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Evaluating the Impact of Fire Emissions Inventories on Air Quality Simulation and Health Impact Assessment during the 2012 Colorado Wildfire Season

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By

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B.S.
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Abstract

Evaluating the Impact of Fire Emissions Inventories on Air Quality Simulation and Health Impact Assessment during the 2012 Colorado Wildfire Season
By Lois Chang

Wildfires are a global phenomenon and pose a threat to human health. Exposure to wildfire smoke has been associated with a variety of cardiovascular and respiratory problems as well as cancer. In order to assess these associations in fire epidemiological studies, it is crucial to utilize methods that most accurately measures concentrations of air pollutants. Recently, researchers have begun using high resolution fire inventories such as Fire INventory from NCAR (FINN) and Quick Fire Emissions Dataset (QFED) to quantify emissions from wildfires. This study evaluated these two fire inventories by comparing their $PM_{2.5}$ estimates to those calculated by Environmental Protection Agency's (EPA's) ground monitor stations, which is considered the golden standard. Then, these fire inventories were applied in a conditional logistic regression that yielded effect estimates for six respiratory and seven cardiovascular endpoint. This study found that QFED generated a higher correlation coefficient and thus, revealed that it more accurately estimated $PM_{2.5}$ than FINN of both 12 km and 4 km resolutions. Additionally, FINN and QFED resulted in similar patterns of significant effect estimates, which suggested that horizontal resolutions was a stronger predictor for effect estimates than the other factors in the fire inventory equations.

Evaluating the Impact of Fire Emissions Inventories on Air Quality Simulation and Health Impact Assessment during the 2012 Colorado Wildfire Season

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1. Introduction:

1.1. Wildfires and Adverse Health Outcomes

Wildfires occur globally and pose threat to human health because they increase levels of air pollutants such as carbon monoxide (CO), nitrogen oxides (NO_x), volatile organic compounds (VOCs), ozone (O_3) and particulate matter ($PM_{2.5}$) in the affected areas (DeBell et al, 2004; Lewtas et al 2007). Exposure to increased levels of ambient CO may contribute to cardiovascular problems (Ritz et al 2002) as well as induce haematological problems and cancer (Kampa et al 2008). NO_x , VOCs, and O_3 are types of gaseous pollutants mainly affect the respiratory system. NO_x and VOCs also interact through a series of reactions in the atmosphere that further produce O_3 in the troposphere.

Among the myriad of air pollutants emitted from wildfires, $PM_{2.5}$ has been most frequently associated with adverse health outcomes (Fowler 2003; NRC, 2004; Pope et al 2009; U.S. EPA, 2004). $PM_{2.5}$ and PM_{10} are two types of particulate matter that are categorized by size (U.S. EPA 2016). $PM_{10,}$ or coarse particles, is defined as a mixture of solids and liquids suspended in the atmosphere that are 2.5 to 10 micrometers in diameter. $PM_{2.5}$ are fine particles that are 2.5 in diameter or less in size. A plethora of literature point to $PM_{2.5}$ as an important category of air pollutants that has shown to greatly impact the mortality and morbidity rates of various populations across the globe (U.S. EPA, 2004b). $PM_{2.5}$ are considered to be hazardous to health because of their physiochemical properties that enable them to be deposited deep into the respiratory system (Dockery and Pope 1994).

$PM_{2.5}$ is comprised of a variety of chemical compounds, including organic compounds, nitrates, sulfates, and various metals (Schlesinger et al 2007). Wildfires directly release $PM_{2.5}$ into the atmosphere and also produce precursor gaseous pollutants such as NO_x, VOCs, and ammonia (NH_3) that can react in the atmosphere to form secondary $PM_{2.5}$ (U.S. EPA, 2004a). Exposure to high concentrations of $PM_{2.5}$ can result in adverse cardiorespiratory health outcomes, since these particulate matters can be deposited in the alveoli of the human lungs and consequently, diffuse into the circulatory system (Dieme et al 2012)). Inhaling $PM_{2.5}$ has been linked to asthma, upper and lower respiratory tract infections, chronic obstructive pulmonary disease (COPD), and ischemic cardiomyopathy. Cancer has also been associated with exposure to wildfire smoke (Adam et al. 2002). Particulate matter can also exacerbate pre-existing conditions such as asthma and cardiovascular diseases (Du et al 2016; Xing et al 2016).

