratory or cardiovascular condition as their primary diagnosis were selected out of the total hospitalization data. Secondary and tertiary diagnoses were unavailable in the dataset. Table 9 shows the respiratory and cardiovascular codes that were used for this analysis.

Table 9: Respiratory and Cardiovascular Categories and ICD-9 CM Codes

Category	ICD-9-CM Code
Respiratory	460-519
Acute respiratory infections	460-465
Acute bronchitis and bronchiolitis	466
Other diseases of the respiratory tract	470-478
Pneumonia and influenza	480-488
Chronic obstructive pulmonary disease (COPD) and allied conditions	490-496
Asthma	493
Pneumoconiosis and other lung diseases due to external agents	500-508
Other diseases of the respiratory system	510-519
Circulatory	390-459
Cardiovascular	393-429
Ischemic	410-414

Independent Variables

There were several independent variables in this case-crossover analysis including $PM_{2.5}$ values, age, and gender.

Modeled $PM_{2.5}$ values

Each modeled air quality $PM_{2.5}$ value represents a mean value, per day, as based on the patient's residential zip code.

Age category

For the analyses using six age categories, the categories were based on the epidemiological analysis addressing climate change and mortality by Jackson, et al., 2010.

- 1 = 15 to 44 (reference age category)
- 2 = 0 to 4
- 3 = 5 to 14
- 4 = 45 to 64
- 5 = 65 to 84
- 6 = 85 and older

For the "sensitive populations" analyses, three categories were assessed:

- 1 = Ages 15-64 (reference age category)
- 2 = Ages 0-14
- 3 = Ages 65 and older

Gender

Males and females were coded as follows:

- 1 = Males (reference category)
- 2 = Females

With the case-crossover analysis, each hospitalization "case" is treated separately and serves as its own "control" group. Using SPSS, the case-crossover study design was performed using a conditional logistic regression for cardiovascular and respiratory hospitalizations, with cases stratified by age and gender. The modeled air quality and date of the case was noted. The control group information consisted of the same-day of the week data for the rest of the study period and the modeled air quality and date of the control are noted. For further clarification, if there were two patients from the same zip code that had a respiratory hospitalization on the same day, they would have been treated as two separate cases.

The modeled air quality data for zip codes located in Okanogan and adjacent counties, described in previous chapters, were used for this analysis. Patient residential zip codes were linked to the zip codes in the modeled air quality dataset so that every zip code had a unique modeled $PM_{2.5}$ value for each day. After a preliminary analysis, it was found that there were patients that lived in outside counties and states. Therefore, residence zip codes of patients that did not align with Census 2010 zip codes were not included in the analysis. The data were coded so that the day of the week and week number of the hospitalization were labeled. Using those codes, up to four controls were created for each hospitalization case. The control data consisted of all of the same identifying patient data, but with the change in modeled air quality value for the patient's residential zip code. Once the data were put together, a binary logistic regression was performed. Two separate analyses were performed. The first analysis' dependent variable was whether the hospitalization was a case or control and the covariates included the modeled $PM_{2.5}$ value, age category of the patient, and gender of the patient. The second analysis was almost the same as the first analysis, with the change of the covariates coded as interaction terms with each other.

In addition to the case-crossover analysis of the patient data described above, several additional case-crossover analyses were performed. Prior to the lag model, modeled air quality values were linked to the same day that a patient was admitted. Patients counted as a case based on their associated modeled air quality value on that day and whether they had a respiratory or cardiovascular illness. The scientific literature found that patients became cases after wildfire events. Delfino, et al. (2009) found the two-day moving average of $PM_{2.5}$ (average of today and yesterday) provided the best fitting model that adequately captured the association between $PM_{2.5}$ and admissions. For this analysis, a 3-day moving average lag model was applied.

Case-crossover analyses were conducted for sensitive populations aged 0 to 14 and 65 and older. The grouping of sensitive populations was done using the same day admission for the associated modeled air quality value, as well as a lag model of a 3 day moving average and median values.

The binary logistic regression was done using the dependent variable of whether one is a control or hospitalization case and the covariates of gender, modeled air quality value, and age category. Additional logistic regression analyses were done to include interaction terms of the various combinations of covariates of age category, gender, and modeled air quality values. The research question to be answered is whether a hospitalization case is a control depending on one's age category, gender, and associated air quality for their residential zip code. Separate logistic regression analyses were done for 6 age categories of 0-4, 5-14, 15-44 (reference age category), 45-64, 65-84, and 85 and older and for sensitive age categories of 0-14, 15-64 (reference age category), and 65 and older. For gender, males were coded as 1 and females coded as 2 and males were used as the reference category.

To summarize, logistic regressions were performed for the following combinations.

- All hospitalizations
- Respiratory Hospitalizations
- Cardiovascular Hospitalizations
    - Interaction terms
    - Lag model (mean/median of 3 days prior)
    - Sensitive populations
        - 0-14, 16-64 (reference), 65+

Results

The summary of results are as follows.

- Results are statistically insignificant using standard epidemiologic approaches.
- Results were more defensible using the mean or median values for modeled air quality for the 3 days prior.
- There was an improvement when 3 sensitive age categories were used instead of 6 age categories.

For Okanogan and its surrounding counties, the logistic regression data for all hospitalizations, respiratory hospitalizations, and cardiovascular hospitalizations and their association with air quality impacts are presented in the Tables 10 through 33. All of the Hosmer and Lemeshow tests indicated adequate goodness of fit because all of the tables contain nonsignificant findings. All of the Hosmer and Lemeshow contingency tables also support the model because the expected distributions correspond to the observations in the dataset. None of the classification tables had shown significant results. In analyzing the results of the logistic regression with and without interaction terms, there were some odds ratios above 1, but at an extremely poor significance level. Logistic regression analyses presented in Tables 10 to 33 show final results for all, respiratory, and cardiovascular hospitalizations, either using or not using a 3-day lag model, and 3 or 6 age categories. In interpreting the results, there was a slight improvement in significance values and odds ratios values when the mean or median values for modeled air quality for the three days prior to the hospitalization were used, compared to when the mean on the same day as the hospitalization was used. Age categories for sensitive and non-sensitive populations using 3 age categories also proved to be a more useful measure as opposed to using 6 age categories.

Although the statistical values were not significant, the odds ratios were comparable and in some cases, even larger than the values from Delfino, et al. (2009). An example of the case-crossover analysis results is presented below. Since the air modeling data used in this analysis were not a good indicator of ground concentration levels and it was still possible to obtain comparable odds ratios, there is large potential for future studies to use similar methodologies and obtain meaningful odds ratios.

An example of the case-crossover analysis results using data from Table 29, "Logistic Regression for respiratory hospitalizations (interaction terms, sensitive, comparison of modeled air quality using median of 3 days prior against mean on hospitalization day, is shown below.

- When accounting for a 3-day lag model (using median value) as opposed to the same day, a patient is 1.522 times more likely to be hospitalized for a respiratory hospitalization.

- A female patient aged 65 or older is 1.043 times more likely to be hospitalized for a respiratory hospitalization, compared to a female patient aged 15-64.
- A patient aged 0-14 is 1.063 times more likely to be hospitalized for a respiratory hospitalization compared to someone aged 15-64.

To compare these results against Delfino, et al. (2009),

- When accounting for a 3-day lag model during the wildfire period, a patient is 1.028 times more likely to be hospitalized for a respiratory hospitalization.
- During the wildfire period, a patient aged 65 or older is 1.030 more likely to be hospitalized for a respiratory hospitalization.
- During the wildfire period, a patient aged 5-19 is 1.027 times more likely to be hospitalized for a respiratory hospitalization. A patient aged 0-4 is 1.045 times more likely to be hospitalized for a respiratory hospitalization.

Public Health Population Analysis

The air quality modeling data files were first converted to a usable form for the analysis in ArcMap, from the common data format (CDF) given by the USFS to a TIFF image. This conversion allowed for each pixel to represent an individual day's worth of data for a unique estimated modeled air quality associated value. The USFS air quality modeling data were merged with 2010 zip code Census population data and Washington CHARS hospitalization data in SPSS. The EPA 24-hour $PM_{2.5}$ standard is 35 $\mu g/m^3$. Although the majority of the data consisted of 0 or low values, the 35 $\mu g/m^3$ standard was still used as the basis of the population impacts. Census 2010 data were obtained for zip code population data and aligned with the zip code of the patient's residence zip code. For the 33-day period, respiratory and cardiovascular hospitalizations were analyzed for whether the associated modeled air quality value (based on the patient's residential zip code) was above 35 $\mu g/m^3$. If the modeled air quality value was above 35 $\mu g/m^3$, the zip code's population count was part of the total population of impacted residents. The 2010 Census data included data by ages. The six age categories as well as total population counts were totaled to estimate the possible population impacted by the Tripod wildfire based on modeled air quality data.

Methods

The methods can be summarized as follows.

- Use modeled $PM_{2.5}$ data with 2010 Census zip code data
- Estimate the total population from zip codes with $PM_{2.5}$ modeled estimates greater than EPA's 24-hour $PM_{2.5}$ standard of 35 ug/m^3.

The public health population analysis was done to answer the following question, "What were the larger population impacts of the Tripod 2006 wildfires?" zip codes within the study area and time frame were analyzed for whether there were any days where the daily maximum $PM_{2.5}$ value was above the EPA 24-hour standard of 35 μg/m^3. The data are organized by the total population, and data for the six age categories for the affected zip codes are also displayed. Air modeling data were only available for 33 days of the wildfire, so the public health impacts are only based on the 33 days, and not the period of the entire wildfire event. This analysis was done for zip codes in Okanogan and its surrounding counties. In ArcMap, county boundaries determined which ZCTAs were included in the analysis. ZCTAs that fell out of the county boundaries were included as long as there was a part of the ZCTA that was still contained within county boundaries. Bordering ZCTAs were not included if they were not part of the counties.

Results

Based on zip codes with modeled air quality values above 35 μg/m^3, 5,972 people were estimated to have been impacted in Okanogan and its surrounding counties (Table 34). Three zip codes came up as having modeled air quality values above 35 μg/m^3 for Okanogan and its adjacent counties. The three zip codes and summary modeled air quality data and best estimates for their locations are as follows:

1. 98822: 10 days of data, maximum modeled air quality value of 435.996 μg/m³, Entiat, Chelan County
2. 98856: 6 days of data, maximum modeled air quality value of 167.680 μg/m³, Twisp, Okanogan County
3. 98862: 1 day of data, modeled air quality value of 60.976 μg/m³, Winthrop, Okanogan County

Conclusions

For the public health population and case-crossover analyses addressing hospital relative rates, there was limited data on the number of respiratory and cardiovascular hospitalizations to begin with. Next, within the limited amount data of respiratory and cardiovascular hospitalizations, data was even more limited for non-zero $PM_{2.5}$ days. The limited data made it difficult to obtain robust relative risks above 1. For the case-crossover study design, the many logistic regression analyses did not show results of significance. However, results did slightly improve when the 3-day lag of mean or median values of modeled air quality were used rather than the mean modeled air quality on the day of the hospitalization. Also, the use of fewer age categories to capture vulnerable populations also proved to be more useful. For the public health population analysis, 5,972 people were estimated to have been impacted when the threshold was 35 μg/m³. However, prior analysis on the modeled air quality data showed that there were not many values at the 24-hour EPA threshold, and that there were more zero $PM_{2.5}$ values. The results from these epidemiologic analyses raise the question of whether the modeled air quality data are valid, or more specifically, whether the modeled air quality data are capturing what is happening at ground concentration levels. Given that the air modeling data contained many zero or small $PM_{2.5}$ values, the estimated public health impact in this analysis is likely to have been a conservative estimate. The next chapter will examine the differences between modeled $PM_{2.5}$ concentrations against monitor $PM_{2.5}$ concentrations, which will allow us to validate whether the model has "ground truth".

Chapter 4: Evaluation of the U.S. Forest Service Air Pollution Model

Introduction

The epidemiologic analyses presented in Chapter 3 were based on air quality modeling data from the USFS, Pacific Northwest Research Station. The focus of this chapter was to evaluate whether these modeled air quality values were representative of air monitor values for ground-level concentrations. Using latitude and longitude data from the air monitors, air monitor data from the EPA and USFS were compared to predicted air model data from the USFS.

Assessing Smoke Impacts on Study Area

Given the erratic nature of wildfires, the smoke plumes associated with wildfires vary. There are some wildfires for which smoke plumes stay within a state, whereas some wildfires travel across country or across international boundaries. Wildfires are complex and it is difficult to assess whether or not a particular area may experience negative air quality impacts, especially for estimates across large areas. Also, there are limitations that need to be addressed regarding the available tools that can show regions impacted by wildfire smoke. The two tools include satellite images and modeled air quality or plume data. Model runs done by the Pacific Wildland Fire Sciences Laboratory provide estimates of the extent of the smoke from the Tripod wildfire. According to the Pacific Wildland Fire Sciences Laboratory team, the smoke from the Tripod wildfire went primarily northeast and it would have been unlikely to travel west over the mountains, nor make it as east as Spokane (Strand, Tara, personal communication, May 23, 2011).

Methods

The methods can be summarized as follows.

Part I

- Using ArcMap,
    - Aggregate 33 data images from USFS air model.
    - Overlay the aggregated image with county boundaries from 2010 Census data

Part II

- Use the latitude and longitude of monitor locations from the EPA (26 monitors) and USFS (7 monitors). Counties assessed include Okanogan, Grant, Chelan, Skagit, Whatcom, Stevens, Adams, Benton, Franklin, Kittitas, Klickitat, Lewis, Pierce, and Yakima.
- Using the air model data in ArcMap, develop an averaged $PM_{2.5}$ value per day for 33 days

There is limited information regarding smoke travel for the 2006 Tripod wildfires, as the information is based on model projections and predicted observations. The USFS's modeled air quality data were used to test the model's prediction on where the most smoke was located in the state. To get a general idea of the model's estimate of air quality impacts, all 33 days of air quality modeling data were summed together and spatially joined with county data. Figure 14 shows the cumulative modeled air quality TIFF image used in ArcMap. The sum of the modeled air quality values allows us to obtain understanding of the cumulative smoke impacts estimated during the 2006 Tripod wildfire. Also, before all of the images were added together cumulatively, each modeled air quality TIFF image contained average values for each day. This analysis served as a preliminary analysis for whether the modeled smoke data were showing an accurate assessment of what was happening at ground concentration levels. The assessment by counties was used because there are numerous zip codes across Washington State and air quality data monitors are also organized by counties. The assessment by counties rather than zip codes also allows for a quicker preliminary analysis and a broad overview of where the model predicted that smoke accumulated during the 33 days.

Results

All of the cumulative $PM_{2.5}$ measurements were summed and the 75th percentile value of these measurements was determined using the formula below. The 75th percentile was selected because it is a percentile that would get close to the "Top 10" most impacted counties.

75th percentile = Sum of all of the cumulative impacts/ (38 counties) * 0.75 = 1100 $\mu g/m^3$

Over the 33 days of available data, there were 14 counties that had a cumulative air quality impact above 1100 $\mu g/m^3$. These counties are listed below, in order of highest cumulative impacts to the lowest:

1. Okanogan
2. Yakima
3. Chelan
4. Lewis
5. Grant
6. Benton
7. Stevens
8. Skamania
9. Adams
10. Pend Oreille
11. Pierce
12. Klickitat
13. Franklin
14. Kittitas

Table 36 shows the data for all Washington counties when all of the 33 days of modeled air quality impacts were summed. Table 37 displays data for cumulative smoke impacts for all 33 days, and the average cumulative impact per day. Table 38 displays descriptive data of maximum, minimum, range, average, and standard deviation for data for zip codes within each county in Washington in the cumulative smoke data set. In the next section, the results show counties and their summed modeled $PM_{2.5}$ concentrations in order of highest cumulative concentrations to the lowest.

Figure 15 shows a map with the top 14 counties with a cumulative, modeled air quality impact above 1099.929 $\mu g/m^3$ with the following breakdowns: 1000-1500, 1700-1950, 2000-3000, 4000-6000, and above 9000 $\mu g/m^3$. Figure 16 was also created to highlight these 14 counties and the hospitals located within the counties. Since the cumulative modeled data predicted a different group of impacted counties from proximity estimates, the public health impacts analysis was redone to reflect this change in counties. Based on proximity, the estimated number of citizens possibly impacted is 5,972 people (shown in Table 34). When assessing the population impact specific for the 14 counties as based upon smoke modeled effects, the estimated population impact is 27,529 people (shown in Table 41). This estimate is for any zip codes where there was at least one modeled day with estimated air quality impacts above 35 $\mu g/m^3$. In performing the hospitalization relative rate analysis for the "Top 14" counties, we expanded the dataset. By performing the hospitalization relative rate analysis, we pick up on six additional zip codes.

Air Quality Model and Monitor Sensitivity Analysis

As shown in this research and other recent scientific literature, air models have a tendency to underestimate the air quality at the ground concentration level and overestimate atmospheric concentrations. As shown in the data analyses thus far, there is a disconnect between air monitoring and air modeling values attributed to the Tripod wildfires. Air quality monitoring data for $PM_{2.5}$ were from the EPA Air Quality DataMart, which comprise of regulated, permanent air quality monitors. Additional $PM_{2.5}$ data were obtained from temporary, non-regulatory monitors from the USFS Pacific Wildland Research Laboratory. The USFS data cannot be called air quality data because the data cannot be used for regulatory enforcement.

The air monitoring data from the EPA and the USFS for Okanogan County contained many values above the EPA's 24-hour $PM_{2.5}$ standard. There also were data from other counties that showed large $PM_{2.5}$ values in the EPA and USFS monitoring data. The $PM_{2.5}$ values from monitors near more populated areas may be attributed to sources other than the Tripod wildfires. Air monitors assess for particulate matter beyond wildfires, whereas the air quality model generates estimates only for particulate matter from the Tripod wildfires. In contrast, the modeled air quality data from the USFS consist of many zero values. For zip codes closer to the wildfire, there were still zero and low $PM_{2.5}$ values. The model could be a poor predictor of air quality at ground concentration levels. If we assume that the air quality model data may hold some truth, the hypothesis is that these zero and low $PM_{2.5}$ modeled air quality values may have more meaning when examining scatter plot trends with the data.

The comparison of the air quality model and monitors serves as an important sensitivity analysis. The primary purpose of this chapter is to evaluate the predictive value of the air modeling data. By comparing the monitor data against the modeled data at the exact same location, one can better understand whether the modeled data are a good prediction of air quality, and whether the zero and low $PM_{2.5}$ modeled air quality values may translate to higher values on the air monitoring scale.

Methods

The USFS air quality model generated estimates, which were compared against actual measurement data from the USFS and EPA. The comparison of air monitoring and modeling data was done using the latitudes and longitude locations of the air monitoring stations. This analysis was done on ArcMap by locating the latitude/longitude of the monitoring stations to estimate the model data's value at the exact latitude/longitude coordinate. The EPA monitor data's latitude and longitude follow the North American Datum (NAD) 1927 (EPA, 2008). The USFS GPS system uses the WGS-84 coordinate system and the model output data are on a spherical shaped earth, which is essentially identical to the NAD 1983 (Strand, Tara, personal communication, May 28, 2012).

This analysis was done for the 14 "top" counties where there was the largest cumulative impact from the Tripod wildfires. For this sensitivity analysis, information on the monitor's latitude, longitude, agency in charge, and city location is shown in Table 35. At each of the monitor's latitude and longitude, daily mean air quality values during the 33-day time period were noted. The air quality values associated with the modeled data were matched by the same latitude and longitude location and also by the nearest zip code. The nearest zip code is of interest since our health and population analysis is by zip code, as are much of available health data. Final data results were displayed through scatter plot graphs showing comparisons of monitoring data against modeled air quality data. The monitor's latitude and longitudinal coordinates were used as the location for assessing both the monitor and modeling data, with a unique, averaged $PM_{2.5}$ value for each of the 33 days.

Results

Within the 14 counties with the highest estimated cumulative smoke impacts, all of the monitor locations were assessed against the model's predictions at the exact same location. Table 38 shows the cumulative descriptive statistics for the USFS monitor (non-enforceable) and the EPA monitor (enforceable) data against what the model predicted. The variable 'N' represents the number of total air monitor concentration values. The value in the range column is the same as the maximum for modeled air quality values because the lowest numbers were the zero concentration values predicted by the model. Table 39 shows the descriptive statistics for just the USFS monitor (non-enforceable) data against what the model predicted. Table 40 shows the descriptive statistics for just the EPA monitor (enforceable) data against what the model predicted. As shown in the many figures, the model predicted zero for the majority of the locations, regardless of their distance to the Tripod wildfires. For all of these scatter plots, R values were added to the figures, and the results show that there was very little correlation between the model and monitor data. Figure 17 shows the modeled data for all of EPA and USFS monitor locations on one figure. Figure 18 shows the USFS monitor locations only, and Figure 19 shows only the EPA monitor locations. However, all of the monitors were on a different scale, depending on their location to the wildfire. Therefore, scatter plots were re-created so that every monitor had its own scatter plot. Even after this separate analysis, none of the locations had any demonstrable correlation between its modeled values and monitor values.

An additional analysis was done for all of the monitor locations by removing any $PM_{2.5}$ values where the model predicted zero for the air quality values. If there were at least five predicted $PM_{2.5}$ values above 10, then a new scatter plot was created to assess whether there was any trend in the modeled data against the monitor data. Figures 20 to 23 show the USFS monitor locations which met these criteria while Figures 24 through 26 show the EPA monitor locations which met these criteria. Although all of these selected monitor locations were in Okanogan County, the county of the Tripod wildfires, there did not appear to be any correlation. Figure 22 for Nespelem shows a negative association, and Figures 21 and 26 show an extremely low positive association that is a nearly zero association.

After assessing all scatter plots, it was determined that the modeled data are not predictive of what was actually occurring at ground concentration levels, or there was no "ground truth". For areas located in Okanogan County that were closer to the wildfires, the estimated modeled air quality impacts did not change much compared to areas that were not estimated to have been impacted from the Tripod wildfires.

It is also interesting to note that the model did predict some smoke impacts in areas located west of the Cascades. The areas west of the Cascades were considered to have been unlikely areas to have been impacted based on smoke travel knowledge from the USFS. Therefore, air monitoring data for Whatcom and Skagit counties should not indicate smoke impact from the Tripod wildfire. However, an analysis of the modeled data found some zip codes west of the Cascades where there were air quality modeled values above zero and a few of these values are documented below.

- 2.248 $\mu g/m^3$: August 16, 98267, Marblemount, WA
- 1.292 $\mu g/m^3$: August 16, 98237, Concrete, WA
- 1.166 $\mu g/m^3$: August 18, 98267, Marblemount, WA

- 0.937 μg/m^3: August 16, 98284, Sedro Wooley, WA
- 0.545 μg/m^3: August 16, 98233, Burlington, WA

In comparing the modeled surface $PM_{2.5}$ concentrations to observation comparisons, it is also important to note that the understanding of modeling fire emissions and smoke dispersion was at its infancy (Strand, Tara, personal communication, April 27, 2012). There are more errors associated with the Tripod model runs compared to a fire in the last two to three years (Strand, Tara, personal communication, April 27, 2012). Through simple experiments, Larkin, et al. (2009) identified some specific issues with the model failure, which are as follows:

1. BlueSky used fire information from ICS-209 reports. This fire information was not the most accurate, with errors in reporting geo-referencing and in daily fire growth.
2. BlueSky did not account for enough impacts from smoldering in the emissions calculations.
3. There were errors in the plume rise scheme. BlueSky uses CALPUFF, which has a built in plume rise schema. Because of the reliance on ICS-209 data, the entirety of the fire was being considered as a single plume and run through the built-in scheme which was developed through smokestack observations.

Conclusions

The analysis in this chapter provided the following results:

1. Modeled data showed smoke plume impacts on different counties and zip codes from estimated impacted counties and zip codes of closer proximity to the wildfire.
2. Modeled data did not show "ground truth", as observed by the monitor data.

3. The majority of the air quality values predicted by the model were zero, regardless of location to the proximity of the wildfire.
4. The model predicted some smoke impacts for areas that were not known to be in the wildfire smoke impact zone.

With these findings, although the modeled air quality data are the highest-spatially available data when looking at zip codes, current models need more work. Unfortunately, air quality monitoring data are too limited to contribute to meaningful analyses with health data. Chapter 5 will address research challenges that came up during this analysis. Chapter 6 will address the policy implications from this research and tie up all of the findings and discussion from the analyses in Chapters 1 through 4.

Chapter 5: Research Limitations

The following research limitations will be addressed in this chapter.