A considerably large amount of effort has been put into establishing policies that regulate the sources and emissions of $PM_{2.5}$ in the U.S. One way the federal government has attempted to regulate $PM_{2.5}$ is by categorizing it under criteria pollutants (U.S. EPA 2011). Criteria pollutants are a set of air pollutants regulated by the EPA that cause smog, acid rain, and that are associated with various health hazards. The EPA has established national ambient air quality standards (NAAQS) for short-term and long-term exposure to $PM_{2.5.}$ The short-term standard is 35 μg/m3, which is calculated by obtaining the 3 year average of the

98^{th} percentile of the daily maximum 24 hour concentration (U.S. EPA 2011). The long-term standard is 12 μg/m3 which is obtained by getting the 3 year average of the annual mean $PM_{2.5}$ concentrations.

Particulate matter has been widely used in fire epidemiological models to quantify their association with emergency department visits and hospitalizations (Reid et al. 2016). In this study, $PM_{2.5}$ is the primary exposure variable of interest due to their high emissions during wildfires and important association with cardiorespiratory diseases.

1.2. 2012 Colorado wildfire season

The geographical context of this study is the 2012 Colorado wildfire season due to the expansive impact it had in destroying homes and posing threats to the health of the residents. In addition to burning down 600 homes and forcing 32,000 to evacuate from areas near actively burning fires, Breanna et al. 2016 found that exposure to the smoke was associated with respiratory diseases. Martin et al. 2013 also found that $PM_{2.5}$ levels were higher than the norm and reached unhealthy levels. The high intensity and long duration of the Colorado wildfire season made it an optimal case study for the purposes of our inquiry.

A series of large wildfires burned from May to July due to extremely dry winter and low precipitation. The summer of 2012 also saw temperatures near and in excess of 100 °F. Smoke released by the large fires such as the High Park fire in

An increase in large wildfires (>405 ha) has been reported across the western U.S. from 1984 to 2011 (Dennison et al 2014). Littell et al 2009 has observed an increase in annual western U.S. burned areas since the 1970's based on observed and reconstructed databases that range from 1916 to 2004. These changes have been ascribed to higher annual mean temperatures that lead to earlier snowmelt and various land use alterations that prolong the wildfire season (Westerling et al 2006; Dennnison et al 2014; Riley et al 2013). The Intergovernmental Panel on Climate Change's moderate emission scenario A1B has predicted that this trend is likely to continue with increased average maximum air temperature and drought severity in these regions (IPCC, 2013).

1.3. Fire Inventories

One of the goals for this study is to assess whether different types of fire inventories and different horizontal resolutions of the same fire inventories lead to varying $PM_{2.5}$ emission estimates. Fire inventories serve as important set of tools to detect changes in atmospheric chemistry that occur from open biomass burnings (e.g...Wiedinmyer et al., 2006). Open biomass burnings are a type of biomass burning that occur outdoors and encompass three main categories, including prescribed burning, agricultural burnings and wildfires. Emissions from wildfires are of special public health interest in recent years due to reasons aforementioned.

In order to characterize emissions from wildfires, fire inventories include variables such as emission mass of species, area burned at a specific time and location, fraction of the biomass that is burned in the fire, and the emission factor of species (Wiedinmyer et al., 2011). Estimated emissions are then integrated into numerical weather prediction models, such as WRF-Chem, to place emissions in a larger meteorological context and to provide a final enumeration of emissions.

Much of the effort to create and enhance these inventories has been driven by the need to account for burning activities on managed lands as well as to inform policy regarding air quality laws and regulations (Battye et al. 2002). With the threat of increasing intensity and frequency of wildfires (e.g., Westerling et al 2006), however, fire inventories are being recognized as important tools to quantify the public health impacts of exposure to fire smoke.

A wide variety of fire inventories exist. However, Fire Inventory from NCAR (FINN) and Quick Fire Emissions Dataset (QFED) are two high temporal and spatial resolution fire inventories that draw interest from the scientific community. Fire Inventory from NCAR version 1.5 (FINNv1.5) is an updated inventory of FINNv1 that provides global estimates of trace gas and particle emissions from open burning of biomass at a daily, 1km resolution. FINN has been utilized in various studies to quantify the air quality and health effects of wildfire events in the Western United States. QFED is a fire inventory developed by NASA with the aim to be included in the NASA Goddard Earth Observing

System (GEOS) modeling and data assimilation systems. QFED emission estimates are based on the fire radiative power (FRP) to estimate emissions of key atmospheric constituents from fire. QFED and FINN both offer high spatial and temporal resolution of estimation of trace gases and aerosols and are the focus of this study.

2. Materials and Methods:

2.1. Aims and Hypothesis

The goal of this study is to evaluate whether different types fire inventories and different horizontal resolutions of the same inventories result in differing $PM_{2.5}$ emission estimates. Specifically, we will be calculating QFED and FINN, both 12 km resolution, and their estimates of $PM_{2.5}$ in the context of the 2012 Colorado wildfire season. Then, we will calculate and compare $PM_{2.5}$ estimates calculated from FINN with 12km horizontal resolution and FINN with 4km horizontal resolution. We also discuss the difference between FINNv1.5 and FINNv2.0 that is in beta.

In order to be able to compare QFED with FINN as well as FINN 4km resolution with FINN 12km resolution, it is integral to assess the accuracy of each of the inventory's calculation of emissions. To accomplish this, each of the inventory will be compared against the EPA's ground monitor stations, which will be considered the gold standard.

Aim 1:

a. To obtain $PM_{2.5}$ estimates from EPA's ground monitor stations over a specific time period (June 5th 2012 to July 6th 2012) and obtain $PM_{2.5}$ data from QFED, FINN 4km resolution and FINN 12km emission dataset for the same time period.

b. Determine the correlation coefficient between each fire emissions dataset and EPA's ground monitor stations for $PM_{2.5}$ estimates.

Hypotheses:

1st hypothesis:

QFED will generally estimate higher $PM_{2.5}$ estimates than FINN 12km resolution, since past analyses have shown this pattern (Park, M et al 2015).

2nd hypothesis:

FINN 4km resolution will detect higher $PM_{2.5}$ than FINN 12km resolution since the higher resolution obtains less diluted fire estimates and better captures the variability, or extreme values, of the fire emissions.

3rd hypothesis:

QFED will yield a higher correlation coefficient than both the 12km and 4km resolution FINN when compared against EPA's ground monitor stations' estimations of $PM_{2.5}$. This hypothesis is proposed with the current understanding of QFED measurements of $PM_{2.5,}$ which is that it generally reports accurate estimates of air pollutants. The FINN and QFED intercomparisons demonstrated

that FINN estimated lower concentrations of air pollutants in the western United States (Park et al. 2015). Consequently, it can be postulated that FINN generally underestimates $PM_{2.5}$**.**

In order to be able to compare inventories and their effect estimates from the Colorado wildfires, we ran a conditional logistic regression developed by Breanna, A., et al 2016.

Aim 2:

To perform regression analysis for each of the fire inventories with emergency department visits and acute hospitalizations for asthma and the dependent variable and $PM_{2.5}$ as the independent variable controlling for temperature, day of the week, and ozone.

Hypothesis:

FINN 12 km resolution and FINN 4 km resolution will produce similar significant results. There are several reasons for making this assertion. Mainly, the theory is that the similar method of detecting wildfires and vegetation layers will play the most important role in determining effect estimates in fire epidemiological models, than the horizontal resolution. We postulate that the horizontal resolution is an unpredictable variable in the fire inventory equations.

Strickland, M., et al 2015 has found that time series analyses produced noticeable biases caused by spatial variability and spatial heterogeneity in outdoor air pollutant concentrations, instrument imprecision, and choice of daily pollutant

metric on effect estimates. The study found that the biases were lessened, although not eliminated, by scaling results to interquartile range (IQR) increases in concentration. In Aim 3, we use the increases in IQR values in concentration for $PM_{2.5}$ for each inventory to obtain the effect estimates.

Aim 3:

To perform the same regression analysis as that of Aim 2, but using increases in IQR values for analyzing effect estimates.

Hypothesis:

Scaling the concentrations of $PM_{2.5}$ to individual IQRs will produce similar patterns of effect estimates across the models as those seen in Aim 2. The reason for this is that horizontal resolutions still remain the same, and the only variable that changed in the epidemiological model is the unit change for the air pollutant concentration.