- Exposure errors
- Hospitalization data
- Modeling data
- Study area
- Zip codes and other spatial issues
- Determining wildfire impacts
- Confounders

Exposure Errors

There are many potential exposure errors. Janes, et al. (2005) state that studies of acute effects have the potential for exposure measurement errors and that there can be discrepancies between ambient and personal exposures. Monitoring data are limited and it is not completely accurate to assign individuals in an entire county to exposure levels from several monitors. With modeling data and satellite data, the data are still being improved. These data sources do not always provide necessary "ground truth" and data scales vary largely between atmospheric concentrations and ground level concentrations of air quality. In addition, for monitoring data, $PM_{2.5}$ concentrations are caused by a variety of external sources and it is challenging to extrapolate that certain $PM_{2.5}$ levels are due to one source, in this case, wildfire smoke. There also are difficulties in making associations with air quality studies due to a few unresolved issues including a lack of demonstrated biological mechanisms for PM-related effects, confounding by co-pollutants (air toxics), characterization of daily and annual background concentrations, and exposure estimates performed outdoors (Hope, 2005).

Hospitalization Data

There are population limitations to performing broader-scale research with hospitalization data. Exposure was based on zip code of residence in the more robust epidemiologic analyses, so this study was unable to account for vacationers. Using the zip code of the hospital has its challenges, as one does not know if a patient's hospitalization was due to the wildfire. The hospitalization data did not give any information on whether patients could have been repeat patients, or whether a patient came in more than once. Smoke from wildfire events is variable and there is potential to misclassify when a patient may have come in during the wildfire event, especially since with no information on patient locations during a given event. Due to limitations in recording and observing forest fire smoke data, wildfire impacts on human health are still not well researched and known. For many wildfires, including the Tripod 2006 wildfires, hospitalization data are limited for rural areas. In addition, the populations impacted depend greatly on how one characterizes the affected populations.

Modeling Data Limitations

For this research, air quality modeling data were the highest spatial level data available for zip code level analysis. In the epidemiologic analyses in Chapter 3, hospitalization data were linked with air quality modeling data. The air quality modeling data were averaged so that each zip code had an associated value per day. In obtaining this calculation spatially, it may have been possible that the

$PM_{2.5}$ values were a conservative estimate. There were larger $PM_{2.5}$ values in specific pixels that became part of a zip code average.

As shown from the analyses in Chapter 4, the air quality modeling data were not an accurate predictor of what was actually happening at ground concentration levels. Since the air quality modeling data were the air quality data used for analysis with the hospitalization data, the exposures of the patients were improperly categorized. The epidemiologic analyses provided in Chapter 3 had limitations given the inaccuracies of the modeling data in terms of impacted locations and modeled air quality values. The EPA's 24-hour air quality standard for $PM_{2.5}$ addresses $PM_{2.5}$ values greater than 35 $\mu g/m^3$. However, the majority of the air quality values were zero, even for locations that were relatively close to the wildfire.

Although the model proved to be inaccurate, there are often differences in scales between modeled and monitor data. Modeled data can often be difficult to relate to ground concentration data due to its focus on higher atmosphere levels, and the tendency to under-predict ground concentration levels.

Ideally, a test should have high sensitivity and high specificity. In this research, the model did not have sensitivity or specificity. Sensitivity refers to the ability of the model to correctly identify those zip codes that had poor air quality from the wildfires. Even zip codes in Okanogan did not show increased impacts, as had been observed from the monitor data. Specificity refers to the ability of the model to correctly identify those zip codes that had no air quality impacts from the wildfires. There were zip codes that were far away from the wildfire and not in the wind direction of the smoke plume that had associated modeled values associated, whereas areas of more likely impact did not have associated values. Many values were predicted by the model to be zero when there actually were observed values. In addition, when zero values were removed to assess any potential correlations as shown in the scatter plots in Chapter 4, there was a weak trend, even when assessing locations closer to the Tripod wildfire.

Study Area

For the epidemiologic analyses of this research, the study area was Okanogan and its surrounding counties. The original assumption was that smoke traveled to surrounding counties. However, wind patterns may have taken the smoke to other directions. The modeling data predicts smoke in different locations, but the analysis in Chapter 4 showed that the modeling data were not an accurate data source. After assessing the air quality modeling data against ground concentration monitor data, the question of which areas were impacted is still a question. How far did the smoke from the Tripod wildfire really travel? The air monitoring data from the USFS and the EPA are limited to several monitors within a county. In addition, the Tripod wildfire was predicted to have had smoke impacts in Canada, but for the purposes of this analysis, research was limited to Washington State. Smoke impacts are difficult to assess, and with any choice in study area, assumptions have to be made.

There are many difficulties in this type of research with assessing wildfire smoke impact beyond the immediate area of a wildfire. Wildfires occur in rural areas, and there is often not a large impacted population to perform a more robust, epidemiological analysis. In this research, the sample size grew to include those residing in counties surrounding Okanogan County. However, it is possible that there may not have been smoke impacts in some areas of these surrounding counties. It is also possible that there were smoke impacts in different areas outside of the surrounding counties. Given the difficulties of using modeled air quality data systems and the limited data from air monitors, additional research is needed to confirm wildfire smoke plume travel.

Zip Codes and Spatial Limitations

In general, there are spatial issues and caution is necessary in interpreting data involving counties, zip codes, ZCTAs, or others. Zip codes are unstable geographical areas. Zip codes change often over time and are determined arbitrarily. Figure 10 shows the varying spatial boundaries across three sets of zip code data, and how using one zip code data set over the other would affect the exposure classification of patients. Zip codes comprise large areas, and it is possible that analysis by zip codes may miss what is happening at finer spatial scales. However, for privacy reasons, zip codes are the finest spatial scale available for research using hospitalization data. Another limitation is that some zip codes can be part of multiple counties, or other boundaries. Since each zip code has its own associated $PM_{2.5}$ value by day, aggregated data for counties may not be meaningful since the modeled values may differ across locations. Counties are also large areas and combining the data by county may also not be meaningful because the modeled data varies greatly across counties. This limitation is demonstrated in the example below.

In Chapter 4, the theoretical idea of comparing air quality data from a monitor station against modeled data for the nearest zip code to that monitor station seems like a plausible idea. However, further analysis (shown below) demonstrates that this technique does not make sense. To demonstrate the limitations and challenges of this type of analysis, zip codes 98862 and 98856 were examined.

Figure 27 shows the map of Washington State:

- Red lines show zip code borders.
- Yellow dots are the monitoring stations.

- The black/white gradient show smoke plumes – with white showing greater presence of smoke.

To determine the average modeled air quality in μg /m^3 for a zip code, the value for each cell (appears as a pixel in this screen shot) is summed, and then divided by the total number of cells within a zip code. This calculation gives an average value for that zip code, and is a coarse aggregation for the scale. In Figure 28, zip code 98862 is on the left, and zip code 98856 is on the right. Table 42 shows the descriptive statistic values for the two zip codes:

Table 42: Descriptive Statistics Values for 98862 and 98856

ZCTA	Count	Min	Max	Range	Mean	Std	Sum
98862	75	0.0435	7.1443	7.1008	1.1800	1.5781	88.5017
98856	22	0.1320	2.2306	2.0985	0.3408	0.4922	7.4972

Regarding zip code 98862 (left)

There is a large difference in values if one assesses the range for zip code 98862. Each pixel or square is approximately 2.8 miles^2. The zip code on the left is about 32 miles across East/West and about 15 miles North/South. Aggregation to the zip code with granular data is coarse, and the range is extremely large for one end of the zip code in comparison to the other.

Regarding zip code 98856 (right)

If the model were an accurate representation of what was happening on the ground, monitoring point 3 would have a $PM_{2.5}$ value of 0.17 μg/m^3. The monitor itself reports 36.33 μg/m^3. This finding is the first issue with using the point's representation as a means of measuring against the model with the values not being close.

The next explanations are based on the assumptions that the model is correct, and assuming that the monitoring point actually gave the same value as the smoke model. The comparison of 0.17 $\mu g/m^3$ against an average of 0.34 $\mu g/m^3$ for the zip code is going to result in a large disparity. Since many monitors could fit inside a single pixel (2.8 miles x 2.8 miles across), it is methodologically questionable to use extremely granular data (the monitoring location) to evaluate the aggregation to the zip code. The main issue is that a point can exist in one part of the zip code with little or no exposure, while high exposures in another part of the zip code may cause an extremely high result. The issue is not with the monitor or the model, but rather, an issue of comparing different levels of granularity and aggregation with one another. This same issue is a huge problem with crime data.

Even if the model was correct, with the monitoring point reporting the same as the model, and an almost uniform spatial distribution of $PM_{2.5}$ throughout the zip code, zip codes do not have one exclusive monitoring station within them. So both monitors #3 and #4 would be tested against the same aggregate value, despite the wide variation between the two monitors. The scale of the aggregation is incompatible with point measurements for testing the validity of the model due to the granularity of the model data available, and the need to aggregate model data to zip codes.

Determining Wildfire Impacts

Given the nature of the data, the sudden occurrence of wildfires, and because wildfires are found in more rural areas, these reasons limit the type of detailed epidemiological analysis that can be conducted. Wildfires are irregular and unpredictable, and are affected by changing wind and weather patterns. It is often difficult to locate where a wildfire is at a given time because the majority of maps and documents only report the area burned. Progression maps color in the whole area burned to date, and do not indicate which part of the wildfire is now burning. Determining impact from a certain distance from the wildfire event has its limitations since wildfire smoke is variable and does not go in an exact distance from the wildfire extent. Therefore, creating a buffer distance from the wildfire event may miss where smoke impacts could have occurred. If one is interested in just the areas that were burning, MODIS satellite heat detects or infrared flight data from the fire are two types of data that would need to be used. (Potter, Brian, personal communication, January 17, 2012)

Confounders

Given the short time frame available for the modeling data, the opportunity to narrow the days of impact was not available. With respiratory hospitalizations, there may be confounders such as seasonality, as pollen counts may exacerbate respiratory conditions at certain times during the year. There may also be other factors that cause certain types of hospitalizations to peak. Ideally, follow up studies could analyze the impact of hospitalizations for the previous or following years. However, exposure data on wildfires are limiting for this type of research. It is widely known within the research literature that there are weekend/holiday effects with hospitalizations. For example, hospitalizations are often higher on days such as Monday. However, this case-crossover analysis with cases also being their own controls adjusts for any day-of-the-week effects.

Chapter 6: Policy Implications, Recommendations, Suggestions for Further Research, and Conclusions

Policy Implications

Global Climate Change Impacts on Wildfires and Health Costs

In a future of possible increased climate change effects, increased occurrences in wildfires and heat waves (which build the environment for wildfires) are projected. As shown by Johnston, et al. (2012), wildfires have a large estimated impact on global mortality, especially in Sub-Saharan Africa and Southeast Asia. Projections show increased frequency and severity of wildfires and longer fire season in western United States (Kovalev, et al. 2009). For Washington State, the best statistical models suggest that wildfire area burns will increase 2-3 times by the 2080s (Littell, et al. 2010).

All of these projections have large economic and health cost implications. Estimating the health costs of climate change is important for informing health policy decisions but these estimates have not been part of the discussion. Prior studies have estimated future health costs related to climate change but these figures are not specific enough to form the basis of health policy decisions (Knowlton, et al. 2011). Economic costs can be estimated either by a willingness to pay (WTP) approach or a cost of illness (COI) approach. These methods estimate health costs in either monetary terms, or physical units such as the number of lives saved or the number of cases of illness avoided (Knowlton, et al. 2011). Another approach is to use indicators such as quality-adjusted life-years, which incorporates both mortality and morbidity effects (Knowlton, et al. 2011). A better understanding of the range of economic impacts of climate change on health risks, such as wildfire impacts, could help prioritize preparedness efforts to reduce vulnerability, costs, and losses, and improve the US population's ability to withstand the effect of climate change (Knowlton, et al. 2011).

Wildfires have the potential to have large hospitalization costs. There have been very few studies that have analyzed wildfire-smoke exposure to estimate health-related economic costs. The 5-day average hospitalization has been documented as $10,000, with willing-to-pay costs to be even greater, as shown in Table 43 (Kochi, et al. 2010). Kochi, et al. (2010) found that the magnitude of these costs depends on three factors: the scale of the wildfire event, demographic characteristics of the population exposed, and the type of adverse health outcomes considered.

The 2003 fires in Southern California covered 736,597 acres and destroyed 3,631 structures, and the cost of responding to the fires was more than $3 billion. Knowlton, et al. 2011 estimated health costs by using both mortality and morbidity data. Mortality estimates associated with smoke inhalation were based on a ratio derived from the 2003 Healthcare Cost and Utilization Project that was applied to hospitalization counts (Knowlton, et al. 2011). Smoke-related morbidity data were taken from the Delfino, et. al (2009) research that determined excess hospital admissions in the affected counties for respiratory and cardiovascular issues. Knowlton, et al. (2011) calculated that health cost estimates from the 2003 Southern California wildfires to be $578 million (in U.S. dollars, 2008), with $545 million from premature deaths and $34 million from respiratory and cardiovascular illnesses.

Projected Public Health Costs from Tripod 2006 Wildfires

For the 33-day study period, respiratory and cardiovascular hospitalization costs are available, independent of exposure data. Since the modeled air quality values were not found to be meaningful, this research did not produce relevant relative risks for use with hospitalization cost data. However, the Delfino, et al. (2009) research did provide relative risk estimates for pre-, during, and post-wildfire periods based on increased $PM_{2.5}$ value of 10 $\mu g/m^3$. Using relative risk estimates from Delfino, et al. (2009) with hospitalization cost data for Okanogan County provided by the Washington State Department of Health, it was possible to estimate attributable costs due to the Tripod 2006 wildfire. The maximum $PM_{2.5}$ value observed over a 24-hour period from EPA monitors was 161 $\mu g/m^3$, from the 118 S Glover St, Twisp, WA monitor. The maximum $PM_{2.5}$ value observed over a 24-hour period from USFS monitors was 1659 $\mu g/m^3$, at the Eight Mile monitor. For the purposes of this analysis, the EPA monitor from Twisp, WA showed a maximum value of 161 $\mu g/m^3$, which was used in this analysis for a more conservative estimate compared to the USFS monitors.

The following formulas were used:

(Wildfire Period Relative Risk) – (Pre-Wildfire Relative Risk) = Difference in Relative Risk

The relative risk estimates from Delfino, et. al (2009) are based on values per 10 $\mu g/m^3$, so

Estimated Percentage of Costs due to Wildfire

= (Difference in Relative Risk) * 161 $\mu g/m^3$ *100%

This value is then multiplied by hospitalization costs in Okanogan County to determine the final hospitalization costs in Okanogan County due to estimated Relative Risks.

Table 43: Estimated Hospitalization Costs in Okanogan County during the 2006 Tripod Wildfire for a 33 day period (August 14 – September 15, 2006)

Health issue	Age	Wildfire Period Relative Risk	Pre-Wildfire Period Relative Risk	Estimated Percentage of Costs due to Wildfire	Hospitalization Costs in Okanogan County	Hospitalization Costs in Okanogan County due to Estimated Relative Risks
Respiratory hospitalizations	All ages	1.028	1.022	9.66%	$844,190	$81,549
Cardiovascular hospitalizations	All ages	1.008	0.992	25.76%	$429,270	$110,580
Asthma (493)	All ages	1.048	0.998	80.50%	$12,510	$10,070
Chronic obstructive pulmonary disease (COPD) and allied conditions (490-496)	All ages	1.038	1.007	49.91%	$79,055	$39,456

Our best estimate of the 2006 Tripod wildfire on respiratory hospitalization costs were about $81,549 and cardiovascular hospitalization costs at $110,580, for a total of $192,129. However, estimated percentage of costs due to the Tripod wildfire are higher for some conditions such as asthma at 80.5 percent association, and chronic obstructive pulmonary disease at 49.91 percent. However, the variability in $PM_{2.5}$ values indicates that hospitalization costs attributable to the wildfire could have been much higher. Since the wildfire event went on for several months, the estimated health costs would have varied, depending on how the study location was defined. These cost estimates were done for only Okanogan County, and smoke from wildfires have the potential to spread across further distances. The USFS has an annual budget of $5.5 billion and spends $2.3 billion, or almost half of its annual budget on suppressing wildfires (USDA, 2013). Public health costs and economic costs from wildfires are generally not considered, yet can be greatly substantial, even with conservative estimates such as our example in Table 43.

Recommendations

1. Increase governmental agency coordination.
2. Improve air monitoring, modeling, and satellite data systems.
3. Further research to address the impact of wildfire events on air quality and hospitalizations. (Future Research Suggestions)

Increase Governmental Agency Coordination.

The research question of how wildfires impact public health and health hospitalizations is an interdisciplinary question because of its impacts—socially, environmentally, economically, and in terms of health. In locating data on air monitoring through the course of this research, it was found that air monitoring and air modeling efforts are done by many governmental agencies. Enforceable and permanent air monitors is compiled in the EPA Air Quality DataMart database. However, non-enforceable air monitors are not shared across agencies. Temporary air monitors provide useful data, often closer to where there are increased exposures to an event such as a wildfire. However, the data are not as publicly accessible, which makes it difficult to know whether such data even exists. Some local health agencies and governmental agencies, including federal agencies such as the EPA and USFS, perform air quality modeling for various public health events. There is a huge potential to coordinate data efforts across local health agencies and other governmental agencies. During wildfire events, it is not clear for citizens to know which agency to contact to receive further information. Just as an example, some agencies that were involved during the Tripod wildfire event include the USFS, EPA, Washington State Department of Health, Washington State Department of Ecology, National Wildfire Coordinating Group, among many others including local health and wildlife agencies. Coordination would likely improve the quality of responses. This research showcases the need for health protection data to be coordinated with air quality and wildfire data, through the respective government agencies.

After the Tripod wildfire, there were some follow-up meetings to discuss future collaborations on research and response. On June 25, 2007, a wildfires and public health response meeting was held in Ellensburg, WA by the Washington State Department of Health, with assistance from the Washington State Department of Ecology, Chelan-Douglas Health Department, and the Public Health Emergency Planning and Response (Washington State Department of Health, 2008). Funding for the meeting was provided by the Washington Environmental Health Tracking grant, which was also a Centers for Disease Control and Prevention grant. On August 6, 2008, a wildfires workshop was organized by the Washington Department of Health to get various agencies that may be working together during a wildfire event together and coordinate plans, and also provide information for health messaging to public health agencies (Washington State Department of Health, 2008). For the 2008 workshop, there was a diverse group of attendees from the natural resources, air quality, health, and forest agencies locally and federally. The main conclusions from the meetings were the need for increased resources at the state, local, and federal level, better coordination among emergency management personnel and between states, research on wildfire health effects on people impacted by the smoke and workers, shelter and equipment including clean air shelters, air conditioners and air conditioners, and preplanning for people at increased risk.

However, due to lack of resources, to the knowledge of the Washington Department of Health, there has not been follow-up on some of these issues nor another meeting with interdisciplinary parties to address these issues.

Most recently, the summer 2012 wildfires in Washington State activated the incident command structure at the Washington Department of Health. There was coordination with local, state, and federal response agencies. Technical support was provided to local health on ambient air quality public health impacts (Bardin, 2012). Over 53,000 N95 respirator masks were provided to local health agencies, documents were created on frequently asked questions on smoke and health in English and Spanish, and indoor air quality technical assistance was provided by the Washington Department of Health (Bardin, 2012). Further interdisciplinary coordination could improve emergency response strategies and data analysis work addressing health impacts from wildfire events.

Improve Air Quality Monitoring, Modeling, and Satellite Data Systems

From the air quality analysis regarding the top wildfire events from 2001 to 2009, and a more in-depth analysis of the 2006 Tripod wildfires, it was found that there are limited air monitors. Wildfires typically occur in more rural areas, where air quality monitoring is sparse compared to more urban areas. As shown in Figure 1, there may be only one to a few permanent air quality monitors for an entire county. By increasing the air monitoring network, it will be possible to improve the assessment of air quality levels for public health protection. Permanent air quality monitors that are tied to enforcement actions are limited. However, there are also temporary monitors that are not tied to enforcement. These temporary monitors are used by many government agencies and research. While permanent monitors are being added, these temporary monitors could greatly inform future public health research. In addition, there is a large potential for novel technologies, which are further addressed in the next section. There are also many improvements that need to be made on air quality modeling and satellite data. There is limited research on air quality modeling efforts in addressing wildfire events, with much of the known research documented in Chapter 1. Air quality models and satellite systems for wildfire events have under predicted the air quality at ground level. Many models are based off of satellite data and most satellite instruments have difficulties distinguishing particles at ground level from those at higher atmospheric levels. In addition, clouds tend to obscure the view, and bright land surfaces, such as snow, desert sand, and those found in certain urban areas can mar measurements (NASA, 2010).

Further Research Suggestions

As mentioned in the previous section, to adequately address the health impacts of $PM_{2.5}$ during wildfire events, there needs to be improved air quality monitoring and modeling data. Future studies could do a similar study design method as Henderson, et al. (2011) by using a combination of data from air quality monitoring networks, air quality modeling, and satellite images. Research is limited in merging the interdisciplinary fields of forest science and environmental health on addressing wildfires and their impact on human health. Future studies should also distinguish exposure impacts to sensitive populations, which would include asthmatics, children, pregnant women, and the elderly (aged 65 years and older), smokers, and individuals with pre-existing conditions. Although the air quality model was not an accurate predictor, more meaningful results were obtained when age categories were categorized by sensitive age categories. Depending on the data, duration and the level of exposure will vary. For example, for this study, air quality modeling data were only available for 33 days.

There are also other study designs to address the limitations of the epidemiological study designs in this research study. This research study design focused on the larger population at risk. There are other possible research designs that focus on a smaller population impacted by wildfire events, as well as upcoming and novel ideas in using new technologies to address the health impacts of wildfire events. For example, research has been done to address smoke exposures by firefighters during wildfire events, using individual exposure monitors. Given the limited air quality monitoring resources available, simpler and more inexpensive air sampling technologies could be employed, such as passive air samplers. Passive air samplers do not use electricity or other highly technical equipment, used by traditional air quality monitors. There is also potential to use cameras from the Department of Transportation and other agencies to assess air quality impacts. There is also research done on using surveillance cameras to measure air quality by detecting particulate matter pollution levels. Research by Wong, et al. (2007) showed that air quality remote monitoring sensors using internet protocol camera and internet video cameras produced real time air quality information with high accuracies, and that internet protocol camera gives an alternative way to overcome the difficulty of obtaining satellite images in the equatorial region and provides real time air quality information. Such surveillance cameras could serve a dual purpose at schools for security as well as part of a larger air monitoring network. There is additional future work to be done in to improve assessing particulate matter and visible range levels using surveillance cameras.

Smartphones could also be used as a tool for participatory air quality monitoring. Hasenfratz, et al. 2012 recently used smartphones to build a large-scale sensor network of mobile devices for participatory air pollution monitoring, and found the process to be feasible through their GasMobile prototype system. The GasMobile prototype system consists of a low-cost ozone sensor to an off-the-shelf smartphone running the Android OS (Hasenfratz, et al. 2012). By involving the general public, the usage of mobile devices helps to raise public awareness and encourages the behavior changes about the environment, as well as providing a large network of air quality data. Future engagement challenges with using smartphone devices to measure air quality include making the process unobtrusive and user-friendly and promoting participation and awareness of this option among the general public. Technical challenges include addressing data quality of mobile sensors as well as in the communication and information systems infrastructure because of the move from isolated well controlled systems to an open and scalable infrastructure where there will be large amounts of data sharing (Hasenfratz, 2012). Recent work has also been done by researchers in Dr. Sukhatme's Robotics Laboratory at the University of Southern California through an Android application called Visibility. The Visibility application allows users to take a photo of the sky while the sun is shining and compare the image to established models of sky luminance toe estimate visibility (Mankin, 2010). The result is sent back to the user and the data are also used to create pollution maps for the region (Ganapati, 2010). However, the work is still in being developed and improved. More recent and active work is being done by computer scientists at System Energy Efficiency Lab in University of California San Diego with their work in building a small fleet of portable pollution sensors that allow users to monitor air quality on smartphones. CitiSense is the only air quality monitoring system capable of delivering real-time data to users' cell phones and home computers, at any time (Patringenaru, 2012). CitiSense sensors detect common pollutants emitted by cars and trucks which include ozone, nitrogen dioxide, and carbon monoxide, so this work would not be relevant to wildfires. However, air quality monitoring and smartphones is a growing and new field, with a lot of exciting future developments and improvements.