2.2. WRF-Chem Model

In this study, the forest fires smoke event of Colorado in 2012 has been simulated using WRF-Chem with FINN and QFED fire emissions datasets. Weather Research and Forecasting Model with Chemistry (WRF-Chem) is a numerical weather prediction system that was used to model hourly $PM_{2.5}$ between June 5th and July 6th 2012 for both FINN and QFED emission inputs. For analyses purposes, the hourly outputs were organized into daily values. FINN was run at both 12 km x 12 km and 4 km x 4 km horizontal resolution. QFED was run at 12 km x 12 km horizontal resolution.

WRF-Chem is a regional model that makes use of chemical compounds in its calculation and allows for coupled simulations of atmospheric chemistry and meteorology (Fast JD et al 2006; Fast JD et al 2009; Grell GA 2005). WRF-Chem is functionally similar to CMAQ, but differs from the version used by Appel et al. 2012 in that WRF-Chem predicts meteorological quantities and air pollution concentrations simultaneously. This allows researchers to update the meteorology quantities more frequently. Although combined meteorology and chemical transport models can be more computationally demanding than standalone chemical transport models, with specified domain and settings, meteorological modeling may account for only about 10% of the total computational expense (Tessum et al 2015).

Many studies have been conducted in evaluating the performance of WRF-Chem in air quality simulations across the contiguous U.S with simulation periods of several weeks or months (Ahmadov et al., 2012; Chuang et al., 2011; Fast et al., 2006; Grell et al., 2005; McKeen et al., 2007; Misenis and Zhang, 2010; Zhang et al., 2010, 2012). Recently, some researchers have modeled the largest fire-induced haze episode in the past decade in Indonesia using WRF-Chem (Aouizerats B et al 2014) with simulations run at 15 km 15 km horizontal resolution. Jaffe et al 2013 also performed simulations with the regional WRF-Chem at a horizontal resolution of 24 x 24 km to quantify O_3 concentrations after wildfires in three U.S. metropolitan regions in the western U.S. WRF-Chem is a

widely used atmospheric model that serve as an important tool in understanding meteorological variables and their effects on air quality.

2.3. FINNv1.5:

FINN emission estimates are calculated from the framework described by Wiedinmyer et al. [2006;2011]. FINN utilizes satellite observations of active fires and land cover in addition to emission factors and estimated fuel loadings to provide daily, 1km open burning emission estimates. FINNv1.5 is an improved version of FINNv1.0 that includes updated emission factors and the inclusion of specific generic vegetation code for temperate evergreen forest. In addition, fuel loadings for crops were set to 1200 g/m^2 (Akagi et al. 2011) and the Global Land Cover (GLC) class was used if Land Cover Type (LCT) was bare or snow.

Both meteorological and chemical processes in WRF-Chem may be sensitive to horizontal grid spacing. In this study, two different horizontal grid spacings were analyzed-12 km and 4 km. 12 km horizontal resolution is often used in the current operational meteorological models (Mass et al., 2002), down from hundreds of kilometers in the late 1950s. Models that are currently under development are designed to operate at even finer scales from 1 to 10 km (Michalakes et al 2001). Models that use finer horizontal spacing, as compared with that at coarser grid spacing, model performance may be better, worse, or similar. The reason for this is that uncertainties exist in the performance of various physical parameterizations and the complexity in chemistry and meteorology and their response to grid

resolution (Jang et al., 1995; Zhang et al., 2006a, b; Wu et al., 2008; Queen and Zhang, 2008). Several studies reported that increasing grid resolution may lead to better reproduction of fine-scale meteorological processes (e.g., Mass et al 2002; Jimenez et al. 2006, Liu and Westphal 2001). However, this does not necessarily mean better overall model accuracy (Gego et al 2005).

2.4. QFEDv2.4:

The biomass burning emissions for QFED are obtained using the FRP approach. The daily-mean FRP and precise location of fires are acquired from the MODIS Collection 5 Active Fire product (MOD14 and MYD14) and the MODIS Geolocation product (MOD03 and MYD03). The category of the vegetation, selection of emission factor, and assigning of FRP to the corresponding QFED vegetation class are determined by the combination of location of fires and the vegetation classification dataset. Each pixel and area for MOD14 and MYD14 are placed into a global grid to allow for the calculation of the biomass burning emissions. QFEDv2.4 is set apart from the previous versions for its sequential approach when treating pixels obscured by clouds (Darmenov et al. 2015). Also, QFEDv2.4 horizontal resolutions are produced at 0.1°x0.1°, which is equivalent to 11.13km x 11.13 km whereas previous versions are available at 0.3124°x0.25°.