There are also other technologies and data that could increase data on impacted residents. During wildfire events, with patient consent, patients could use their waiting room time to participate in future studies. To streamline the process, mobile technologies such as the Ipad could be used. To increase the number of potential patients, future research could look at 911 calls and ambulance data and link the data to hospitalization data. Additional future work will also need to be done in emergency preparedness and response. For workers and citizens, such areas include rescue and response, improving communication, and risk management strategies and techniques. Wildfires often occur in and affect rural communities, who are vulnerable populations because medical services are generally harder to access or unavailable in rural communities.

Conclusion

The following five points are key findings of this research.

1. Air quality impacts from wildfires are difficult to assess. There is also limited research literature assessing health hospitalizations from wildfire events, especially using modeled air quality and satellite data systems.
2. Air monitor data from the EPA and the USFS showed that there were higher than normal air quality impacts during the 2006 Tripod wildfire event.
3. No significant results were found for modeled air quality data systems and their impacts on cardiovascular and respiratory hospitalizations in several epidemiological analyses by hospital zip codes and residential zip codes.
4. Current air quality model data systems are not accurate predictors of ground-level air monitors.
5. Policy recommendations to improve this type of research include increasing governmental agency coordination, improving the air quality monitoring network, and having further research on the impact of wildfire events on air quality and hospitalizations, using air quality monitor and observational data systems, air quality model data systems, and satellite data systems.

As the analyses have shown, air quality impacts from wildfires are difficult to assess. Wildfires are variable, complex, and occur in areas with a limited monitoring network. With modeling and satellite data, it is so important to have "ground truth". Existing modeled and satellite data focus on higher atmosphere level and may not show "ground truth". It is important to understand how the smoke travels during wildfire events. This research supports the literature finding that existing air quality models need further improvements. Existing air quality monitoring networks are too limited to be the main source of data. A combination of high quality resolution data encompassing air quality monitoring, air quality modeling, and satellite data would be ideal, if there are available data to address the impact of wildfires on air quality and human health.

In a future of possible climate change impacts, wildfires are predicted to increase in severity and frequency, which has large public health and economic consequences. The summer of 2012 has seen many severe wildfires in Washington State, as shown in Figure 29. Although there is still much work to be done to improve available air monitoring, air modeling, and satellite data, this research has shown that it is possible to use diverse datasets to answer the research question of how wildfire smoke impacts hospitalizations.

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Chapter 8: Tables and Figures

Chapter 2: Characterization of Air Pollution

Table 1: Major Washington Wildfires from 2001-2009 and Available Air Quality Data

Dates (Start and controlled end dates)	County (location)	Name of Fire/Complex	Acres Burned	Number of available EPA Air Quality DataMart Monitors
8/12/01 - 8/26/01	Okanogan (Western portion of Colville Reservation, 12 miles south of Okanogan)	Virginia Lake Fire/Virginia Lake Complex	36,680 - 36,685	1
8/12/01 - 8/29/01	Okanogan (12 miles south of Okanogan)	St. Mary's Mission/Virginia Lake Complex	32,980 - 33,071	1
8/12/01 - 11/19/01	Chelan/Okanogan	Rex Creek, Rex Creek Complex	55,913	Okanogan (1)
8/17/02	Okanogan	Quartz Mountain Complex/Quartz Mountain Complex	12,144	2
6/29/03 - 10/28/03	Okanogan	Fawn Peak Complex/Fawn Peak Complex	81,343	3
6/29/03 - 10/28/03 (*12/31/03)	Okanogan (Methow Forest)	Farewell	81,343	3
8/5/03 - 1/26/04 (*10/30/03)	Okanogan (Methow Forest)	Needles	21,300	3
6/26/04 - 11/1/04	Chelan (Chelan Forest)	Pot Peak/Sisi Ridge Complex	17,226	1
7/18/04 - 11/1/04	Chelan (Chelan Forest)	Deep Harbor, Pot Peak/Sisi Ridge Complex	29,700	1
7/24/06 - 11/9/06 (*12/1/06)	Okanogan (Okanogan, Methow Forest)	Tripod Complex	113,011 (175,184 when combined with Spur Peak)	3
8/22/06 - 11/9/06 (*12/1/06)	Okanogan (Methow Forest)	Tatoosh	51,671	3
7/3/06 - 11/9/06 (*12/1/06)	Okanogan (Methow Forest)	Spur Peak	62,173	3
8/21/06 - 12/1/06	Columbia/Garfield (Walla Walla)	Columbia Complex	109,402	Columbia (1)
8/5/07 - 1/11/08 (*1/7/08)	Chelan (Chelan, Chelan Forest)	Domke	11,791	3

Figure 1: Historical and Current EPA Air Quality DataMart Monitors Addressing $PM_{2.5}$ Concentrations

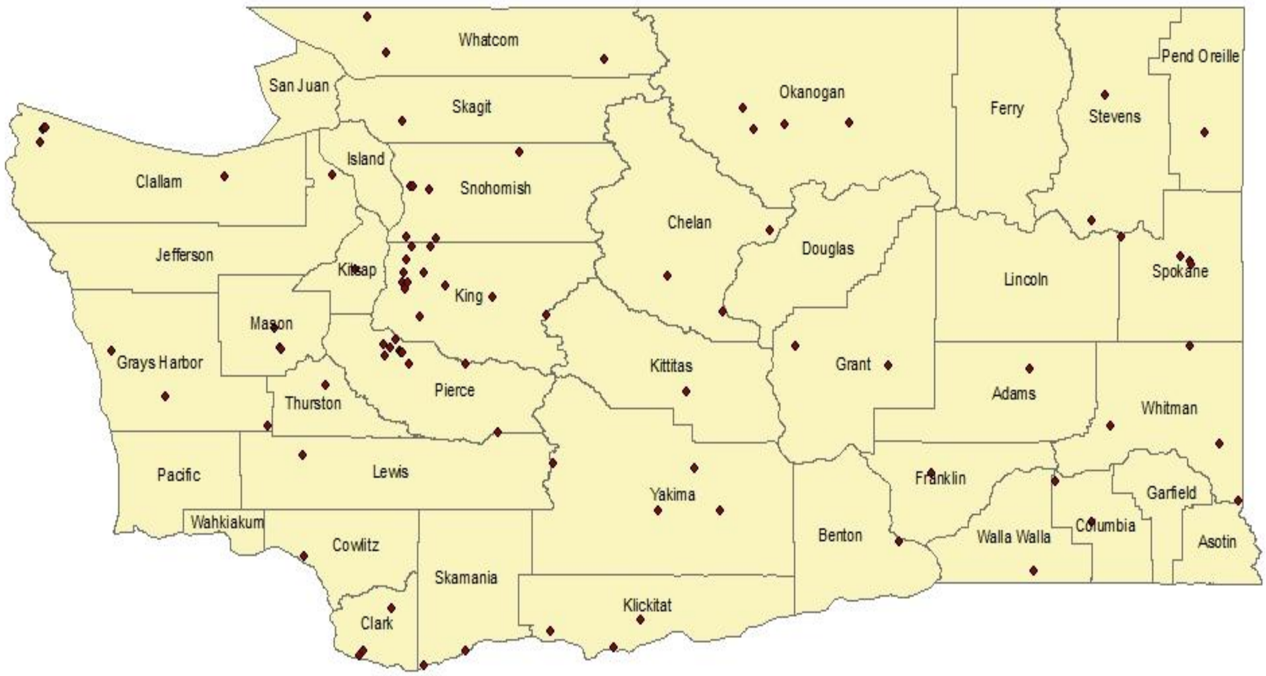


Figure 2: BlueSky Framework (Pacific Northwest Research Station, 2006)

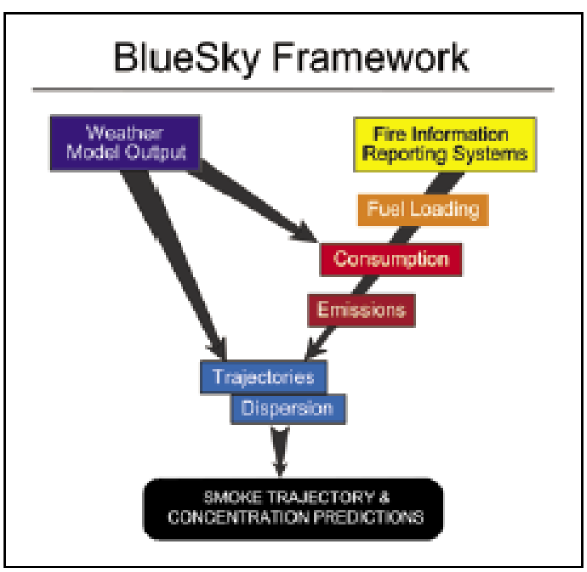
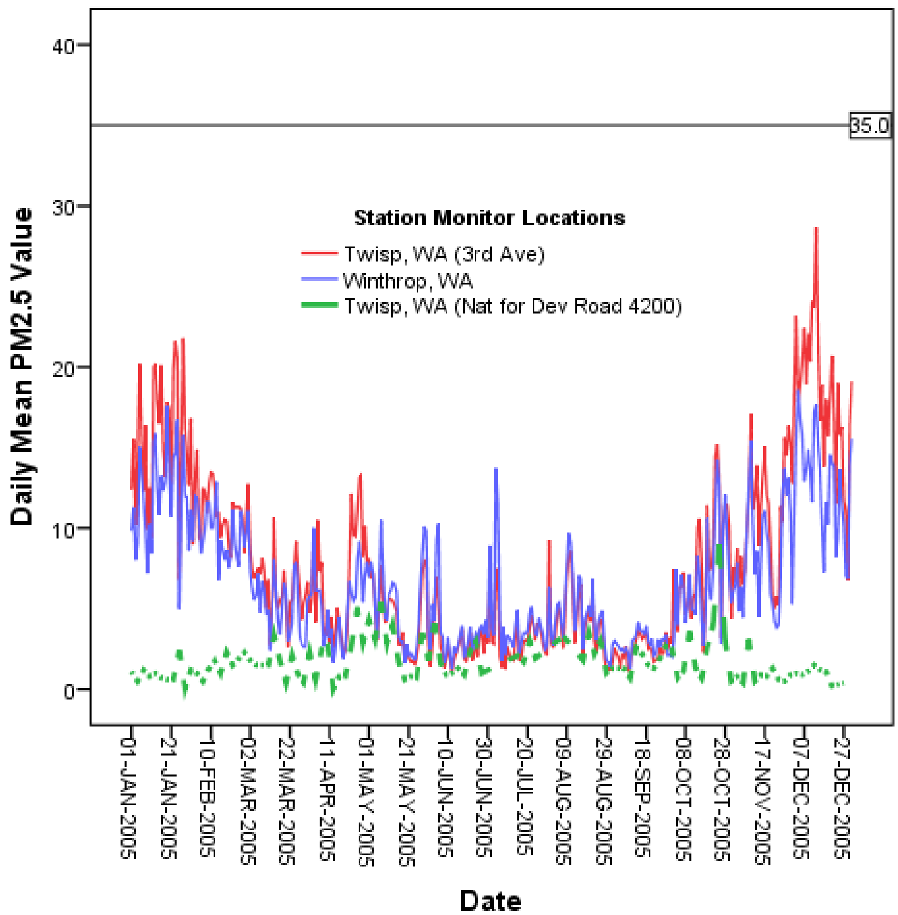
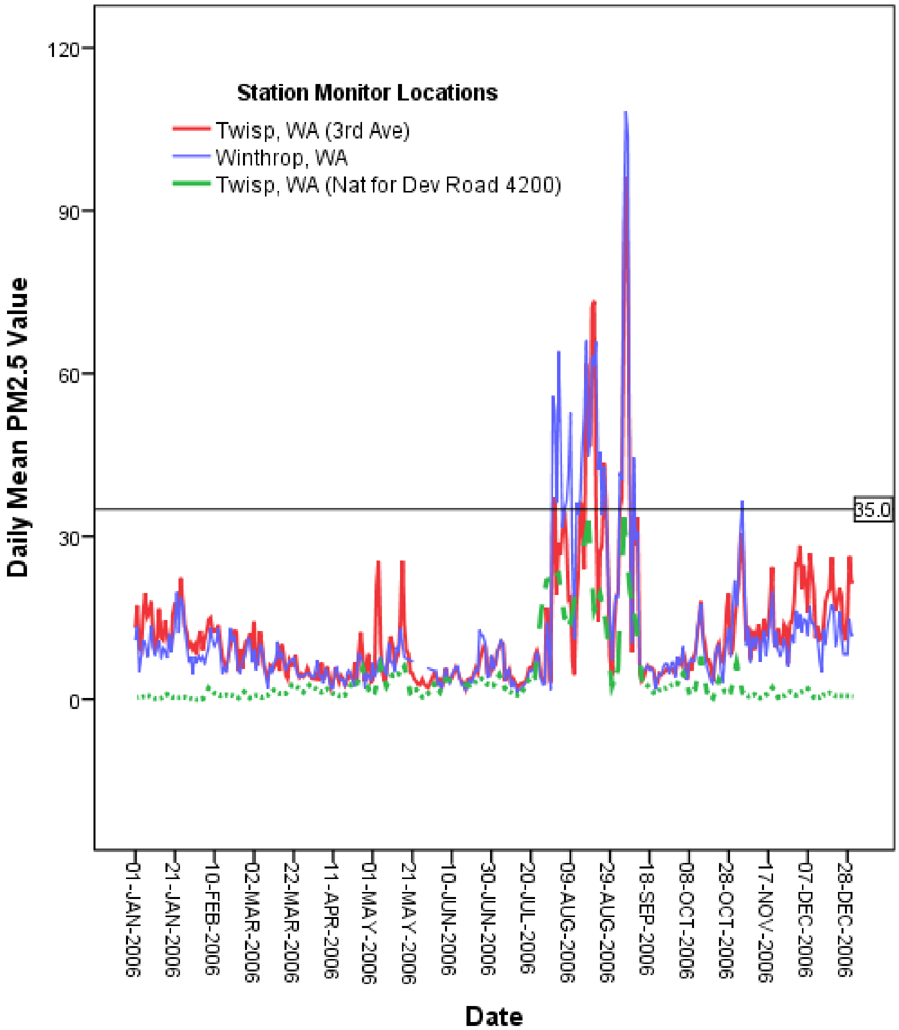


Figure 3: 2005 EPA Air Quality DataMart Data for Okanogan County



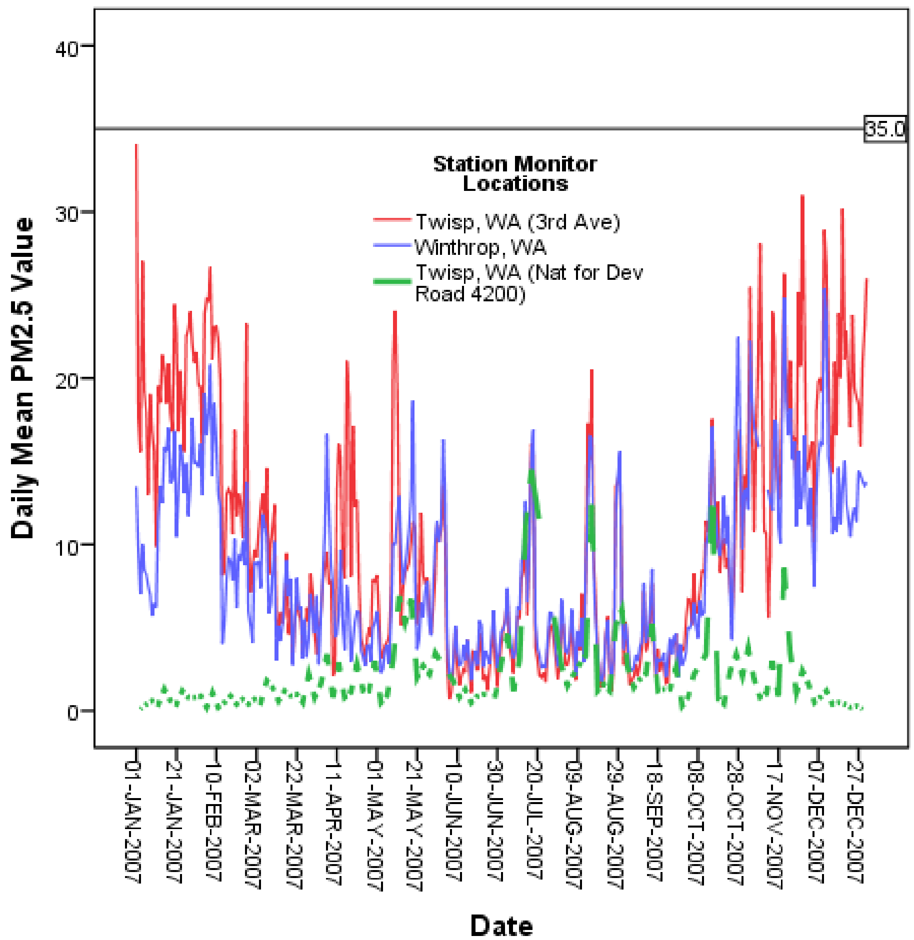
Note: Reference line indicates U.S. EPA's PM2.5 24-hour standard of 35 µg/m³.

Figure 4: 2006 EPA Air Quality DataMart Data for Okanogan County



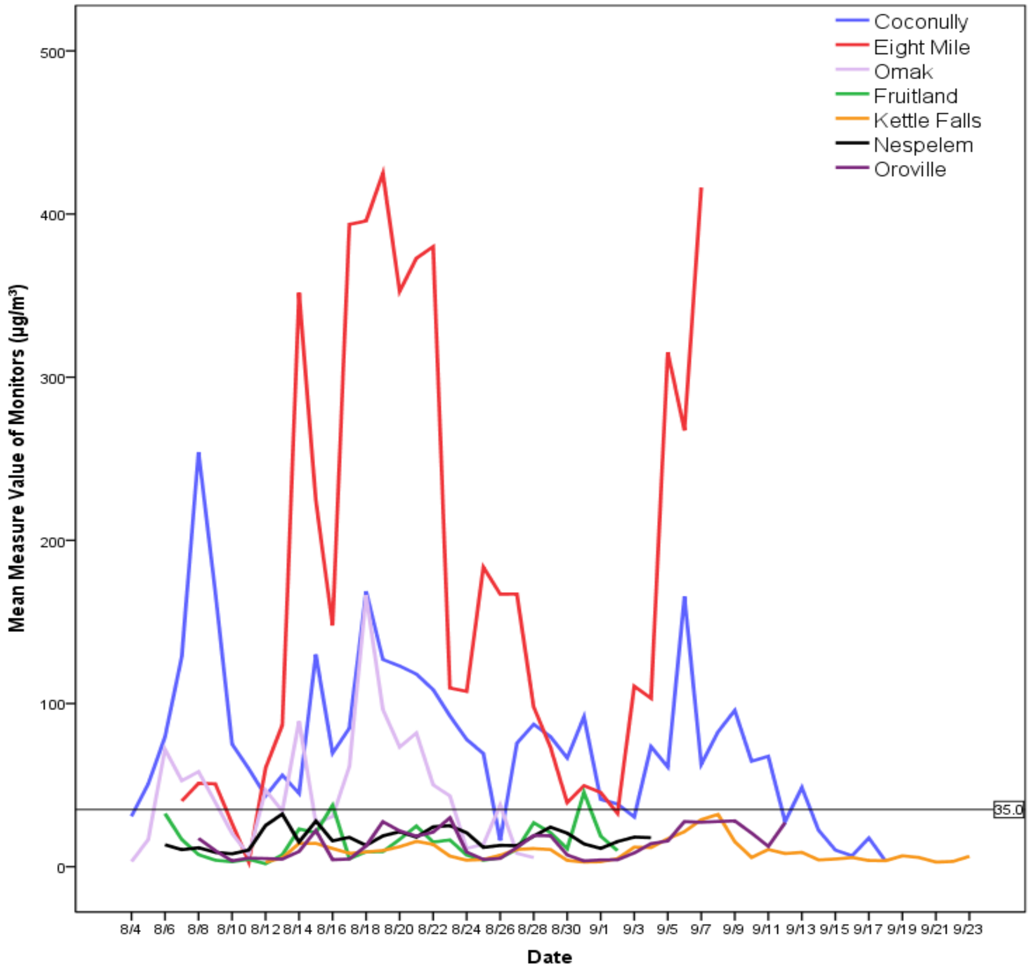
Note: Reference line indicates U.S. EPA's PM2.5 24-hour standard of 35 µg/m³.

Figure 5: 2007 EPA Air Quality DataMart Data for Okanogan County



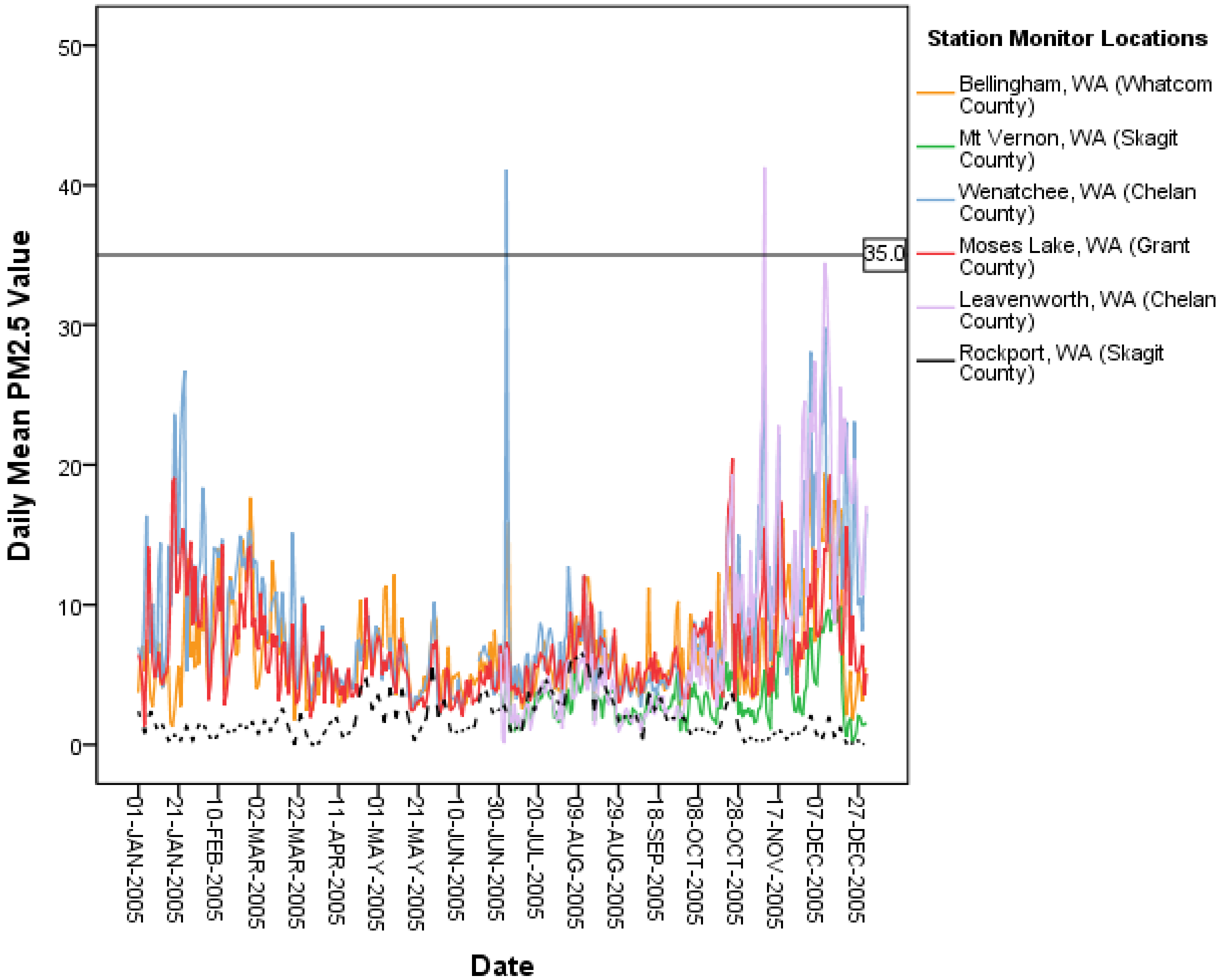
Note: Reference line indicates U.S. EPA's PM2.5 24-hour standard of 35 µg/m³.

Figure 6: Air Quality Monitoring Data from U.S. Forest Service Pacific Wildland Fire Sciences Laboratory for August and September 2006



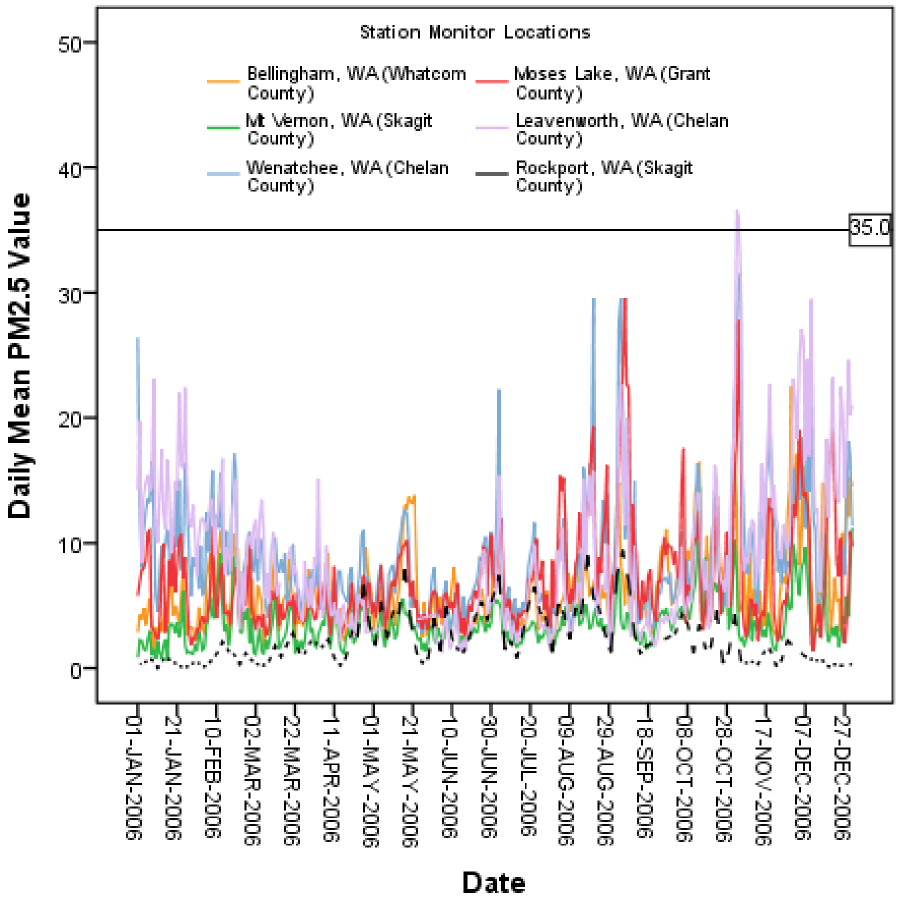
Note: Reference line indicates U.S. EPA's PM2.5 24-hour standard of 35 ug/m³.

Figure 7: 2005 EPA Air Quality DataMart Data for Counties Surrounding Okanogan County



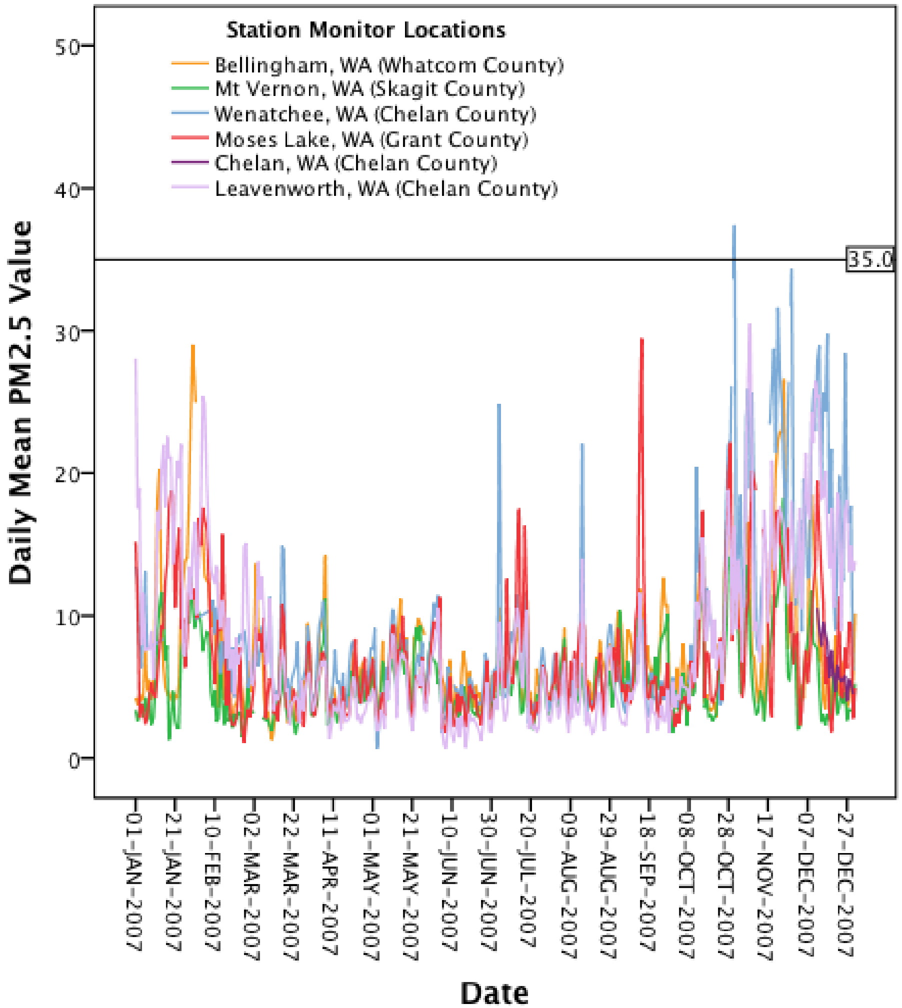
Note: Reference line indicates U.S. EPA's PM2.5 24-hour standard of 35 µg/m³.

Figure 8: 2006 EPA Air Quality DataMart Data for Counties Surrounding Okanogan County



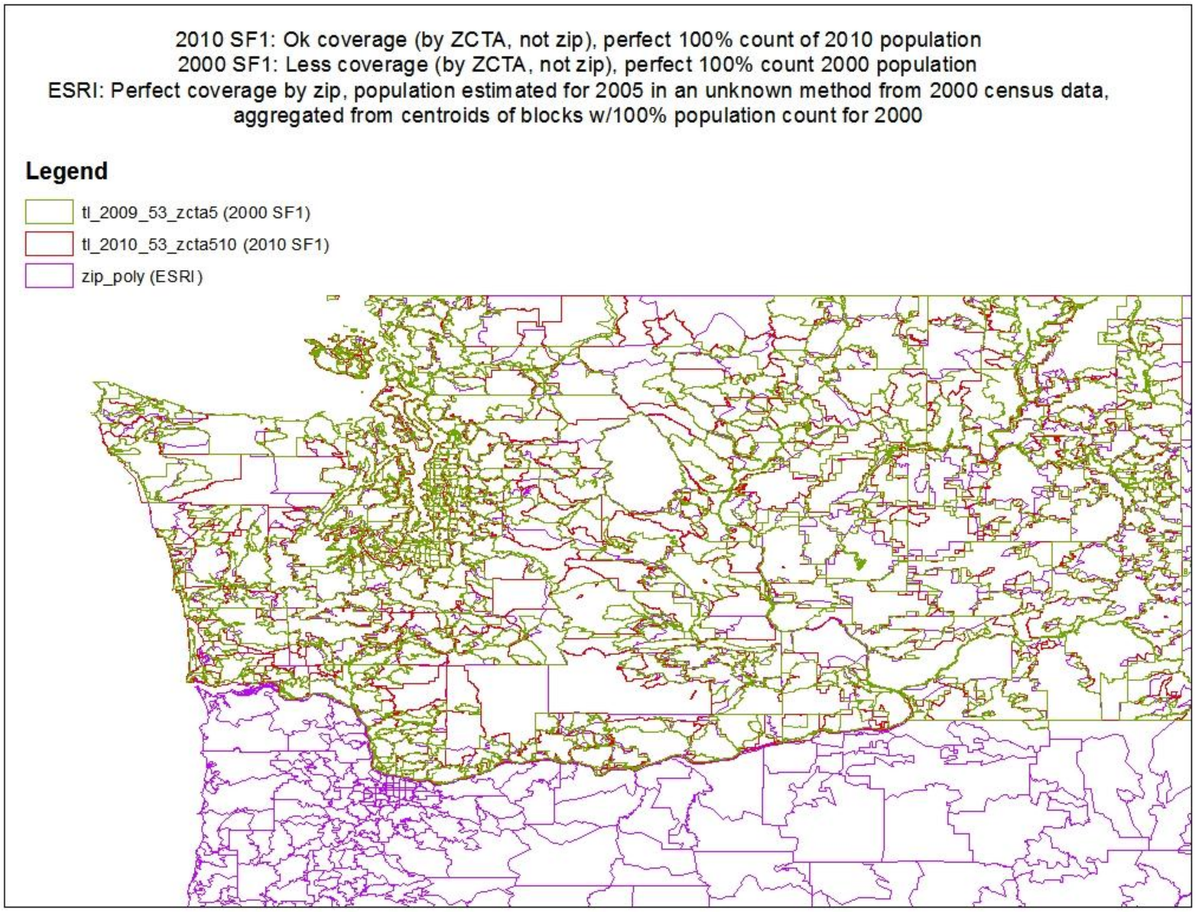
Note: Reference line indicates U.S. EPA's PM2.5 24-hour standard of 35 ug/m3

Figure 9: 2007 EPA Air Quality DataMart Data for Counties Surrounding Okanogan County



Note: Reference line indicates U.S. EPA's PM2.5 24-hour standard of 35 μg/m³.

Figure 10: Spatial Coverage Differences for 2000 and 2010 Census Data and 2006 ESRI Data for Washington Zip Codes



Chapter 3: Epidemiologic Analysis of Air Pollution Impacts on Hospitalizations

Figure 11: Hospital Locations and Surrounding Counties Based on Proximity

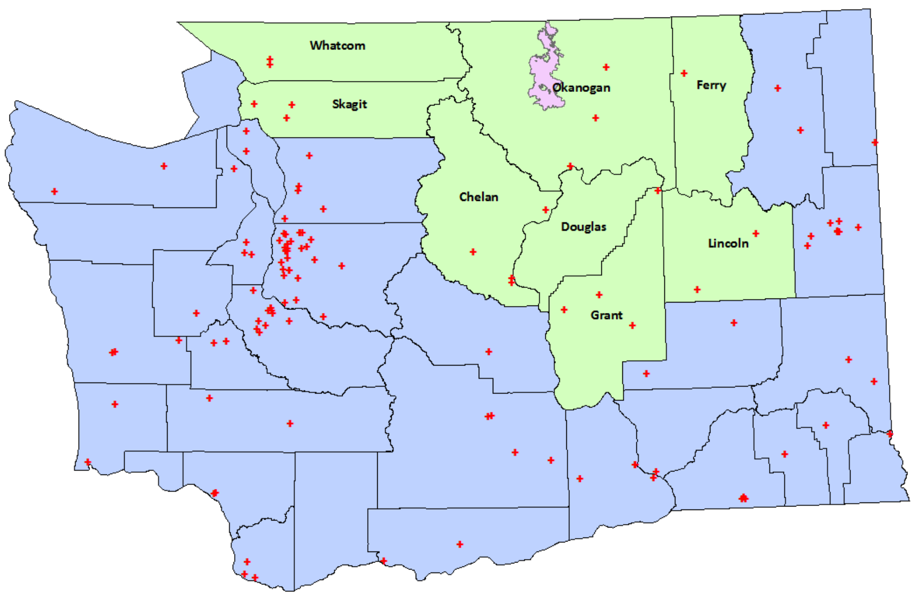


Figure 12: Selected Hospitals with Relative Risks Greater than 1 for Respiratory Hospitalizations

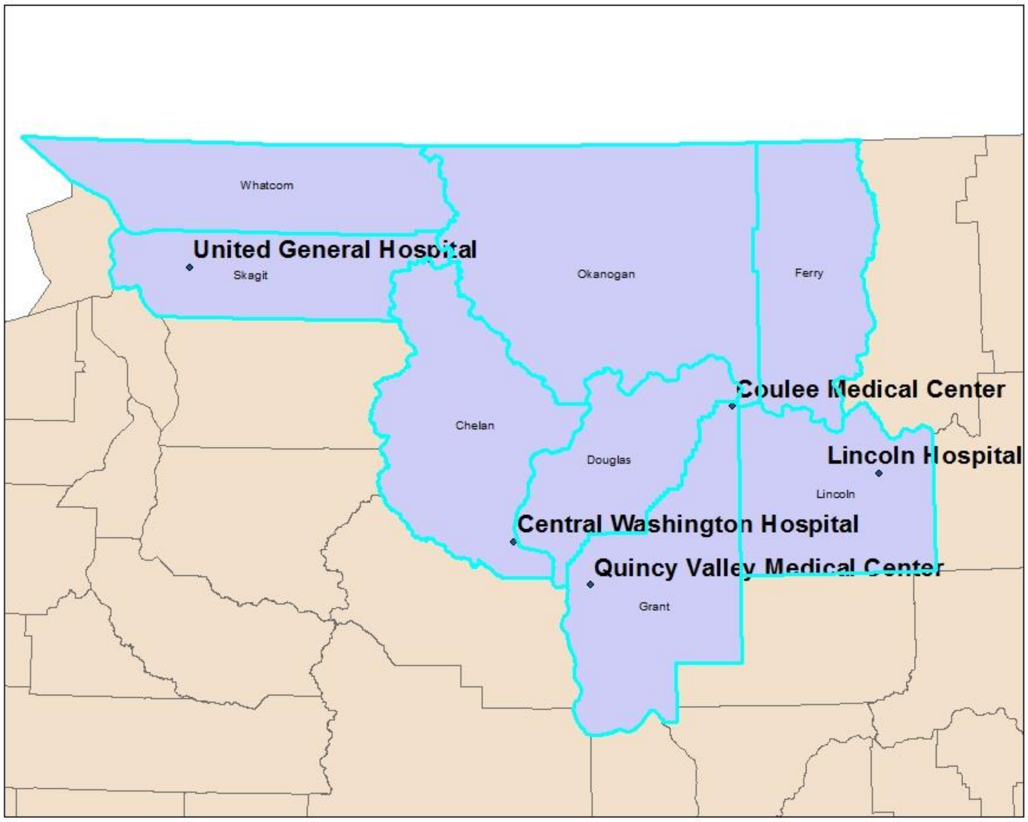


Figure 13: Selected Hospitals with Relative Risks Greater than 1 for Cardiovascular Hospitalizations

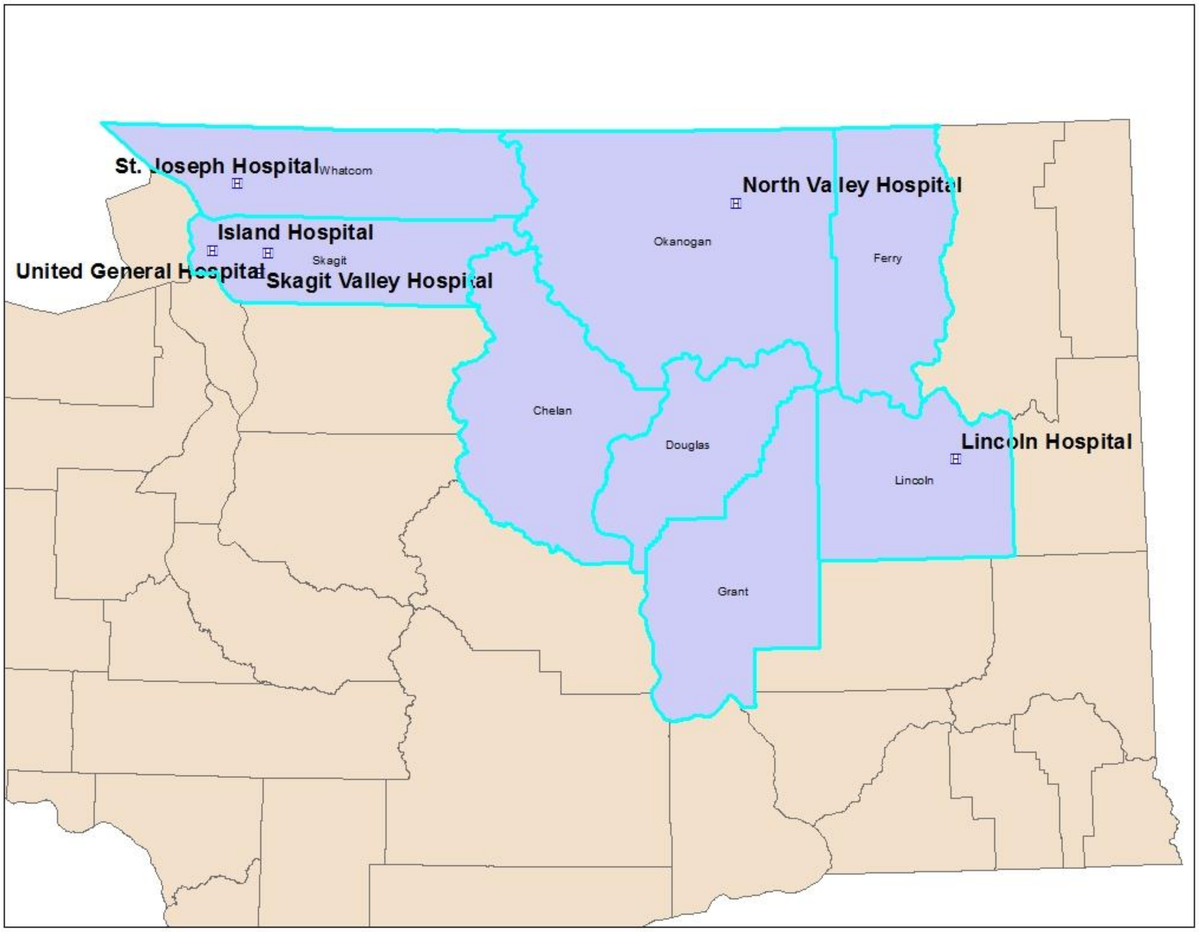


Table 2: Respiratory Hospitalizations from August 14 to September 15, 2006 (Zero $PM_{2.5}$ values and values greater than zero in parentheses if there is a change)

Hospital	County	Respiratory Hospitalization		Total Hospitalizations
		No	Yes	
Cascade Medical Center	Chelan	9	1	10
Central Washington Hospital	Chelan	701 (655)	56 (51)	757 (706)
Columbia Basin Hospital	Grant	16 (15)	8	24 (23)
Coulee Community Hospital	Grant	30 (28)	3	33 (31)
Ferry County Memorial Hospital	Ferry	20	5	25
Island Hospital	Skagit	198 (123)	20 (17)	218 (140)
Lake Chelan Community Hospital	Chelan	29 (26)	1 (0)	30 (26)
Lincoln Hospital	Lincoln	28 (25)	13	41 (38)
Mid-Valley Hospital	Okanogan	95 (92)	16	111 (108)
North Valley Hospital	Okanogan	30 (29)	4	34 (33)
Odessa Memorial Hospital	Lincoln	8	0	8
Okanogan-Douglas Hospital	Okanogan	52	3	55
PeaceHealth Saint Joseph	Whatcom	1,120 (1,008)	67 (62)	1,187 (1,070)
Quincy Valley Medical Center	Grant	4	2	6
Samaritan Hospital	Grant	265 (253)	20	285 (273)
Skagit Valley Hospital	Skagit	518 (440)	39 (37)	557 (447)
United General Hospital	Skagit	95 (84)	10	105 (94)
Wenatchee Valley Hospital	Chelan	90 (84)	0	90 (84)
Total		**3,308 (2,955)**	**268 (252)**	**3,576 (3,207)**

Table 3: Cardiovascular Hospitalizations from August 14 to September 15, 2006 (Zero $PM_{2.5}$ values and values greater than zero in parentheses if there is a change)

Hospital	County	Cardiovascular Hospitalization		Total Hospitalizations
		No	Yes	
Cascade Medical Center	Chelan	8	2	10
Central Washington Hospital	Chelan	651 (608)	106 (98)	757 (706)
Columbia Basin Hospital	Grant	21 (20)	3	24 (23)
Coulee Community Hospital	Grant	31 (29)	2	33 (31)
Ferry County Memorial Hospital	Ferry	24	1	25
Island Hospital	Skagit	202 (131)	16 (9)	218 (140)
Lake Chelan Community Hospital	Chelan	28 (24)	2	30 (26)
Lincoln Hospital	Lincoln	35 (32)	6	41 (38)
Mid-Valley Hospital	Okanogan	108 (105)	3	111 (108)
North Valley Hospital	Okanogan	30 (29)	4	34 (33)
Odessa Memorial Hospital	Lincoln	7	1	8
Okanogan-Douglas Hospital	Okanogan	54	1	55
PeaceHealth Saint Joseph	Whatcom	965 (894)	222 (176)	1187 (1070)
Quincy Valley Medical Center	Grant	6	0	6
Samaritan Hospital	Grant	267 (255)	18	285 (273)
Skagit Valley Hospital	Skagit	505 (428)	52 (49)	557 (477)
United General Hospital	Skagit	99 (88)	6	105 (94)
Wenatchee Valley Hospital	Chelan	90 (84)	0	90 (84)
Total		**3,131 (2,826)**	**445 (381)**	**3,576 (3,207)**

Table 4: Respiratory Hospitalizations on Non-Zero $PM_{2.5}$ Days[1]

Hospital Name	Respiratory Hospitalizations	Date of Hospitalization	Modeled $PM_{2.5}$ value ($\mu g/m^3$)
Samaritan Hospital	1	8/18	9.9
Columbia Basin Hospital	1	8/18	2.9
Central Washington Hospital	1	8/18	1.4
Quincy Valley Medical Center	1	8/17	1.1
United General Hospital	1	8/16	0.9
Coulee Community Hospital	1	8/18	0.9
Skagit Valley Hospital	1	8/16	0.4
Lincoln Hospital	1	8/15	0.4
PeaceHealth Saint Joseph	3	8/16	0.3
Okanogan-Douglas Hospital	1	8/17	0.2
Mid-Valley Hospital	1	8/17	0.2
Lincoln Hospital	1	8/18	9.4 E-2
Central Washington Hospital	3	8/14	6.0 E-2
North Valley Hospital	1	8/17	6.0 E-2
Lake Chelan Community Hospital	1	9/15	3.4 E-2
Mid-Valley Hospital	1	9/13	2.2 E-2
Central Washington Hospital	5	8/16	8.0 E-3
Central Washington Hospital	1	8/15	4.9 E-3
Mid-Valley Hospital	1	8/15	3.5 E-3
United General Hospital	1	8/14	3.4 E-3
Skagit Valley Hospital	2	8/14	2.8 E-3
PeaceHealth Saint Joseph	2	8/14	1.7 E-3
Mid-Valley Hospital	1	9/12	1.5 E-3
Skagit Valley Hospital	1	8/18	8.9 E-4
PeaceHealth Saint Joseph	1	8/18	5.6 E-4
PeaceHealth Saint Joseph	3	8/17	4.5 E-4
Mid-Valley Hospital	1	8/15	2.4 E-4
United General Hospital	1	8/15	1.2 E-4
PeaceHealth Saint Joseph	1	8/15	6.3 E-5
North Valley Hospital	1	9/7	4.6 E-8
Mid-Valley Hospital	1	8/28	8.5 E-13
Okanogan-Douglas Hospital	1	8/23	2.8 E-19

[1] In consistent with EPA NAAQS, all $PM_{2.5}$ values were rounded to the first decimal place for values less than 35 $\mu g/m^3$. For values greater than 35 $\mu g/m^3$, no decimals are reported and values are rounded to the nearest whole number. (http://www.epa.gov/scram001/guidance/guide/Update_to_the_24-hour_PM25_Modeled_Attainment_Test.pdf)