2.5. Difference between Fire Inventories:

QFED and FINN differ their method of detecting fires and categorizing vegetation type. FINN uses MODIS active fire product to detect fires in 1km

pixels that are burning at the time of overpass under relatively cloud-free conditions. The MODIS Rapid Response (MRR) fire detections are utilized to specify burn time and location, and the MODIS vegetation Continuous Fields (VCF) and Land Cover Type (LCT) products are used to identify the type and density of the vegetation burned at each fire point. QFED uses MODIS Fire Radiative Power (FRP), which provides information on the measured radiant heat output of detected fires. The vegetation cover used by FINN and QFED differ in that FINN uses MODIS Collection 5 Land Cover Type (LCT) while QFED utilizes IGBP-INPE dataset.

2.6 Methods:

2.6.1. Comparison with Observations:

In order to compare $PM_{2.5}$ estimates from models and ground-based observations, ground-truthing analyses was conducted using EPA's AQS Data Mart. The AQS Data Mart is a database that contains every measured value that the EPA has collected through the national ambient air monitoring program. Daily arithmetic mean for both parameters were obtained for comparison analyses. EPA values were treated as the golden standard for emission estimates.

We used ArcMap10.3.1 to map out the specific locations of EPA's ground monitor stations and the models estimations of $PM_{2.5}$. Spatial Join was utilized to pair each monitors to the nearest estimation of air pollutants from each model. To

evaluate the fire emission inventories and to compare the estimates with those of EPA's monitor stations, linear regression analyses were conducted.

2.6.2. Statistical Analysis:

To retrieve the effect estimates for the fire inventories, a conditional logistic regression was performed. This approach was used to estimate associations between $PM_{2.5}$ concentrations and the occurrence of ED and acute hospitalizations for upper respiratory disease, pneumonia, bronchitis, chronic obstructive pulmonary diseases (COPD), asthma and wheeze and respiratory diseases. The cases were categorized using the primary International Classification of Diseases version 9 (ICD 9). The data and methods are described in detail in Alman et al., 2016. Three different lag periods were evaluated: lag 0, lag 0-1 moving average, and lag 0-1-2 moving average.

Conditional logistic regression was chosen because it allowed for easily matching a grid to itself over the study period, with the grids being the strata. This allowed us to control for demographic variables, which likely wouldn't vary within a grid over the 32-day period, but would likely vary from grid to grid. Conditional logistic regression is a method of matching in case control studies, which leads to tighter confidence intervals, that is more precision around the odds ratio than would be achieved without matching.

3. Results

Figures 1, 2 and 3 show the results for the correlation coefficients. For $PM_{2.5}$, there was a total of 224 matched observations for FINNv1.5, 223 matched pairs for QFEDv2.4. The highest linear correlation coefficient was found between QFEDv2.4 and EPA's monitor stations in the measurement of $PM_{2.5}$ with 0.547, followed by FINNv1.5 4 km resolution and EPA's monitor stations measuring $PM_{2.5}$ with a correlation coefficient of 0.305. The lowest correlation coefficient was between FINNv1.5 12 km resolution and EPA's monitor stations that resulted in a coefficient of 0.268.

Odds ratios were determined for respiratory and cardiovascular endpoints for continuous change in 1 hour as well as 24 hour $PM_{2.5}$ concentrations for QFED 12 km resolution, FINN 12 km resolution and FINN 4 km resolution. The results are presented in Tables 1 through 6. The statistically significant results appear to be similar between FINN 12 km resolution and QFED 12 km resolution. For instance, the association between $PM_{2.5}$ concentration and asthma and wheeze for all ages are significant for both QFED 12 km resolution and FINN 12 km resolution for both 1 hour and 24 hour continuous changes. The estimates also increase with increasing lag. For FINN 12 km resolution, the odds ratios for 24 hour $PM_{2.5}$ concentrations lag 0, lag 0-1, lag 0-1-2 are 1.011 (1.004, 1.018), 1.118 (1.067, 1.171), and 1.177 (1.106, 1.253), respectively. For QFED 12 km resolution, the odds ratios for 24 hour $PM_{2.5}$ concentrations lag 0, lag 0-1, lag 0-1-2 are 0-1-2, are 1.017 (1.011, 1.024), 1.130 (1.083, 1.179), and 1.161 (1.104,

1.221), respectively. This pattern can be observed with the different age groups, with increasing odds ratios with higher lags.

For FINN 12 km resolution and QFED 12 km resolution, the 24 hour-mean respiratory disease odds ratios for all ages are very similar. For FINN, the odds ratios for lag 0, lag 0-1, and lag 0-1-2, are 1.008 (1.004, 1.012), 1.060 (1.32, 1.090), and 1.075 (1.039, 1.113) respectively. For QFED, the odds ratios for lag 0, lag 0-1, and lag 0-1-2, are 1.008 (1.004, 1.011), 1.042 (1.009, 1.075), and 1.052 (1.025, 1.079), respectively.

QFED results seem to be generally higher than that of FINN 12 km resolution. Amid the many examples, the lag 0, 0-1, and 0-1-2 for 24-h $PM_{2.5}$ concentrations for QFED for asthma and wheeze for all ages are 1.017 (1.011, 1.024), 1.130 (1.083, 1.179), and 1.161 (1.104, 1.221), respectively. Comparatively, the lag 0, 0-1, and 0-1-2 for 24-h $PM_{2.5}$ concentrations for FINN 12 km resolution for asthma and wheeze for all ages are 1.011 (1.004, 1.018), 1.118 (1.067, 1.171) and 1.177 (1.106, 1.253), respectively.

FINN 4 km resolution presents its effect estimates far differently than FINN 12 km and QFED 12 km resolution odds ratios. The asthma and wheeze for ages 65+ for lags 0-1 and 0-1-2 show random error. The wide confidence intervals for the effect estimates show that they do not convey valuable information about $PM_{2.5}$ and asthma and wheeze for ages 65+.

In an attempt to reduce biases in calculating the odds ratios in this study, increases in IQR was utilized to determine the effect estimates. Generally, when comparing QFED with FINN 12 km resolution, the significant results are higher for the QFED odds ratios than those of FINN 12 km resolution. For instance, lag 0-1 and lag 0-1-2 for asthma and wheeze for all ages with a continuous change in 1 h $PM_{2.5}$ concentrations for FINN 12 km resolution is 1.011 (1.007, 1.015) and 1.015 (1.010, 1.021), respectively. Lag 0-1 and lag 0-1-2 for asthma and wheeze for all ages with a continuous change in 24 h $PM_{2.5}$ concentrations for QFED is 1.026 (1.018, 1.034) and 1.030 (1.021, 1.039), respectively. These are just a few of many examples that show that QFED with its IQR increases estimate higher significant results than FINN 12 km resolution with its IQR increases.

Broadly, the association seen in QFED and its IQR increases is similar to FINN 12 km resolution and its IQR increases. This conclusion was reached by roughly comparing the cardiovascular and respiratory endpoints which showed to be significant. Specifically, the 24 hour mean ORs for QFED and FINN appear to generate significant results for the OR outputs. For instance, asthma and wheeze, bronchitis, and COPD seem to have significant results that parallel one another.

4. Discussions:

4.1. Interpretation of Results

Due to the multifaceted nature of this study, there were five a priori hypotheses regarding the association between $PM_{2.5}$ and ED and acute hospitalizations for selected cardiovascular and respiratory diseases. The first postulated that QFED will estimate higher $PM_{2.5}$ estimates than FINN 12km resolution. Figure 1 to 3 shows that QFED generally records higher $PM_{2.5}$ than FINN 12 km resolution. This result is consistent from past studies that compared QFED and FINN estimation of air pollutants from wildfires. Although the study conducted by Park et al. 2015 used carbon monoxide (CO) as the representative indicator for air pollutants, CO can be treated as a general predictor of how other air pollutants, such as $PM_{2.5}$ will be quantified by the fire inventories.

The second hypothesis posited that FINN 4km resolution will detect higher $PM_{2.5}$ than FINN 12km resolution since the higher resolution obtains less diluted fire estimates and better captures the variability, or extreme values, of the fire emissions. Figures 1, 2 and 3 show that FINN 4 km resolution generally records higher $PM_{2.5}$ than FINN 12 km resolution. The results show this hypothesis to be correct, leading to the conclusion that higher resolutions may more accurately reveal the size and number of active fires within each grid. Consequently, FINN 4km resolution is able to report the extreme, or higher estimations for $PM_{2.5}$ concentrations.