Table 5: Cardiovascular Hospitalizations on Non-Zero $PM_{2.5}$ Days

Hospital Name	Respiratory Hospitalizations	Date of Hospitalization	Modeled $PM_{2.5}$ value ($\mu g/m^3$)
Samaritan Hospital	1	8/18	9.9
Columbia Basin Hospital	1	8/18	2.9
Central Washington Hospital	5	8/18	1.4
United General Hospital	1	8/16	0.9
Central Washington Hospital	1	8/17	0.9
North Valley Hospital	1	8/15	0.7
Skagit Valley Hospital	1	8/16	0.5
Lincoln Hospital	1	8/15	0.4
Columbia Basin Hospital	2	8/15	0.3
PeaceHealth Saint Joseph	8	8/16	0.3
Island Hospital	1	8/16	0.2
Samaritan Hospital	1	8/15	0.2
Samaritan Hospital	1	8/14	0.1
Lake Chelan Community Hos	1	8/23	6.9 E-2
Central Washington Hospital	3	8/14	6.0 E-2
North Valley Hospital	1	9/11	5.5 E-2
Lake Chelan Community Hos	1	8/29	3.2 E-2
Columbia Basin Hospital	1	8/16	3.0 E-2
Central Washington Hospital	3	8/16	8.0 E-3
Central Washington Hospital	3	8/15	4.9 E-3
Skagit Valley Hospital	2	8/14	2.8 E-3
North Valley Hospital	1	9/5	2.1 E-3
PeaceHealth Saint Joseph	11	8/14	1.7 E-3
United General Hospital	1	8/18	1.3 E-3
Skagit Valley Hospital	1	8/18	8.9 E-4
Skagit Valley Hospital	5	8/17	6.4 E-4
Island Hospital	1	8/18	6.1 E-4
PeaceHealth Saint Joseph	7	8/18	5.6 E-4
PeaceHealth Saint Joseph	6	8/17	4.5 E-4
Island Hospital	1	8/17	3.9 E-4
Skagit Valley Hospital	2	8/15	1.1 E-4
Island Hospital	1	8/15	7.2 E-5
PeaceHealth Saint Joseph	10	8/15	6.3 E-5
Mid-Valley Hospital	1	8/31	2.2 E-5

Table 6: Comparison of R's for Hospitalizations (based on hospital zip code) on Non-Zero and Zero Modeled Particulate Matter Days

Hospital	Zip Code	Respiratory Hospitalization R	Respiratory Hospitalizations on Non-Zero PM Days	Cardiovascular Hospitalization R	Cardiovascular Hospitalizations on Non-Zero PM Days
Cascade Medical Center	98826	0	0	0	0
Central Washington Hospital	98801	1.217	10	0.923	15
Columbia Basin Hospital	98823	0.8	1	0.6/0 = N/A	3
Coulee Community Hospital	99133	2.8	1	0	0
Ferry County Memorial Hospital	99166	0	0	0	0
Island Hospital	98221	0	0	1.867	4
Lake Chelan Community Hospital	98816	0.030/(0/0) = N/A	1	0.060/(0/0) = N/A	2
Lincoln Hospital	99122	2.818	2	3.1	1
Mid-Valley Hospital	98841	0.335	5	0.368	1
North Valley Hospital	98855	0.571	2	1.714	3
Odessa Memorial Hospital	99159	0/0 = N/A	0	0	0
Okanogan-Douglas Hospital	98812	0.235	1	0	0
PeaceHealth Saint Joseph	98225	0.982	10	1.307	42
Quincy Valley Medical Center	98848	5.6	1	0/0 = N/A	0
Samaritan Hospital	98837	0.295	1	0.7	2
Skagit Valley Hospital	98273	0.64	4	1.502	11
United General Hospital	98284	3.107	3	3.625	2
Wenatchee Valley Hospital	98001	0/0 = N/A	0	0/0 = N/A	0

Table 7: Number of Non-Zero/Zero PM Days and Respiratory Hospitalizations on Non-Zero/Zero PM Days

Hospital	Zip Code	Respiratory Hospitalizations on Non-Zero PM Days	Respiratory Hospitalizations on Zero PM Days	Number of Non-Zero PM Days	Number of Zero PM Days
Cascade Medical Center	98826	0	1	9	24
Central Washington Hospital	98801	10	46	5	28
Columbia Basin Hospital	98823	1	7	5	28
Coulee Community Hospital	99133	1	2	5	28
Ferry County Memorial Hospital	99166	0	5	5	28
Island Hospital	98221	0	20	5	28
Lake Chelan Community Hospital	98816	1	0	33	0
Lincoln Hospital	99122	2	11	2	31
Mid-Valley Hospital	98841	5	11	19	14
North Valley Hospital	98855	2	2	21	12
Odessa Memorial Hospital	99159	0	0	5	28
Okanogan-Douglas Hospital	98812	1	4	17	16
PeaceHealth Saint Joseph	98225	10	57	5	28
Quincy Valley Medical Center	98848	1	1	5	28
Samaritan Hospital	98837	1	19	5	28
Skagit Valley Hospital	98273	4	35	5	28
United General Hospital	98284	3	7	4	29
Wenatchee Valley Hospital	98001	0	0	5	28

Table 8: Number of Non-Zero/Zero PM Days and Cardiovascular Hospitalizations on Non-Zero/Zero PM Days

Hospital	Zip Code	Cardiovascular Hospitalizations on Non-Zero PM Days	Cardiovascular Hospitalizations on Zero PM Days	Number of Non-Zero PM Days	Number of Zero PM Days
Cascade Medical Center	98826	0	2	9	24
Central Washington Hospital	98801	15	91	5	28
Columbia Basin Hospital	98823	3	0	5	28
Coulee Community Hospital	99133	0	2	5	28
Ferry County Memorial Hospital	99166	0	5	5	28
Island Hospital	98221	4	12	5	28
Lake Chelan Community Hospital	98816	2	0	33	0
Lincoln Hospital	99122	1	5	2	31
Mid-Valley Hospital	98841	1	2	19	14
North Valley Hospital	98855	3	1	21	12
Odessa Memorial Hospital	99159	0	1	5	28
Okanogan-Douglas Hospital	98812	0	1	17	16
PeaceHealth Saint Joseph	98225	42	180	5	28
Quincy Valley Medical Center	98848	0	0	5	28
Samaritan Hospital	98837	2	16	5	28
Skagit Valley Hospital	98273	11	41	5	28
United General Hospital	98284	2	4	4	29
Wenatchee Valley Hospital	98001	0	0	5	28

Table 10: Logistic Regression for All Hospitalizations (non-lag, non-sensitive)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	mean	-.009	.028	.101	1	.751	.991	.937	1.048
	Ages 15-44			.034	5	1.000			
	Ages 0-4	-.003	.129	.000	1	.983	.997	.774	1.285
	Ages 5-14	-.009	.197	.002	1	.963	.991	.674	1.456
	Ages 45-64	-.009	.056	.028	1	.867	.991	.888	1.105
	Ages 65-84	-.006	.052	.012	1	.912	.994	.898	1.101
	Ages 85 and older	.000	.073	.000	1	.996	1.000	.867	1.152
	Female	-.002	.043	.003	1	.958	.998	.916	1.086
	Constant	-1.338	.050	713.122	1	.000	.262		

a. Variable(s) entered on step 1: mean, agecat_reference, sex.

Table 11: Logistic Regression for All Hospitalizations (non-lag, sensitive)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	Mean	-.009	.028	.100	1	.751	.991	.937	1.048
	Female	.000	.042	.000	1	.999	1.000	.922	1.085
	Ages 15-64			.000	2	1.000			
	Ages 0-14	.000	.108	.000	1	.999	1.000	.809	1.235
	Ages 65 and older	.000	.042	.000	1	.996	1.000	.921	1.085
	Constant	-1.344	.039	1163.145	1	.000	.261		

a. Variable(s) entered on step 1: mean, sex, agecat_sensitive_reference.

Table 12: Logistic Regression for All Hospitalizations (interaction terms, non-lag, non-sensitive)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	mean	-.012	.073	.026	1	.873	.988	.856	1.141
	Female	-.011	.094	.015	1	.904	.989	.823	1.188
	mean by Female	-.036	.065	.314	1	.575	.964	.849	1.095
	Ages 15-44			.189	5	.999			
	Ages 0-4	-.007	.184	.001	1	.971	.993	.692	1.425
	Ages 5-14	-.025	.260	.009	1	.923	.975	.586	1.623
	Ages 45-64	-.028	.104	.071	1	.789	.973	.794	1.192
	Ages 65-84	-.029	.100	.082	1	.775	.972	.799	1.182
	Ages 85 and older	.010	.135	.005	1	.942	1.010	.775	1.315
	Ages 15-44 * mean			3.958	5	.555			
	Ages 0-4 by mean	-.138	.233	.352	1	.553	.871	.552	1.375
	Ages 5-14 by mean	.177	1.062	.028	1	.868	1.193	.149	9.564
	Ages 45-64 by mean	.060	.076	.624	1	.430	1.062	.915	1.233
	Ages 65-84 by mean	.079	.077	1.059	1	.303	1.082	.931	1.259
	Ages 85 and older by mean	-.328	.262	1.568	1	.210	.720	.431	1.204
	Ages 15-44 * male			.032	5	1.000			
	Ages 0-4 by female	.027	.267	.010	1	.921	1.027	.609	1.732
	Ages 5-14 by female	.003	.419	.000	1	.994	1.003	.441	2.280
	Ages 45-64 by female	.014	.125	.012	1	.911	1.014	.794	1.294
	Ages 65-84 by female	.019	.118	.025	1	.874	1.019	.808	1.285
	Ages 85 and older by female	.006	.161	.001	1	.969	1.006	.734	1.378
	Constant	-1.327	.086	238.776	1	.000	.265		

Table 13: Logistic Regression for All Hospitalizations (interaction terms, non-lag, sensitive)

Variables in the Equation

		B	S.E.	Wald	Df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	mean	.021	.057	.132	1	.717	1.021	.914	1.140
	female	.002	.058	.001	1	.971	1.002	.895	1.122
	mean by female	-.047	.062	.575	1	.448	.954	.845	1.077
	Ages 15-64			.010	2	.995			
	Ages 0-14	.006	.144	.002	1	.968	1.006	.758	1.334
	Ages 65 and older	-.005	.067	.006	1	.938	.995	.873	1.134
	Ages 15-64 * mean			.567	2	.753			
	Ages 0-14 by mean	-.154	.216	.511	1	.475	.857	.561	1.308
	Ages 65 and older by mean	.009	.065	.020	1	.888	1.009	.889	1.146
	Ages 15-64 * male			.008	2	.996			
	Ages 0-14 by female	.015	.219	.005	1	.945	1.015	.661	1.559
	Ages 65 and older by female	.006	.085	.005	1	.944	1.006	.851	1.189
	Constant	-1.345	.048	770.837	1	.000	.261		

a. Variable(s) entered on step 1: mean, sex, mean * sex , agecat_sensitive_reference, agecat_sensitive_reference * mean , agecat_sensitive_reference * sex .

Table 14: Logistic Regression for Respiratory Hospitalizations (non-lag, non-sensitive)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	mean	.012	.101	.015	1	.902	1.013	.830	1.235
	Ages 15-44			.059	5	1.000			
	Ages 0-4	-.052	.354	.021	1	.884	.950	.474	1.902
	Ages 5-14	-.049	.465	.011	1	.917	.953	.383	2.371
	Ages 45-64	-.030	.281	.012	1	.914	.970	.559	1.684
	Ages 65-84	-.005	.261	.000	1	.985	.995	.596	1.661
	Ages 85 and older	-.036	.285	.016	1	.900	.965	.553	1.685
	female	-.008	.145	.003	1	.954	.992	.746	1.318
	Constant	-1.305	.249	27.494	1	.000	.271		

a. Variable(s) entered on step 1: mean, agecat_reference, sex.

Table 15: Logistic Regression for Respiratory Hospitalizations (non-lag, sensitive)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	mean	.012	.101	.015	1	.903	1.012	.830	1.235
	female	-.011	.143	.006	1	.938	.989	.747	1.310
	Ages 15-64			.023	2	.989			
	Ages 0-14	-.030	.257	.014	1	.907	.970	.586	1.606
	Ages 65 and older	.006	.159	.001	1	.970	1.006	.737	1.374
	Constant	-1.325	.151	77.252	1	.000	.266		

a. Variable(s) entered on step 1: mean, sex, agecat_sensitive_reference.

Table 16: Logistic Regression for Respiratory Hospitalizations (interaction terms, non-lag, non-sensitive)

Variables in the Equation

		B	S.E.	Wald	Df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	mean	-.240	.390	.380	1	.538	.787	.366	1.688
	female	-.168	.477	.124	1	.725	.845	.332	2.152
	mean by female	.314	.363	.747	1	.387	1.369	.672	2.791
	Ages 15-44			.193	5	.999			
	Ages 0-4	-.112	.484	.054	1	.816	.894	.346	2.307
	Ages 5-14	.078	.554	.020	1	.888	1.081	.365	3.202
	Ages 45-64	-.102	.411	.062	1	.803	.903	.404	2.018
	Ages 65-84	-.073	.378	.038	1	.846	.929	.443	1.949
	Ages 85 and older	-.074	.440	.029	1	.865	.928	.392	2.197
	Ages 15-44 * mean			1.068	5	.957			
	Ages 0-4 by mean	.062	.587	.011	1	.916	1.064	.337	3.365
	Ages 5-14 by mean	-23.443	33.572	.488	1	.485	.000	.000	2.485E18
	Ages 45-64 by mean	.064	.235	.075	1	.784	1.067	.672	1.692
	Ages 65-84 by mean	-.344	.627	.301	1	.583	.709	.208	2.421
	Ages 85 and older by mean	-.117	.537	.048	1	.827	.890	.311	2.547
	Ages 15-44 * male			.108	5	1.000			
	Ages 0-4 by female	.146	.722	.041	1	.840	1.157	.281	4.765
	Ages 5-14 by female	.210	1.320	.025	1	.873	1.234	.093	16.402
	Ages 45-64 by female	.130	.569	.052	1	.820	1.138	.373	3.471
	Ages 65-84 by female	.167	.527	.100	1	.752	1.181	.421	3.318
	Ages 85 and older by female	.113	.583	.038	1	.846	1.120	.357	3.507
	Constant	-1.223	.343	12.698	1	.000	.294		

Variable(s) entered on step 1: mean, sex, mean * sex , agecat_reference, agecat_reference * mean , agecat_reference * sex .

Table 17: Logistic Regression for Respiratory Hospitalizations (interaction terms, non-lag, sensitive)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	mean	-.204	.356	.330	1	.566	.815	.406	1.638
	female	-.079	.263	.091	1	.763	.924	.552	1.546
	mean by female	.319	.365	.766	1	.381	1.376	.673	2.815
	Ages 15-64			.018	2	.991			
	Ages 0-14	-.041	.327	.016	1	.901	.960	.505	1.823
	Ages 65 and older	-.004	.234	.000	1	.986	.996	.630	1.574
	Ages 15-64 * mean			.446	2	.800			
	Ages 0-14 by mean	-.039	.662	.003	1	.953	.962	.263	3.522
	Ages 65 and older by mean	-.266	.399	.443	1	.506	.767	.351	1.676
	Ages 15-64 * male			.033	2	.983			
	Ages 0-14 by female	.055	.543	.010	1	.919	1.057	.364	3.065
	Ages 65 and older by female	.057	.320	.032	1	.857	1.059	.566	1.982
	Constant	-1.294	.190	46.353	1	.000	.274		

Table 18: Logistic Regression for Cardiovascular Hospitalizations (non-lag, non-sensitive)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	mean	-.163	.160	1.039	1	.308	.849	.620	1.163
	Ages 15-44			.018	3	.999			
	Ages 0-4	-.011	.294	.001	1	.971	.989	.556	1.759
	Ages 5-14	-.024	.284	.007	1	.933	.976	.560	1.704
	Ages 45-64	-.008	.312	.001	1	.979	.992	.538	1.827
	Female	.004	.119	.001	1	.972	1.004	.795	1.268
	Constant	-1.322	.278	22.687	1	.000	.267		

a. Variable(s) entered on step 1: mean, agecat_reference, sex.

Table 19: Logistic Regression for Cardiovascular Hospitalizations (non-lag, sensitive)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
Step 1[a]	mean	-.164	.160	1.043	1	.307	.849	.620	1.162
	Female	.006	.118	.002	1	.962	1.006	.798	1.267
	Ages 0-14	-.011	.124	.008	1	.928	.989	.775	1.262
	Constant	-1.332	.107	154.113	1	.000	.264		

a. Variable(s) entered on step 1: mean, sex, agecat_sensitive_reference.

Table 20: Logistic Regression for Cardiovascular Hospitalizations (interaction terms, non-lag, non-sensitive)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	mean	-3.125	4.118	.576	1	.448	.044	.000	140.663
	Female	-.039	.560	.005	1	.945	.962	.321	2.885
	mean by female	-.385	.483	.636	1	.425	.680	.264	1.753
	Ages 15-44			.185	3	.980			
	Ages 0-4	-.145	.386	.140	1	.708	.865	.406	1.844
	Ages 5-14	-.148	.379	.152	1	.697	.863	.410	1.814
	Ages 45-64	-.184	.439	.176	1	.675	.832	.352	1.966
	Ages 15-44 * mean			1.256	3	.740			
	Ages 0-4 by mean	3.034	4.125	.541	1	.462	20.780	.006	67413.277
	Ages 5-14 by mean	3.167	4.122	.590	1	.442	23.728	.007	76589.051
	Ages 45-64 by mean	3.766	4.209	.801	1	.371	43.211	.011	165364.249
	Ages 15-44 * male			.062	3	.996			
	Ages 0-4 by female	.097	.609	.025	1	.873	1.102	.334	3.632
	Ages 5-14 by female	.044	.583	.006	1	.940	1.045	.333	3.276
	Ages 45-64 by female	.101	.640	.025	1	.874	1.106	.316	3.876
	Constant	-1.202	.364	10.938	1	.001	.300		

a. Variable(s) entered on step 1: mean, sex, mean * sex , agecat_reference, agecat_reference * mean , agecat_reference * sex .

Table 21: Logistic Regression for Cardiovascular Hospitalizations (interaction terms, non-lag, sensitive)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	mean	-.205	.312	.430	1	.512	.815	.442	1.503
	female	.051	.218	.055	1	.814	1.053	.686	1.615
	mean by female	-.454	.503	.817	1	.366	.635	.237	1.700
	Ages 0-14	-.017	.157	.011	1	.915	.983	.723	1.338
	Ages 0-14 by mean	.298	.391	.581	1	.446	1.347	.626	2.900
	Ages 0-14 by female	-.033	.259	.016	1	.899	.968	.583	1.608
	Constant	-1.337	.122	120.132	1	.000	.263		

a. Variable(s) entered on step 1: mean, sex, mean * sex , agecat_sensitive_reference, agecat_sensitive_reference * mean , agecat_sensitive_reference * sex .

Table 22: Logistic Regression for All Hospitalizations (interaction terms, non-sensitive, comparison of modeled air quality using mean of 3 days prior against mean on hospitalization day)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
Step 1[a]	mean	-.041	.087	.219	1	.640	.960	.810	1.138
	mean_321daysbefore	-.062	.139	.200	1	.654	.940	.716	1.234
	Ages 15-44			.434	5	.994			
	Ages 0-4	**.010**	**.193**	**.003**	**1**	**.959**	**1.010**	**.692**	**1.475**
	Ages 5-14	**.073**	**.277**	**.070**	**1**	**.791**	**1.076**	**.626**	**1.851**
	Ages 45-64	-.046	.110	.175	1	.675	.955	.770	1.185
	Ages 65-84	-.032	.106	.090	1	.764	.969	.787	1.192
	Ages 85 and older	-.001	.142	.000	1	.993	.999	.756	1.320
	Female	-.001	.099	.000	1	.994	.999	.823	1.213
	Ages 15-44 by mean			4.224	5	.518			
	Ages 0-4 by mean	-.141	.265	.284	1	.594	.868	.516	1.460
	Ages 5-14 by mean	**1.459**	**1.213**	**1.446**	**1**	**.229**	**4.300**	**.399**	**46.331**
	Ages 45-64 by mean	**.025**	**.093**	**.073**	**1**	**.787**	**1.025**	**.855**	**1.230**
	Ages 65-84 by mean	**.071**	**.089**	**.637**	**1**	**.425**	**1.074**	**.902**	**1.279**
	Ages 85 and older by mean	-.373	.318	1.380	1	.240	.689	.370	1.283
	Ages 15-44 by male			.586	5	.989			
	Ages 0-4 by female	-.191	.291	.428	1	.513	.826	.467	1.463
	Ages 5-14 by female	-.127	.448	.080	1	.777	.881	.366	2.121
	Ages 45-64 by female	**.013**	**.132**	**.010**	**1**	**.919**	**1.013**	**.783**	**1.312**
	Ages 65-84 by female	-.012	.125	.009	1	.926	.988	.774	1.263
	Ages 85 and older by female	-.012	.170	.005	1	.942	.988	.707	1.379
	Ages 15-44 by mean_321daysbefore			3.503	5	.623			
	Ages 0-4 by mean_321daysbefore	**.115**	**.342**	**.112**	**1**	**.737**	**1.121**	**.574**	**2.191**
	Ages 5-14 by mean_321daysbefore	-.383	.715	.287	1	.592	.682	.168	2.769
	Ages 45-64 by mean_321daysbefore	**.241**	**.146**	**2.729**	**1**	**.099**	**1.272**	**.956**	**1.693**

Ages 65-84 by mean_321daysbefore	**.109**	**.140**	**.605**	**1**	**.436**	**1.115**	**.847**	**1.469**
Ages 85 and older by mean_321daysbefore	**.176**	**.213**	**.680**	**1**	**.410**	**1.192**	**.785**	**1.812**
mean_321daysbefore by female	**.027**	**.123**	**.049**	**1**	**.826**	**1.028**	**.807**	**1.308**
mean by female	-.032	.078	.166	1	.683	.969	.831	1.129
Constant	-1.328	.091	214.294	1	.000	.265		

a. Variable(s) entered on step 1: mean, mean_321daysbefore, agecat_reference, sex, agecat_reference * mean , agecat_reference * sex , agecat_reference * mean_321daysbefore , mean_321daysbefore * sex , mean * sex .

Table 23: Logistic Regression for All Hospitalizations (interaction terms, non-sensitive, comparison of modeled air quality using median of 3 days prior against mean on hospitalization day)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	Mean	-.048	.081	.354	1	.552	.953	.813	1.117
	female	-.009	.095	.008	1	.928	.991	.823	1.195
	mean by female	**.001**	**.073**	**.000**	**1**	**.991**	**1.001**	**.867**	**1.156**
	Ages 15-44			.447	5	.994			
	Ages 0-4	-.011	.187	.004	1	.952	.989	.685	1.427
	Ages 5-14	-.022	.266	.007	1	.935	.978	.580	1.649
	Ages 45-64	-.042	.106	.160	1	.689	.959	.779	1.179
	Ages 65-84	-.040	.102	.153	1	.696	.961	.787	1.173
	Ages 85 and older	**.022**	**.137**	**.027**	**1**	**.870**	**1.023**	**.782**	**1.338**
	Ages 15-44 by mean			4.192	5	.522			
	Ages 0-4 by mean	-.112	.238	.221	1	.639	.894	.561	1.425
	Ages 5-14 by mean	**.401**	**1.101**	**.133**	**1**	**.716**	**1.493**	**.173**	**12.921**
	Ages 45-64 by mean	-.008	.089	.009	1	.925	.992	.833	1.180
	Ages 65-84 by mean	**.088**	**.082**	**1.159**	**1**	**.282**	**1.092**	**.931**	**1.281**
	Ages 85 and older by mean	-.393	.299	1.728	1	.189	.675	.376	1.213
	Ages 15-44 by male			.302	5	.998			
	Ages 0-4 by female	-.104	.277	.141	1	.707	.901	.523	1.551
	Ages 5-14 by female	-.047	.438	.012	1	.914	.954	.404	2.250
	Ages 45-64 by female	**.006**	**.127**	**.002**	**1**	**.962**	**1.006**	**.784**	**1.290**
	Ages 65-84 by female	**.024**	**.120**	**.041**	**1**	**.839**	**1.025**	**.810**	**1.297**
	Ages 85 and older by female	-.022	.164	.017	1	.895	.979	.710	1.350
	median_of_means_321daysbefore	**.076**	**.172**	**.196**	**1**	**.658**	**1.079**	**.771**	**1.511**
	Ages 15-44 by median_of_means_321daysbefore			1.424	5	.922			

Ages 0-4 by median_of_means_321daysbefore	-.066	.772	.007	1	.932	.936	.206	4.246
Ages 5-14 by median_of_means_321daysbefore	-.302	1.396	.047	1	.829	.739	.048	11.401
Ages 45-64 by median_of_means_321daysbefore	**.154**	**.168**	**.840**	**1**	**.359**	**1.167**	**.839**	**1.622**
Ages 65-84 by median_of_means_321daysbefore	-.005	.171	.001	1	.976	.995	.711	1.392
Ages 85 and older by median_of_means_321daysbefore	**.146**	**.317**	**.212**	**1**	**.645**	**1.157**	**.622**	**2.154**
median_of_means_321daysbefore by female	-.037	.147	.063	1	.802	.964	.722	1.286
Constant	-1.326	.087	230.596	1	.000	.265		

a. Variable(s) entered on step 1: mean, sex, mean * sex , agecat_reference, agecat_reference * mean , agecat_reference * sex , median_of_means_321daysbefore, agecat_reference * median_of_means_321daysbefore , median_of_means_321daysbefore * sex .

Table 24: Logistic Regression for All Hospitalizations (interaction terms, sensitive, comparison of modeled air quality using mean of 3 days prior against mean on hospitalization day)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	mean	-.035	.071	.248	1	.619	.965	.839	1.110
	mean_321daysbefore	**.069**	**.100**	**.472**	**1**	**.492**	**1.071**	**.880**	**1.304**
	female	**.015**	**.062**	**.062**	**1**	**.804**	**1.015**	**.900**	**1.146**
	mean_321daysbefore by female	-.026	.109	.057	1	.812	.974	.787	1.207
	mean by female	-.028	.076	.142	1	.707	.972	.838	1.127
	Ages 15-64			.115	2	.944			
	Ages 0-14	**.048**	**.152**	**.099**	**1**	**.753**	**1.049**	**.779**	**1.414**
	Ages 65 and older	-.003	.071	.002	1	.964	.997	.867	1.146
	Ages 15-64 by male			.362	2	.834			
	Ages 0-14 by female	-.140	.236	.350	1	.554	.870	.548	1.381
	Ages 65 and older by female	-.019	.091	.045	1	.832	.981	.821	1.172
	Ages 15-64 by mean_321daysbefore			.284	2	.868			
	Ages 0-14 by mean_321daysbefore	-.130	.281	.212	1	.645	.878	.506	1.525
	Ages 65 and older by mean_321daysbefore	**.022**	**.111**	**.039**	**1**	**.844**	**1.022**	**.822**	**1.270**
	Ages 15-64 by mean			.286	2	.867			
	Ages 0-14 by mean	-.092	.217	.181	1	.671	.912	.596	1.395
	Ages 65 and older by mean	**.019**	**.078**	**.062**	**1**	**.804**	**1.019**	**.876**	**1.187**
	Constant	-1.355	.052	683.974	1	.000	.258		

a. Variable(s) entered on step 1: mean, mean_321day

Table 25: Logistic Regression for All Hospitalizations (interaction terms, sensitive, comparison of modeled air quality using median of 3 days compared against mean on hospitalization day)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	Mean	-.056	.067	.703	1	.402	.945	.829	1.078
	Female	**.008**	**.059**	**.017**	**1**	**.896**	**1.008**	**.897**	**1.132**
	mean by female	**.007**	**.070**	**.009**	**1**	**.924**	**1.007**	**.878**	**1.155**
	median_of_means_321daysbefore	**.165**	**.130**	**1.599**	**1**	**.206**	**1.179**	**.913**	**1.521**
	median_of_means_321daysbefore by female	-.063	.137	.214	1	.643	.938	.717	1.228
	Ages 15-64			.012	2	.994			
	Ages 0-14	**.013**	**.147**	**.007**	**1**	**.932**	**1.013**	**.759**	**1.351**
	Ages 65 and older	-.003	.068	.002	1	.965	.997	.872	1.140
	Ages 15-64 by mean			.709	2	.701			
	Ages 0-14 by mean	-.087	.216	.162	1	.687	.917	.600	1.401
	Ages 65 and older by mean	**.048**	**.071**	**.450**	**1**	**.502**	**1.049**	**.913**	**1.205**
	Ages 15-64 by median_of_means_321daysbefore			.200	2	.905			
	Ages 0-14 by median_of_means_321daysbefore	-.152	.658	.053	1	.818	.859	.236	3.123
	Ages 65 and older by median_of_means_321daysbefore	-.055	.136	.163	1	.687	.947	.725	1.236
	Ages 15-64 by male			.184	2	.912			
	Ages 0-14 by female	-.095	.228	.173	1	.677	.910	.582	1.421
	Ages 65 and older by female	**.003**	**.087**	**.001**	**1**	**.975**	**1.003**	**.845**	**1.189**
	Constant	-1.354	.050	743.099	1	.000	.258		

a. Variable(s) entered on step 1: mean, sex, mean * sex , median_of_means_321daysbefore, median_of_means_321daysbefore * sex , agecat_sensitive_reference, agecat_sensitive_reference * mean , agecat_sensitive_reference * median_of_means_321daysbefore , agecat_sensitive_reference * sex .

Table 26: Logistic Regression for Respiratory Hospitalizations (interaction terms, non-sensitive, comparison of modeled air quality using mean of 3 days prior compared against mean on hospitalization day)

Variables in the Equation

		B	S.E.	Wald	Df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	**Mean**	**.084**	**.380**	**.049**	**1**	**.824**	**1.088**	**.516**	**2.293**
	mean_321daysbefore	-.346	.923	.140	1	.708	.708	.116	4.321
	female	-.300	.489	.377	1	.539	.741	.284	1.932
	mean_321daysbefore by female	-.311	.489	.405	1	.525	.733	.281	1.911
	mean by female	-.031	.388	.006	1	.937	.970	.454	2.073
	Ages 15-44			.354	5	.997			
	Ages 0-4	-.176	.499	.124	1	.724	.839	.315	2.230
	Ages 5-14	-.093	.584	.025	1	.874	.912	.290	2.863
	Ages 45-64	-.241	.428	.318	1	.573	.786	.340	1.818
	Ages 65-85	-.132	.391	.115	1	.735	.876	.407	1.885
	Ages 85 and older	-.132	.454	.084	1	.771	.876	.360	2.135
	Ages 15-44 * mean			1.006	5	.962			
	Ages 0-4 by mean	-.419	.690	.368	1	.544	.658	.170	2.542
	Ages 5-14 by mean	-19265.629	11230286.275	.000	1	.999	.000	.000	.
	Ages 45-64 by mean	**.075**	**.256**	**.085**	**1**	**.770**	**1.078**	**.652**	**1.781**
	Ages 65-84 by mean	-1.263	1.702	.551	1	.458	.283	.010	7.950
	Ages 85 and older by mean	-.065	.532	.015	1	.902	.937	.330	2.657
	Ages 15-44 * mean_321daysbefore			3.215	5	.667			
	Ages 0-4 by mean_321daysbefore	**3.000**	**4.112**	**.532**	**1**	**.466**	**20.077**	**.006**	**63544.422**
	Ages 5-14 by mean_321daysbefore	-12317.977	204795.791	.004	1	.952	.000	.000	.

Ages 45-64 by mean_321daysbefore	**.848**	**.998**	**.723**	**1**	**.395**	**2.336**	**.331**	**16.503**
Ages 65-84 by mean_321daysbefore	**.116**	**.973**	**.014**	**1**	**.905**	**1.123**	**.167**	**7.556**
Ages 85 and older by mean_321daysbefore	**.132**	**1.188**	**.012**	**1**	**.911**	**1.141**	**.111**	**11.712**
Ages 15-44 * male			**.305**	**5**	**.998**			
Ages 0-4 by female	**.074**	**.749**	**.010**	**1**	**.922**	**1.076**	**.248**	**4.674**
Ages 5-14 by female	**11.635**	**158.410**	**.005**	**1**	**.941**	**112932.998**	**.000**	**7.791E139**
Ages 45-64 by female	**.249**	**.591**	**.177**	**1**	**.674**	**1.282**	**.403**	**4.079**
Ages 65-84 by female	**.258**	**.544**	**.226**	**1**	**.634**	**1.295**	**.446**	**3.758**
Ages 85 and older by female	**.229**	**.601**	**.145**	**1**	**.703**	**1.257**	**.387**	**4.080**
Constant	-1.111	.353	9.928	1	.002	.329		

a. Variable(s) entered on step 1: mean, mean_321daysbefore, sex, mean_321daysbefore * sex , mean * sex , agecat_reference, agecat_reference * mean , agecat_reference * mean_321daysbefore , agecat_reference * sex .

Table 27: Logistic Regression for Respiratory Hospitalizations (interaction terms, non-sensitive, comparison of modeled air quality of median of 3 days prior against mean on hospitalization day)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	mean	-.349	.409	.728	1	.393	.706	.317	1.572
	female	-.190	.480	.158	1	.691	.827	.323	2.117
	mean by female	**.430**	**.376**	**1.308**	**1**	**.253**	**1.538**	**.735**	**3.216**
	Ages 15-44			.453	5	.994			
	Ages 0-4	-.117	.490	.057	1	.811	.890	.341	2.322
	Ages 5-14	**.021**	**.558**	**.001**	**1**	**.969**	**1.022**	**.342**	**3.048**
	Ages 45-64	-.227	.421	.289	1	.591	.797	.349	1.821
	Ages 65-84	-.096	.385	.062	1	.804	.909	.427	1.932
	Ages 85 and older	-.144	.449	.103	1	.748	.866	.359	2.088
	Ages 15-44 * mean			.620	5	.987			
	Ages 0-4 by mean	**.383**	**.679**	**.318**	**1**	**.573**	**1.466**	**.387**	**5.550**
	Ages 5-14 by mean	-23.476	53.133	.195	1	.659	.000	.000	1.075E35
	Ages 45-64 by mean	**.058**	**.239**	**.060**	**1**	**.807**	**1.060**	**.664**	**1.693**
	Ages 65-84 by mean	-.078	.580	.018	1	.893	.925	.297	2.882
	Ages 85 and older by mean	**.018**	**.525**	**.001**	**1**	**.973**	**1.018**	**.363**	**2.850**
	Ages 15-44 * male			.323	5	.997			
	Ages 0-4 by female	**.020**	**.743**	**.001**	**1**	**.979**	**1.020**	**.238**	**4.379**
	Ages 5-14 by female	**.228**	**1.323**	**.030**	**1**	**.863**	**1.256**	**.094**	**16.803**
	Ages 45-64 by female	**.234**	**.576**	**.165**	**1**	**.684**	**1.264**	**.408**	**3.912**
	Ages 65-84 by female	**.236**	**.531**	**.198**	**1**	**.657**	**1.266**	**.447**	**3.584**
	Ages 85 and older by female	**.141**	**.592**	**.057**	**1**	**.811**	**1.152**	**.361**	**3.674**
	median_of_means_321daysbefore	**.157**	**1.512**	**.011**	**1**	**.917**	**1.171**	**.060**	**22.654**
	Ages 15-44 * median_of_means_321daysbefore			2.258	5	.812			

	Ages 0-4 by median_of_means_321daysbefore	-11.032	17.896	.380	1	.538	.000	.000	2.766E10
	Ages 5-14 by median_of_means_321daysbefore	**1.097**	**18.317**	**.004**	**1**	**.952**	**2.994**	**.000**	**1.169E16**
	Ages 45-64 by median_of_means_321daysbefore	**.321**	**1.545**	**.043**	**1**	**.836**	**1.378**	**.067**	**28.461**
	Ages 65-84 by median_of_means_321daysbefore	-.590	1.578	.140	1	.709	.554	.025	12.223
	Ages 85 and older by median_of_means_321daysbefore	-.031	1.765	.000	1	.986	.969	.031	30.805
	median_of_means_321daysbefore by female	-.492	.815	.364	1	.546	.611	.124	3.022
	Constant	-1.169	.349	11.235	1	.001	.311		

a. Variable(s) entered on step 1: mean, sex, mean * sex , agecat_reference, agecat_reference * mean , agecat_reference * sex , median_of_means_321daysbefore, agecat_reference * median_of_means_321daysbefore , median_of_means_321daysbefore * sex .

Table 28: Logistic Regression for Respiratory Hospitalizations (interaction terms, sensitive, comparison of modeled air quality using mean of 3 days prior against mean on hospitalization day)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
Step 1[a]	**Mean**	**.031**	**.364**	**.007**	**1**	**.932**	**1.032**	**.506**	**2.104**
	mean_321daysbefore	**.279**	**.314**	**.790**	**1**	**.374**	**1.322**	**.714**	**2.445**
	female	-.146	.279	.275	1	.600	.864	.500	1.493
	mean_321daysbefore by female	-.198	.428	.213	1	.644	.821	.355	1.900
	mean by sex(1)	**.067**	**.374**	**.032**	**1**	**.859**	**1.069**	**.513**	**2.226**
	Ages 15-64			.010	2	.995			
	Ages 0-14	**.026**	**.343**	**.006**	**1**	**.939**	**1.027**	**.524**	**2.011**
	Ages 65 and older	**.023**	**.248**	**.009**	**1**	**.925**	**1.024**	**.630**	**1.663**
	Ages 15-64 by male			.103	2	.950			
	Ages 0-14 by female	-.039	.573	.005	1	.946	.962	.313	2.959
	Ages 65 and older by female	**.088**	**.337**	**.069**	**1**	**.793**	**1.092**	**.564**	**2.116**
	Ages 15-64 by mean_321daysbefore			2.093	2	.351			
	Ages 0-14 by mean_321daysbefore	-.889	1.526	.339	1	.560	.411	.021	8.182
	Ages 65 and older by mean_321daysbefore	-.561	.403	1.932	1	.165	.571	.259	1.258
	Ages 15-64 by mean			.500	2	.779			
	Ages 0-14 by mean	-.141	.534	.069	1	.792	.869	.305	2.476
	Ages 65 and older by mean	-.325	.462	.494	1	.482	.723	.292	1.787
	Constant	-1.266	.202	39.263	1	.000	.282		

a. Variable(s) entered on step 1: mean, mean_321daysbefore, sex, mean_321daysbefore * sex , mean * sex , agecat_sensitive_reference, agecat_sensitive_reference * sex , agecat_sensitive_reference * mean_321daysbefore , agecat_sensitive_reference * mean .

Table 29: Logistic Regression for Respiratory Hospitalizations (interaction terms, sensitive, comparison of modeled air quality using median of 3 days prior against mean on hospitalization day)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	Mean	-.312	.369	.715	1	.398	.732	.355	1.509
	Female	-.038	.270	.020	1	.887	.962	.567	1.632
	mean by female	**.427**	**.377**	**1.284**	**1**	**.257**	**1.532**	**.732**	**3.206**
	median_of_means_321daysbefore	**.420**	**.393**	**1.144**	**1**	**.285**	**1.522**	**.705**	**3.287**
	median_of_means_321daysbefore by Female	-.328	.683	.231	1	.631	.720	.189	2.746
	Ages 15-64			.049	2	.976			
	Ages 0-14	**.062**	**.334**	**.034**	**1**	**.854**	**1.063**	**.553**	**2.046**
	Ages 65 and older	**.047**	**.241**	**.038**	**1**	**.845**	**1.048**	**.653**	**1.682**
	Ages 15-64 by mean			.264	2	.876			
	Ages 0-14 by mean	**.290**	**.653**	**.197**	**1**	**.657**	**1.336**	**.372**	**4.802**
	Ages 65 and older by mean	-.066	.381	.030	1	.862	.936	.443	1.976
	Ages 15-64 by median_of_means_321daysbefore			2.463	2	.292			
	Ages 0-14 by median_of_means_321daysbefore	-10.432	12.532	.693	1	.405	.000	.000	1370158.106
	Ages 65 and older by median_of_means_321daysbefore	-.801	.593	1.822	1	.177	.449	.140	1.436
	Ages 15-64 by male			.088	2	.957			
	Ages 0-14 by female	-.112	.566	.039	1	.843	.894	.295	2.709
	Ages 65 and older by female	**.042**	**.326**	**.016**	**1**	**.898**	**1.043**	**.550**	**1.976**
	Constant	-1.325	.196	45.474	1	.000	.266		

a. Variable(s) entered on step 1: mean, sex, mean * sex , median_of_means_321daysbefore, median_of_means_321daysbefore * sex , agecat_sensitive_reference, agecat_sensitive_reference * mean , agecat_sensitive_reference * median_of_means_321daysbefore , agecat_sensitive_reference * sex .

Table 30: Logistic Regression for Cardiovascular Hospitalizations (interaction terms, non-sensitive, comparison of modeled air quality using mean of 3 days prior against mean on hospitalization day)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	Mean	-2.944	4.596	.410	1	.522	.053	.000	429.886
	mean_321daysbefore	**.200**	**.382**	**.274**	**1**	**.601**	**1.221**	**.578**	**2.583**
	female	-.044	.575	.006	1	.939	.957	.310	2.955
	mean_321daysbefore by female	**.063**	**.418**	**.022**	**1**	**.881**	**1.065**	**.469**	**2.416**
	mean by female	-.080	.447	.032	1	.858	.923	.384	2.218
	Ages 15-44			.430	3	.934			
	Ages 0-4	-.198	.399	.248	1	.619	.820	.375	1.792
	Ages 5-14	-.243	.391	.387	1	.534	.784	.364	1.688
	Ages 45-64	-.169	.451	.140	1	.708	.845	.349	2.043
	Ages 15-44 * mean			1.860	3	.602			
	Ages 0-4 by mean	**2.848**	**4.599**	**.383**	**1**	**.536**	**17.250**	**.002**	**141729.881**
	Ages 5-14 by mean	**2.794**	**4.609**	**.367**	**1**	**.544**	**16.342**	**.002**	**137032.502**
	Ages 0-4 by mean	**4.305**	**4.746**	**.823**	**1**	**.364**	**74.095**	**.007**	**811430.664**
	Ages 15-44 * mean_321daysbefore			2.045	3	.563			
	Ages 0-4 by mean_321daysbefore	-.389	.468	.691	1	.406	.677	.271	1.697
	Ages 5-14 by mean_321daysbefore	**.112**	**.459**	**.059**	**1**	**.807**	**1.118**	**.455**	**2.748**
	Ages 45-64 by mean_321daysbefore	**.386**	**.620**	**.387**	**1**	**.534**	**1.470**	**.437**	**4.953**
	Ages 15-44 * male			**.363**	**3**	**.948**			
	Ages 0-4 by female	**.156**	**.623**	**.062**	**1**	**.803**	**1.169**	**.344**	**3.965**
	Ages 5-14 by female	**.065**	**.598**	**.012**	**1**	**.914**	**1.067**	**.330**	**3.444**
	Ages 45-64 by female	-.089	.660	.018	1	.893	.915	.251	3.340
	Constant	-1.172	.374	9.829	1	.002	.310		

a. Variable(s) entered on step 1: mean, mean_321daysbefore, sex, mean_321daysbefore * sex , mean * sex , agecat_reference, agecat_reference * mean , agecat_reference * mean_321daysbefore , agecat_reference * sex .

Table 31: Logistic Regression for Cardiovascular Hospitalizations (interaction terms, non-sensitive, comparison of modeled air quality using median of 3 days prior against mean on hospitalization day)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	mean	-3.427	4.346	.622	1	.430	.032	.000	162.455
	female	-.026	.563	.002	1	.963	.974	.323	2.939
	mean by female	**.017**	**.391**	**.002**	**1**	**.965**	**1.017**	**.473**	**2.188**
	Ages 15-44			.250	3	.969			
	Ages 0-4	-.166	.393	.178	1	.673	.847	.392	1.829
	Ages 5-14	-.177	.385	.211	1	.646	.838	.394	1.783
	Ages 45-64	-.216	.446	.234	1	.628	.806	.336	1.931
	Ages 15-44 by mean			1.787	3	.618			
	Ages 0-4 by mean	**3.308**	**4.349**	**.579**	**1**	**.447**	**27.336**	**.005**	**137474.087**
	Ages 5-14 by mean	**3.149**	**4.353**	**.523**	**1**	**.469**	**23.309**	**.005**	**118311.661**
	Ages 45-64 by mean	**4.239**	**4.444**	**.910**	**1**	**.340**	**69.369**	**.011**	**420263.596**
	Ages 15-44 by male			.151	3	.985			
	Ages 0-4 by female	**.110**	**.613**	**.032**	**1**	**.858**	**1.116**	**.336**	**3.711**
	Ages 5-14 by female	**.015**	**.586**	**.001**	**1**	**.979**	**1.016**	**.322**	**3.205**
	Ages 45-64 by female	-.027	.647	.002	1	.966	.973	.274	3.461
	median_of_means_321daysbefore	**.087**	**.699**	**.016**	**1**	**.901**	**1.091**	**.277**	**4.298**
	Ages 15-44 by median_of_means_321daysbefore			5.381	3	.146			
	Ages 0-4 by median_of_means_321daysbefore	-.713	1.108	.414	1	.520	.490	.056	4.300
	Ages 5-14 by median_of_means_321daysbefore	**.452**	**.798**	**.321**	**1**	**.571**	**1.572**	**.329**	**7.503**
	Ages 45-64 by median_of_means_321daysbefore	**2.017**	**1.160**	**3.025**	**1**	**.082**	**7.517**	**.774**	**72.972**
	median_of_means_321daysbefore by female	-.874	.721	1.469	1	.226	.417	.102	1.715
	Constant	-1.176	.369	10.150	1	.001	.308		

a. Variable(s) entered on step 1: mean, sex, mean * sex , agecat_reference, agecat_reference * mean , agecat_reference * sex , median_of_means_321daysbefore, agecat_reference * median_of_means_321daysbefore , median_of_means_321daysbefore * sex .

Table 32: Logistic Regression for Cardiovascular Hospitalizations (interaction terms, sensitive, comparison of modeled air quality using mean of 3 days prior against mean on hospitalization day)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	Mean	-.155	.295	.275	1	.600	.857	.480	1.528
	mean_321daysbefore	-.092	.255	.128	1	.720	.913	.553	1.505
	female	**.094**	**.230**	**.165**	**1**	**.684**	**1.098**	**.699**	**1.724**
	mean_321daysbefore by female	**.214**	**.341**	**.396**	**1**	**.529**	**1.239**	**.635**	**2.417**
	mean by female	-.234	.540	.188	1	.664	.791	.274	2.280
	Ages 0-14	-.045	.169	.073	1	.788	.956	.687	1.330
	Ages 0-14 by female	-.114	.273	.173	1	.677	.893	.523	1.524
	Ages 0-14 by mean_321daysbefore	**.417**	**.329**	**1.611**	**1**	**.204**	**1.518**	**.797**	**2.892**
	Ages 0-14 by mean	**.218**	**.513**	**.180**	**1**	**.672**	**1.243**	**.455**	**3.398**
	Constant	-1.354	.132	105.909	1	.000	.258		

a. Variable(s) entered on step 1: mean, mean_321daysbefore, sex, mean_321daysbefore * sex , mean * sex , agecat_sensitive_reference, agecat_sensitive_reference * sex , agecat_sensitive_reference * mean_321daysbefore , agecat_sensitive_reference * mean .

Table 33: Logistic Regression for Cardiovascular Hospitalizations (interaction terms, sensitive, comparison of modeled air quality using median of 3 days prior against mean on hospitalization day)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	Mean	-.193	.330	.341	1	.559	.825	.431	1.576
	Female	**.060**	**.222**	**.073**	**1**	**.788**	**1.062**	**.687**	**1.641**
	mean by female	-.076	.483	.025	1	.875	.927	.359	2.389
	median_of_means_321daysbefore	-.417	.585	.508	1	.476	.659	.209	2.075
	median_of_means_321daysbefore by female	-.468	.467	1.006	1	.316	.626	.251	1.563
	Ages 0-14	-.019	.161	.014	1	.907	.982	.717	1.344
	Ages 0-14 by mean	-.017	.437	.002	1	.969	.983	.418	2.314
	Ages 0-14 by median_of_means_321daysbefore	**.937**	**.661**	**2.007**	**1**	**.157**	**2.552**	**.698**	**9.333**
	Ages 0-14 by female	-.086	.264	.106	1	.744	.918	.547	1.539
	Constant	-1.331	.125	112.576	1	.000	.264		

a. Variable(s) entered on step 1: mean, sex, mean * sex , median_of_means_321daysbefore, median_of_means_321daysbefore * sex , agecat_sensitive_reference, agecat_sensitive_reference * mean , agecat_sensitive_reference * median_of_means_321daysbefore , agecat_sensitive_reference * sex .

Table 34: Public Health Population Impacts in Okanogan and Surrounding Counties (Based on proximity)

Zip Code	Total Population (based on 2010 U.S. Census Populations)	Dates above 35 μg/m³	Maximum modeled $PM_{2.5}$ value (μg/m³) above 35 μg/m³
98822	1,874	9/15 9/16 9/12 9/3 9/7 9/2 9/11 9/5 9/4 9/1	436 332 324 318 253 227 188 138 116
98856	2,182	8/17 9/15 9/1 9/14 8/25 9/3	168 165 138 82 63 58
98862	1,916	8/20	61
	SUM: 5,972		

Table 35: 2006 Counties of Interest and $PM_{2.5}$ Air Quality Monitors[2]

County	Latitude	Longitude	Agency	City
Okanogan*[3]	48.364267	-120.121115	EPA	Twisp
	48.477198	-120.190562	EPA	Winthrop
	48.387531	-119.928671	EPA	Twisp Forest
	48.555533	-119.750983	USFS	Conconully
	48.599983	-120.166950	USFS	Eight Mile site
	48.962167	-119.445617	USFS	Oroville
	48.131817	-118.971000	USFS	Nespelem
Grant*	47.130336	-119.272598	EPA	Moses Lake
Chelan*	47.412222	-120.318333	EPA	Wenatchee
	47.598863	-120.664702	EPA	Leavenworth
Skagit	48.410311	-122.337849	EPA	Mount Vernon
	48.731420	-121.065815	EPA	Rockport
	48.544722	-117.903611	EPA	Colville
Whatcom	48.762778	-122.440278	EPA	Bellingham
	48.731420	-121.065815	EPA	North Cascades
Stevens*	48.070967	-118.198717	USFS	Fruitland
	48.601967	-118.05955	USFS	Kettle Falls
Adams*	47.128611	-118.381944	EPA	Ritzville
Benton*	46.21835	-119.204153	EPA	Kennewick
Franklin*	46.575597	-119.000705	EPA	Mesa
Kittitas*	46.996111	-120.545278	EPA	Ellensburg
	47.399815	-121.427096	EPA	Snoqualmie Pass
Klickitat*	45.664223	-121.001945	EPA	Lyle
	45.749818	-121.401159	EPA	White Salmon
Lewis*	46.624347	-121.386869	EPA	Naches
Pierce*	47.2656	-122.3858	EPA	Tacoma
	47.211	-122.357	EPA	Puyallup
	47.1864	-122.4517	EPA	Tacoma Sheridan
	47.14	-122.3003	EPA	Puyallup (Two)
	46.784722	-121.738333	EPA	Packwood
Yakima**	46.38024	-120.33266	EPA	Toppenish
	46.59678	-120.512215	EPA	Yakima

[2] Air quality monitors were not available for Lincoln, Douglas, and Ferry counties in the EPA Air Quality DataMart during the time period of this analysis.

[3] Asterisks (*) indicate counties that were later determined to have had smoke impacts above 1000 $\mu g/m^3$ based on cumulative model data.

Table 36: Cumulative Smoke Impacts in Washington Counties during 33-Day Study Period

County	Sum of 33 days for county (ug/m^3)	Average per day for county (ug/m^3)	Area (meters squared)
Okanogan	9,757	296	13,826,900,000
Yakima	9,065	275	11,243,100,000
Chelan	5,770	175	7,681,610,000
Lewis	4,786	145	6,407,160,000
Grant	2,861	87	7,157,870,000
Benton	2,392	72	4,574,050,000
Stevens	1,929	58	6,599,200,000
Skamania	1,909	58	4,120,140,000
Adams	1,859	56	5,080,340,000
Pend Oreille	1,705	52	3,683,680,000
Pierce	1,441	44	4,574,050,000
Klickitat	1,391	42	4,853,380,000
Franklin	1,330	40	3,282,140,000
Kittitas	1,149	34.8	6,110,370,000
Douglas	979	29.7	4,835,920,000
Ferry	910	27.6	5,883,420,000
Lincoln	906	27.5	6,005,620,000
Whitman	608	18.4	5,621,540,000
Walla Walla	597	18.1	3,369,430,000
Whatcom	547	16.6	6,564,290,000
Spokane	545	16.5	4,556,590,000
Skagit	512	15.5	4,940,670,000
Cowlitz	496	15.0	2,950,440,000
Snohomish	448	13.6	5,831,040,000
Clark	361	10.9	1,798,200,000
Grays Harbor	300	9.1	5,865,960,000
Columbia	244	7.4	2,164,820,000
Garfield	201	6.1	1,937,860,000
Asotin	179	5.4	1,710,900,000
King	134	4.1	5,883,420,000
Jefferson	123	3.7	5,656,460,000
Mason	121	3.7	2,810,770,000
Clallam	57	1.7	6,878,540,000
Pacific	57	1.7	3,020,270,000
Wahkiakum	17.8	0.5	855,452,000
Thurston	14.2	0.4	2,077,530,000
Island	13.2	0.4	1,309,370,000
Kitsap	10.6	0.3	1,466,490,000
San Juan	7.3	0.2	1,641,070,000

Table 37: Smoke Impact Statistics for Washington Zip Codes during 33-Day Study Period

County	Minimum (ug/m^3)	Maximum (ug/m^3)	Range (ug/m^3)	Average (ug/m^3)	Standard Deviation (ug/m^3)
Okanogan	1.5	674.1	672.6	12.3	34.5
Yakima	2.4	63.3	61.0	14.1	12.7
Chelan	1.3	2729.8	2728.5	13.1	129.8
Lewis	0.1	63.9	63.8	13.0	19.0
Grant	1.5	15.9	14.4	7.0	4.0
Benton	4.9	14.0	9.0	9.1	2.3
Stevens	1.7	19.5	17.8	5.1	2.8
Skamania	2.4	36.7	34.3	8.1	6.8
Adams	1.5	15.6	14.1	6.4	4.5
Pend Oreille	2.3	41.6	39.2	8.1	7.1
Pierce	0.1	66.3	66.3	5.5	10.4
Klickitat	3.1	8.8	5.7	5.0	1.3
Franklin	1.8	13.4	11.6	7.1	3.0
Kittitas	0.4	12.3	11.9	3.3	2.3
Douglas	1.5	6.5	5.1	3.5	1.1
Ferry	1.4	10.1	8.7	2.7	1.6
Lincoln	1.6	10.0	8.5	2.6	1.4
Whitman	1.5	2.4	1.0	1.9	0.3
Walla Walla	1.8	5.3	3.6	3.1	0.9
Whatcom	0.0	4.6	4.6	1.5	1.2
Spokane	1.7	2.6	0.9	2.1	0.2
Skagit	0.2	8.4	8.2	1.8	1.6
Cowlitz	0.3	6.4	6.1	2.9	1.7
Snohomish	0.1	5.3	5.2	1.3	1.0
Clark	3.1	5.0	1.9	3.5	0.3
Grays Harbor	0.0	4.8	4.7	0.9	0.9
Columbia	1.6	2.6	1.0	2.0	0.2
Garfield	1.7	2.0	0.3	1.8	0.1
Asotin	1.7	2.1	0.4	1.8	0.1
King	0.1	11.6	11.6	0.4	0.9
Jefferson	0.1	12.1	12.1	0.4	0.7
Mason	0.1	26.7	26.7	0.7	2.9
Clallam	0.0	0.4	0.4	0.1	0.1
Pacific	0.1	0.6	0.5	0.3	0.1
Wahkiakum	0.3	0.7	0.4	0.4	0.1
Thurston	0.1	0.9	0.9	0.1	0.1
Island	0.1	0.3	0.2	0.2	0.0
Kitsap	0.1	0.2	0.1	0.1	0.0
San Juan	0.0	0.2	0.1	0.1	0.0

Table 38: Descriptive Statistics for U.S. Forest Service (non-enforceable) and U.S. Environmental Protection Agency (enforceable) Monitor Data Compared Against U.S. Forest Service Model Data

Descriptive Statistics

	N	Range	Minimum	Maximum	Sum	Mean		Std. Deviation	Variance	Skewness		Kurtosis	
							Std. Error				Std. Error		Std. Error
Model air concentration values	1056	62.962	0.000	62.962	267.534	0.253	0.073	2.367	5.605	21.733	0.075	528.992	0.150
Ground monitor air concentration values	832	424.550	0.400	424.950	18238.130	21.921	1.591	45.900	2106.795	5.926	0.085	41.168	0.169
Valid N (listwise)	832												

Table 39: Descriptive Statistics for U.S. Forest Service Monitor Data (non-enforceable) Compared Against U.S. Forest Service Model Data

Descriptive Statistics

	N	Range	Minimum	Maximum	Sum	Mean		Std. Deviation	Variance	Skewness		Kurtosis	
							Std. Error				Std. Error		Std. Error
Model air concentration values	231	6.037	0.000	6.037	45.271	0.196	0.047	0.718	0.515	5.666	0.160	36.916	0.319
Ground monitor air concentration values	178	422.090	2.860	424.950	10211.280	57.367	6.555	87.451	7647.640	2.751	0.182	7.482	0.362
Valid N (listwise)	178												

Table 40: Descriptive Statistics for U.S. Environmental Protection Agency Monitor Data (enforceable) Compared Against U.S. Forest Service Model Data

Descriptive Statistics

	N	Range	Minimum	Maximum	Sum	Mean		Std. Deviation	Variance	Skewness		Kurtosis	
							Std. Error				Std. Error		Std. Error
Model air concentration values	825	62.962	0.000	62.962	222.263	0.269	0.092	2.652	7.031	19.766	0.085	429.963	0.170
Ground monitor air concentration values	654	107.890	0.400	108.290	8026.850	12.273	0.513	13.132	172.441	3.452	0.096	15.966	0.191
Valid N (listwise)	654												

Table 41: Public Health Population Impacts in 14 Counties (Based on cumulative smoke impacts)

Zip Code[4]	Total Population (based on 2010 U.S. Census Populations)	Dates above 35 μg/m³	Maximum modeled $PM_{2.5}$ value (μg/m³) above 35 μg/m³
98822	1,874	9/15 9/16 9/12 9/3 9/7 9/2 9/11 9/5 9/4 9/1	435.996 346.961 332.432 323.826 317.620 252.697 227.288 188.272 138.143 115.757
98856	2,182	8/17 9/15 9/1 9/14 8/25 9/3	167.680 164.991 138.195 82.093 62.615 58.235
98862	1,916	8/20	60.976
98937	3,355	8/17	62.962
98903	13,522	8/17	61.853
98377	2,043	8/17	36.617
98361	1,209	8/17	63.469
98355	634	8/17	35.853
98304	794	8/17	41.547
	SUM: 27,529		

[4] Two zip codes that had associated modeled air quality were not included in this table because there were no zip code population data associated with them; those two zip codes were 98229 and 99144.

Figure 14: 33-Day Air Quality Sum of Modeled Smoke Impacts

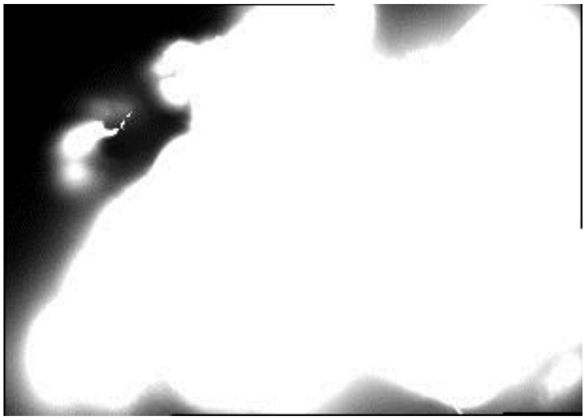


Figure 15: Top 14 Counties (75th percentile) Impacted by Cumulative Wildfire Smoke

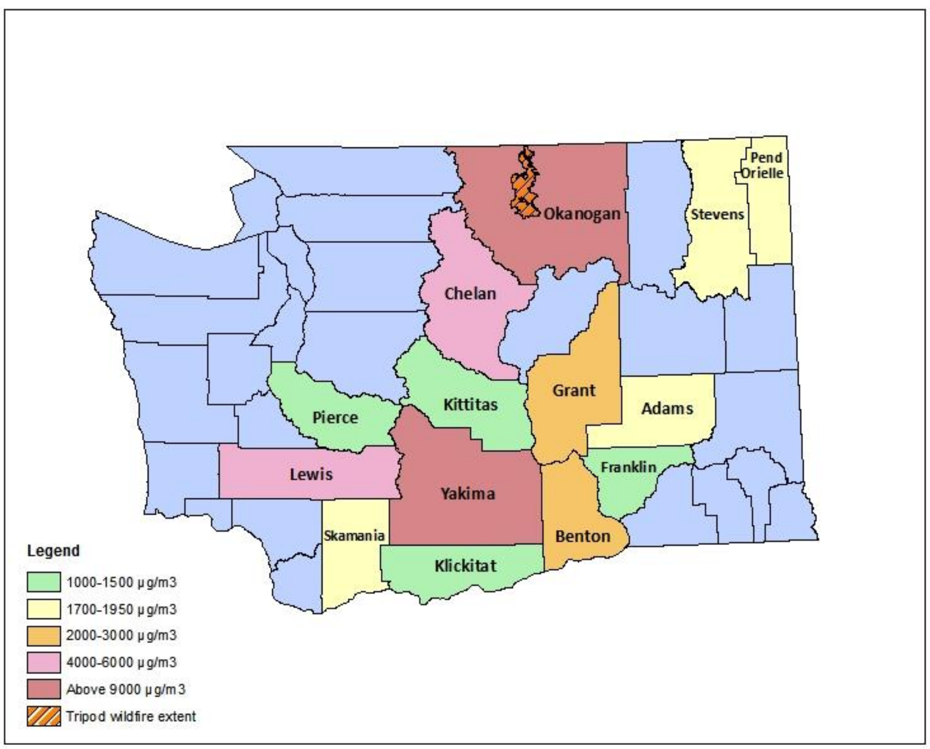


Figure 16: Hospital Locations and 14 Counties of Cumulative Smoke Impacts

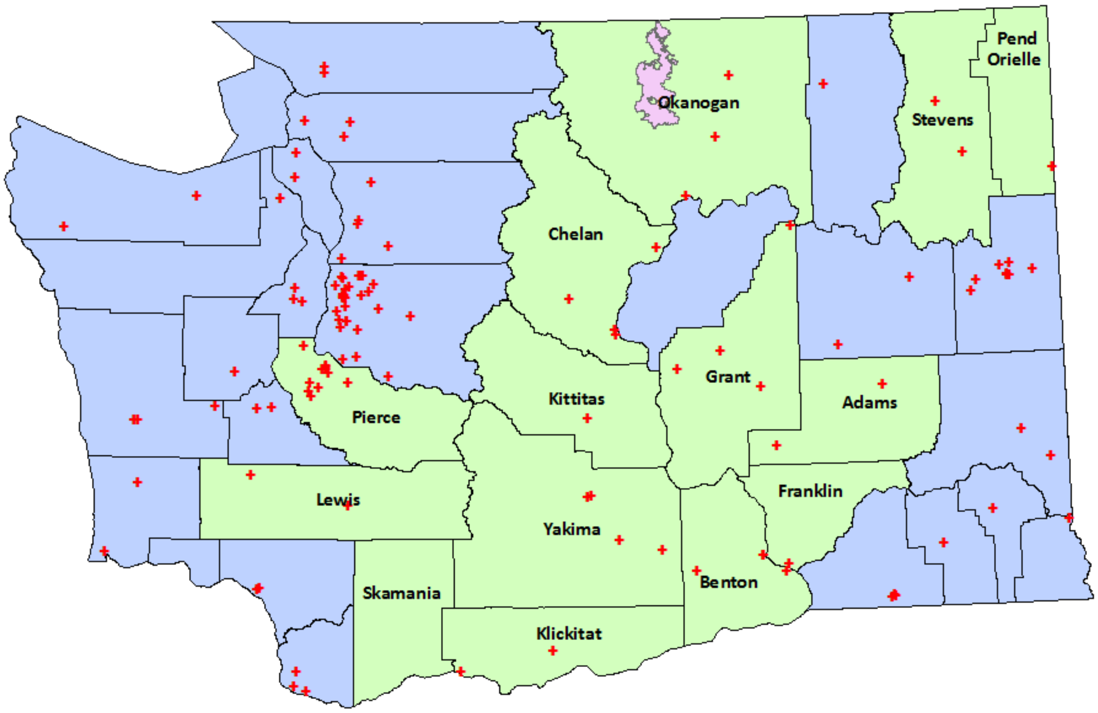


Figure 17: Modeled $PM_{2.5}$ Values (U.S. Forest Service model) Versus Actual Monitor $PM_{2.5}$ Values (U.S. Forest Service and U.S. EPA from August 14 to September 15, 2006 Daily Averages

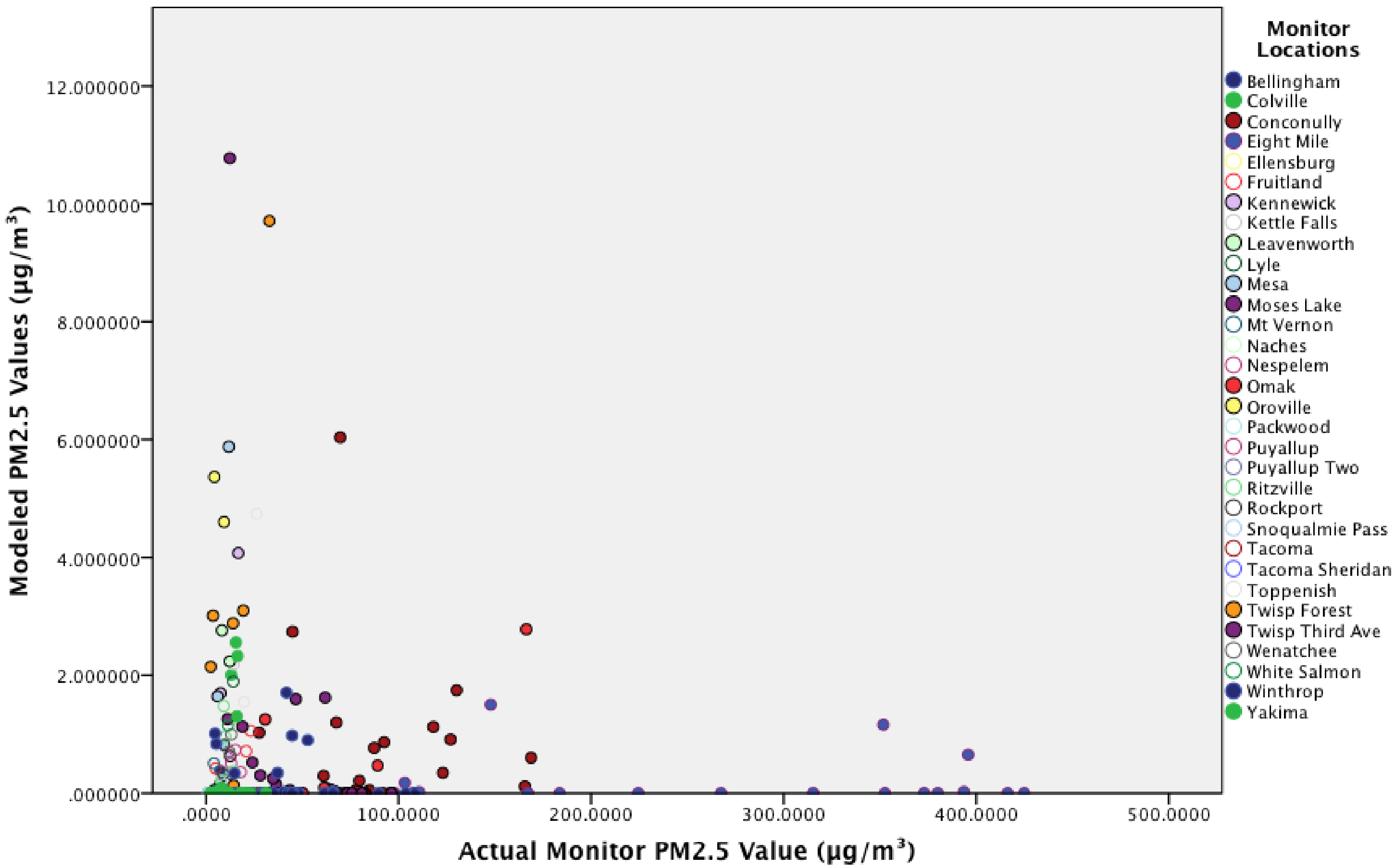


Figure 18: Modeled $PM_{2.5}$ Values (U.S. Forest Service model) Versus Actual Monitor $PM_{2.5}$ Values (U.S. Forest Service only) from August 14 to September 15, 2006 Daily Averages

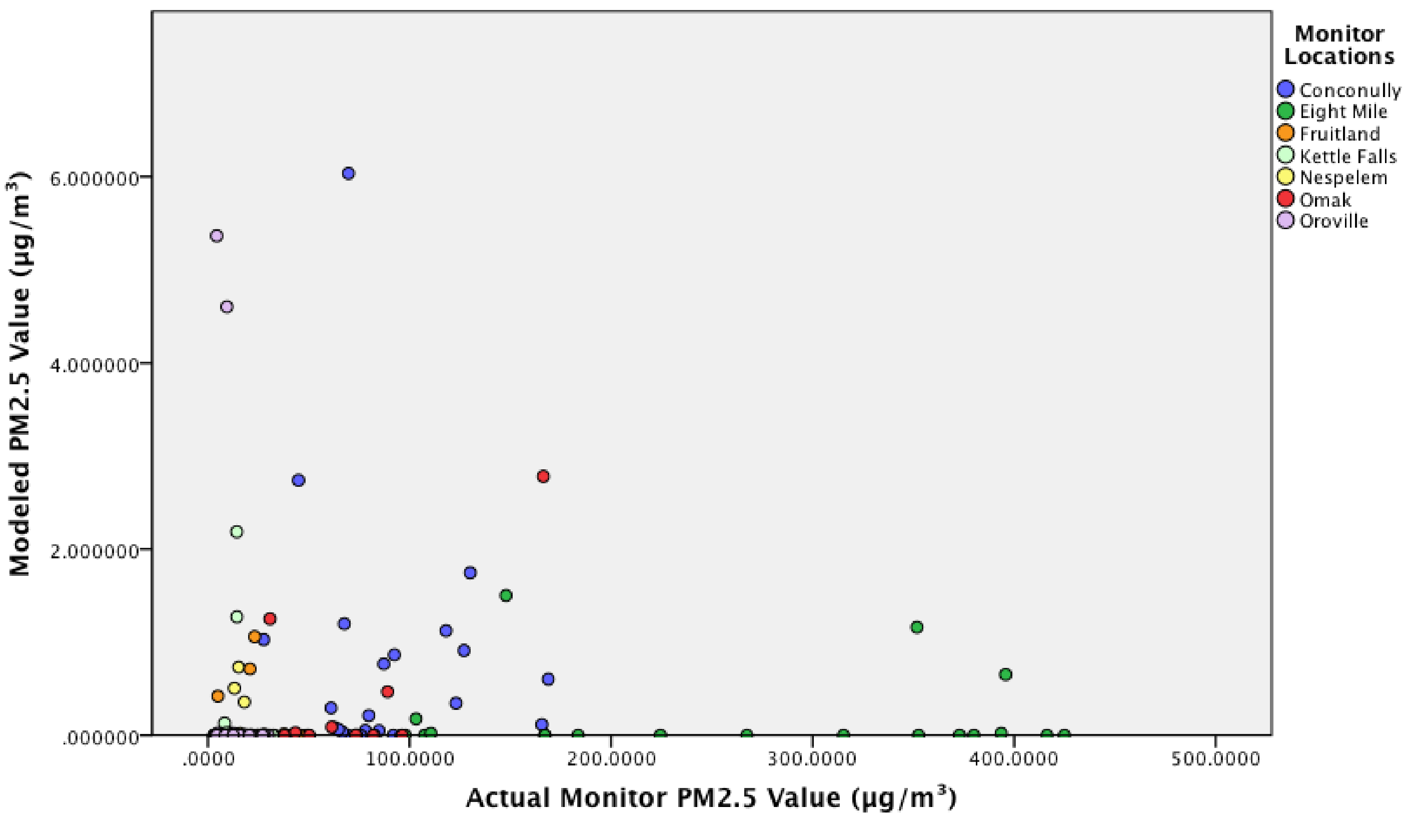


Figure 19: Modeled $PM_{2.5}$ Values (U.S. Forest Service model) Versus Actual Monitor $PM_{2.5}$ Values (U.S. EPA) from August 14 to September 15, 2006 Daily Averages

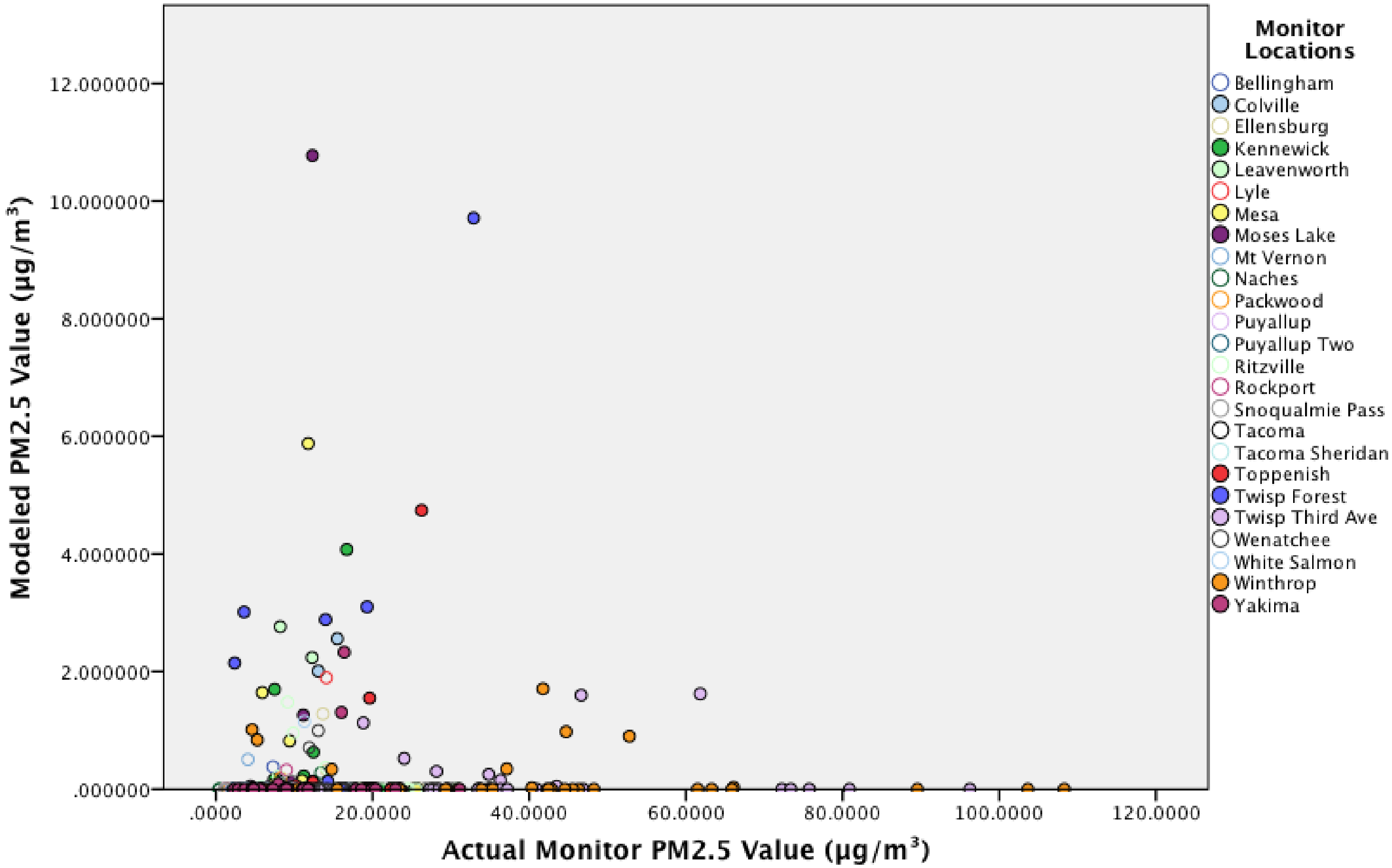


Figure 20: Model versus Monitor $PM_{2.5}$ Values for Conconully (Okanogan County, USFS)

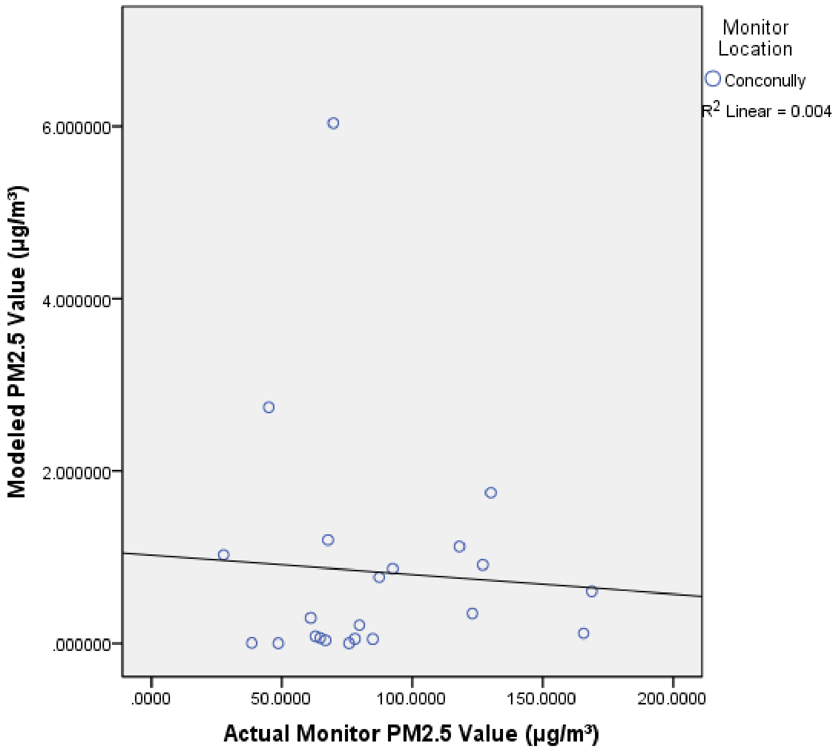


Figure 21: Model versus Monitor $PM_{2.5}$ Values for Eight Mile (Okanogan County, USFS)

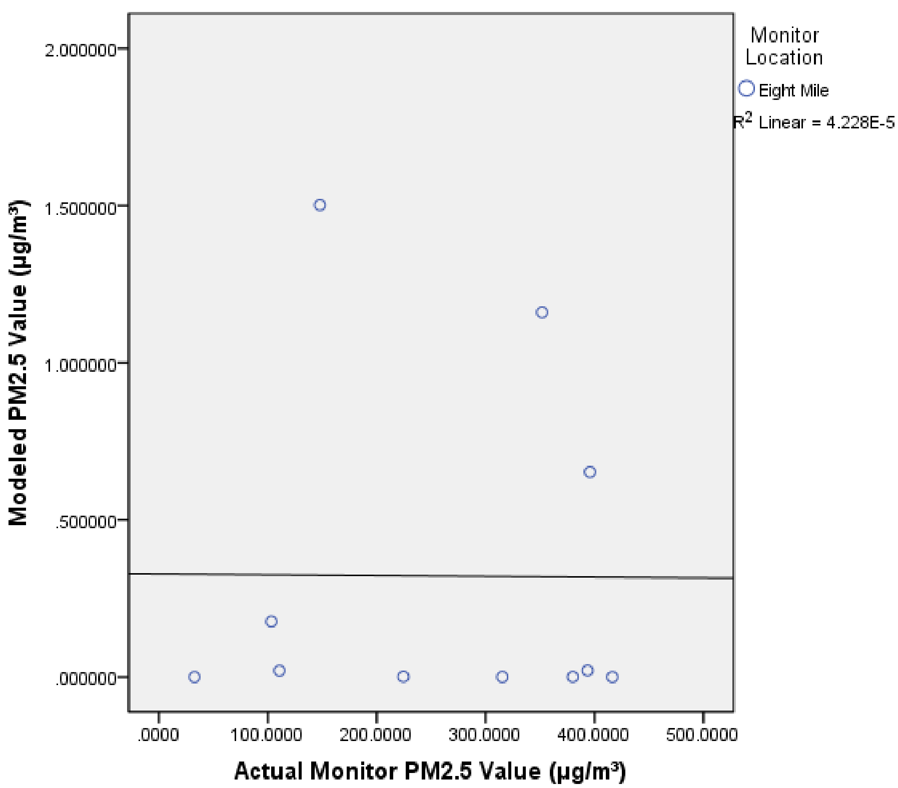


Figure 22: Model versus Monitor $PM_{2.5}$ Values for Nespelem (Okanogan County, USFS)

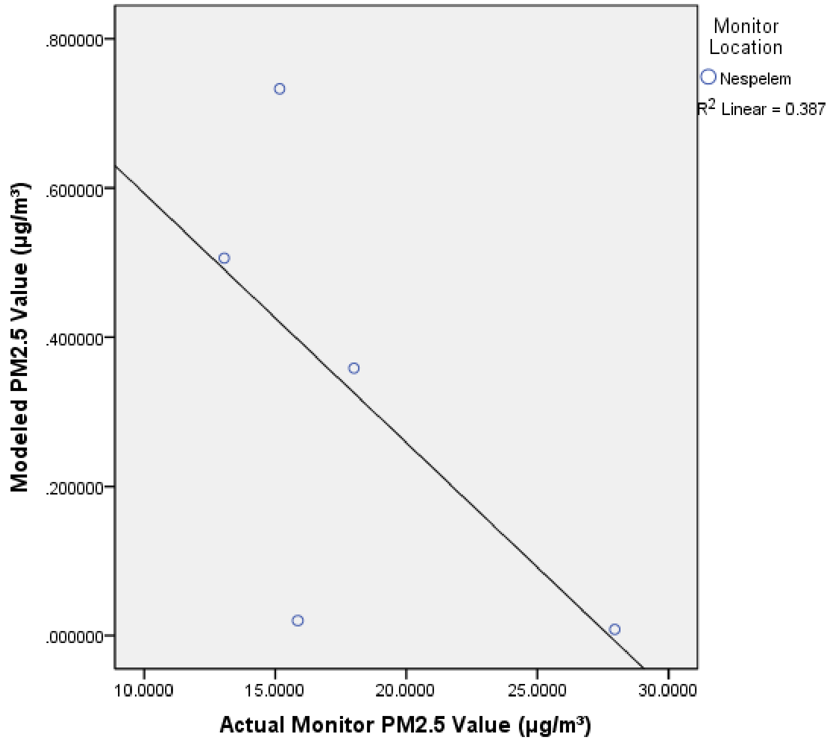


Figure 23: Model versus Monitor $PM_{2.5}$ Values for Omak (Okanogan County, USFS)

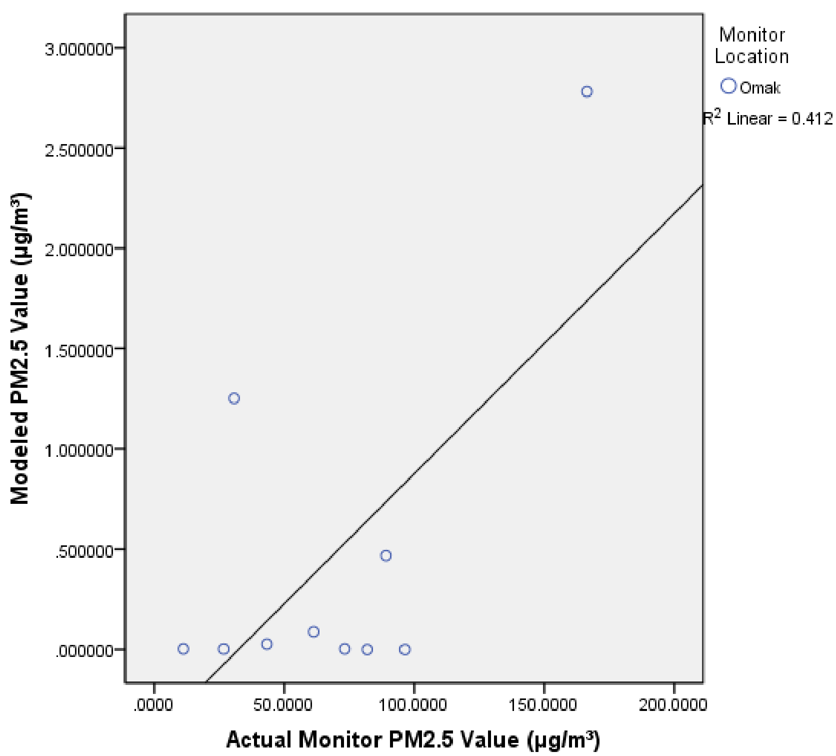


Figure 24: Model versus Monitor $PM_{2.5}$ Values for Twisp Forest (Okanogan County, EPA)

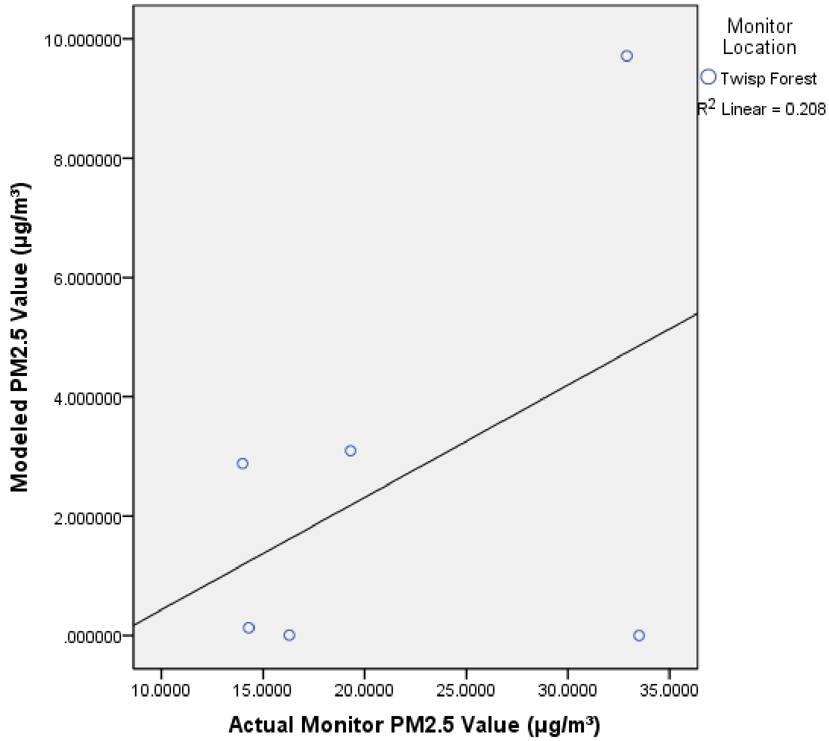


Figure 25: Model versus Monitor $PM_{2.5}$ Values for Twisp Third Ave (Okanogan County, EPA)

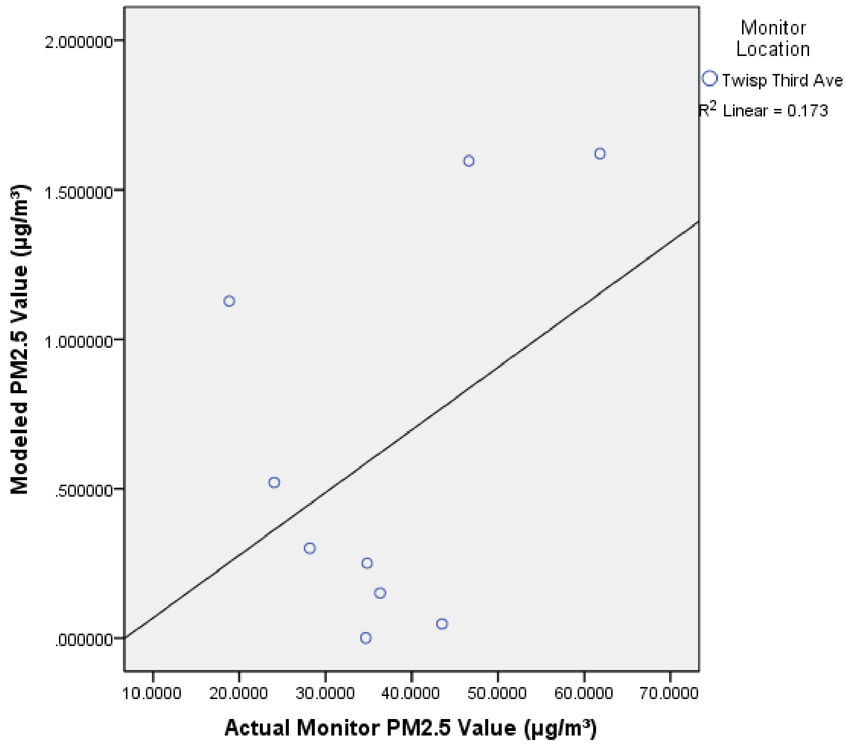
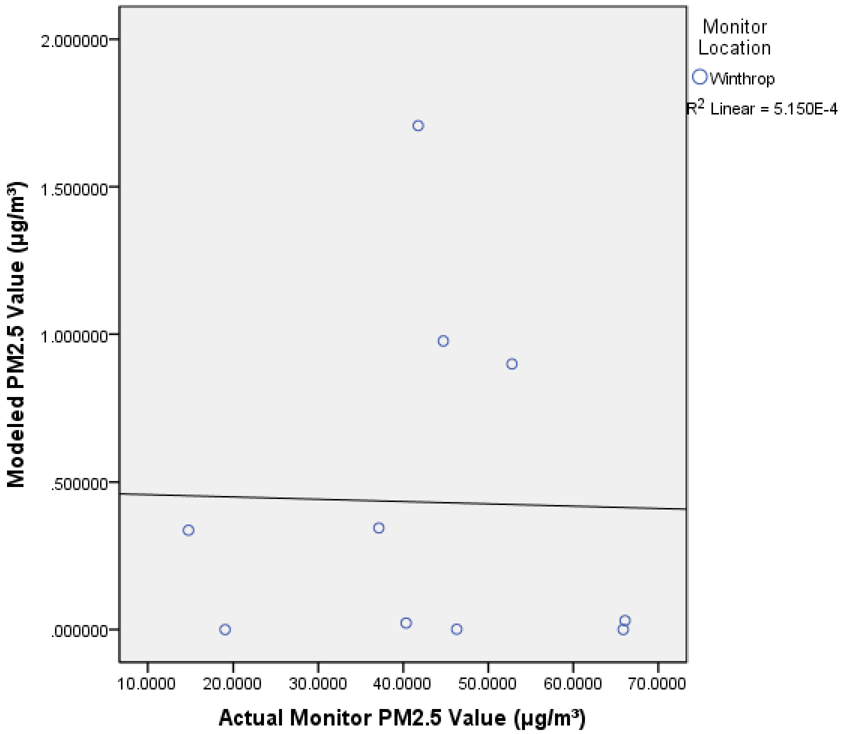


Figure 26: Model versus Monitor $PM_{2.5}$ Values for Winthrop (Okanogan County, EPA)



Chapter 5: Research Limitations

Figure 27: Monitoring Locations in Washington State against Modeled Smoke Plume on August 14, 2006

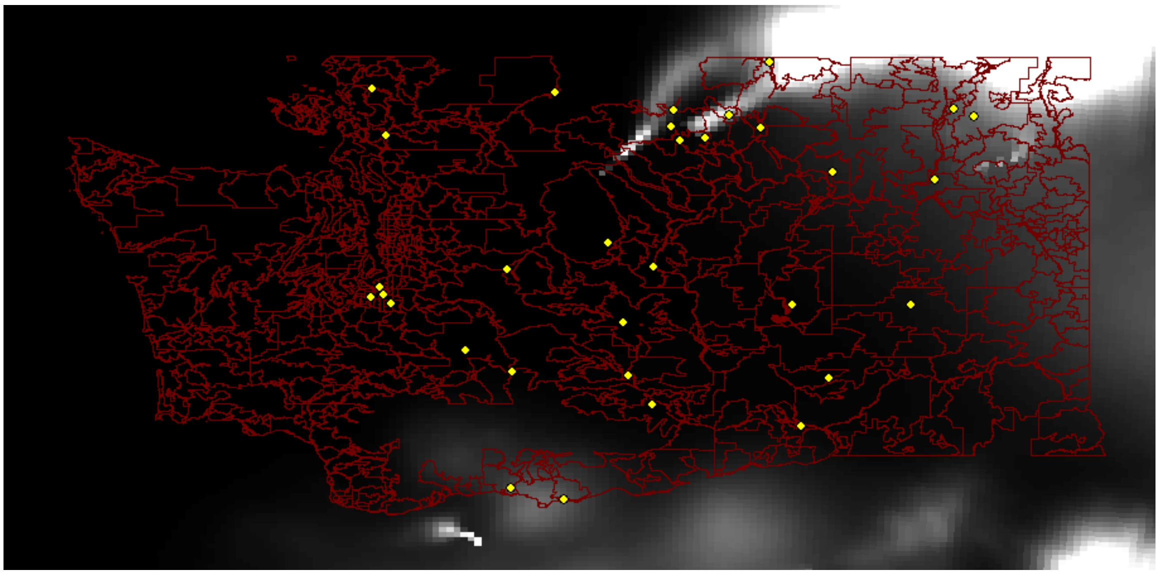


Figure 28: Monitoring Stations in Zip Codes 98862 and 98856 Within Modeled Smoke Plume on August 14, 2006

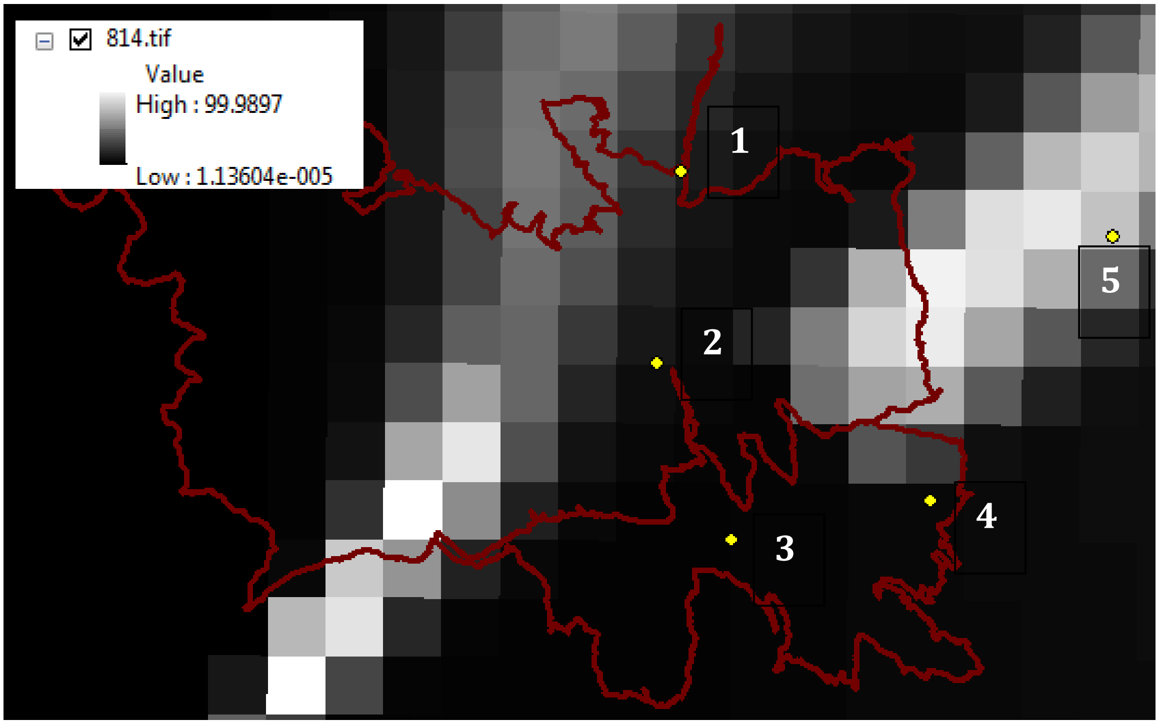


Table 43: Per-unit Economic Value Used in U.S. EPA (1999) (Kochi, et al. 2010)

	U.S. EPA value (US$ 2007)	Dickie and Messman (2004)
Mortality	$7,600,000	
Hospital admissions		
All respiratory (ICD-9 460-519)	$10,971	
All cardiovascular (ICD-9 393-429)	$15,105	
Emergency department visits for asthma	$308	
Respiratory illness and symptoms		
Acute bronchitis (ICD-9 466)	$71	$202 (adult), $380 (child)
Asthma attack of moderate or worse asthma day (ICD-9 493)	$50	
Acute respiratory symptoms (ICD-9 460-465)	$28	1-day symptom: $90 (adult), $190 (child)
Upper respiratory symptoms (ICD-9 470-478—diseases of upper respiratory tract)	$30	
Lower respiratory symptoms (Bronchitis = ICD-9 466, 490, 491)	$19	
Shortness of breath, chest tightness or wheeze	$8	1-day shortness of breath: $190 (child)
Work days loss	$131	
Mid restricted-activity days	$60	

Chapter 7: Conclusion

Figure 29: NASA MODIS Satellite Image from September 19, 2012[6]

[6] Image obtained from: http://www.nasa.gov/mission_pages/fires/main/usa/20120920-wash.html?fb_action_ids=3965989862366&fb_action_types=og.likes&fb_source=hovercard