The third hypothesis proposed that QFED will yield a higher correlation coefficient than both the 12km and 4km resolution FINN when compared against

EPA's ground monitor stations' estimates of $PM_{2.5}$. The Pearson's correlation coefficients show that QFED more accurately captures the concentrations of $PM_{2.5}$. Validation of QFED is nearly impossible because the direct field measurement is very complex. Alternatively, comparison of emission calculation can be made between inventories. The QFED was compared with the commonly used GFED, the FRP based GFAS and the FLAMBE inventories with monthly mean emissions in various regions (Darmenov and da Silva, 2013). The results from 2003-2010 demonstrate that QFED values are distributed within a reasonable range. The correlation coefficient confirm past research that showed that QFED closely estimates the actual concentrations of air pollutants.

The fourth hypothesis asserted that FINN 12 km resolution and FINN 4 km resolution will produce similar patterns of significant odds ratios (ORs). The examples of ORs given in the prior section show this trend to be false. Instead, FINN 12 km resolution and QFED of the same resolution showed similar patterns of significant results. This may be explained by the theory that horizontal resolutions play a more important role in the epidemiological model's estimation of effect estimates. Subsequently, it can be stated that differences in vegetation layers and method of detecting wildfires are relatively weaker variables in the fire inventory equations and their measurement of $PM_{2.5}$.

The last hypothesis investigated the odds ratios across models by scaling the concentrations of $PM_{2.5}$ to individual IQRs. It postulated that no significant

changes would occur in regards to inter-model comparisons. This hypothesis implies that FINN 4 km resolution and FINN 12 km resolution would yield similar patterns for the significant effect estimates. However, the results show that FINN 12 km resolution and QFED shared more similarities in regards to the significant results. This can be explained by previous discussions on the dominant role that horizontal resolutions play in the fire inventories.

4.2. Potential Biases and Limitations

This study evaluates the accuracy of models that estimate air pollutants during wildfires by attempting to validate FINN and QFED using EPA's monitors as the gold standard. Several issues arise with the study's method of validation. Although EPA's monitors are widely considered the gold standard of detecting air pollutants, wildfires create smoke plumes that exist too high up in the atmosphere for the EPA monitors to effectively detect $PM_{2.5}$. EPA ground monitor stations are also spatially and temporally sparse. For these reasons, the process of ground-truthing inevitably presents the challenges of acquiring the optimal method of measuring the true value of $PM_{2.5}$.

Another major limitation to the study is that the fire epidemiological model utilized in this study do not use EPA's ground-based measurements, which is theoretically more accurate than the models. There is no means to make meaningful comparisons between the models' effect estimates and the "true" odds ratios generated by an epidemiological model that incorporates the actual

estimates of air pollutants. One way to address the issue of sparse monitors is to simply place EPA monitors evenly throughout the state of Colorado that has the capacity to detect air pollutants in the smoke plumes. This would allow for a more effective and accurate process of validating the models.

When examining the effect estimates produced from scaling the $PM_{2.5}$ concentrations to the increases in IQR, a clear limitation is the absence of true odds ratios. Having access to true odds ratios would allow for us to evaluate whether using the IQR values reduced biases in the epidemiological models. Since this is not a part of the study, we can only conduct an inter-model comparison in regards to the patterns of significant effect estimates.

For the purposes of this study, it is imperative to understand the mechanisms behind acquiring the true effect estimates. As mentioned before, an improved and increased spatial and temporal coverage of EPA monitors would more accurately reproduce the associations between exposure to wildfire air pollutants and adverse health outcomes. Since this is not possible, we can only generate potential scenarios that would best reflect the relationship between air pollutant exposure and cardiovascular and respiratory health problems. Due to the nature of this study's epidemiological research, ED visits and hospitalizations dataset are obvious choices for outcome variables. Ecological time series are also the dominating type of research conducted to assess the impact of wildfires on human health. However, a stronger study would be cohort research that follows a selected

population and to describe the health outcomes of interest. Only a few wildfire epidemiological studies are based upon cohort studies.

5. Conclusion

This study evaluated FINN 12 km and 4 km resolution and QFED 12 km resolution in order to validate the $PM_{2.5}$ estimates. This research found the importance of horizontal resolution in generating odds ratios than other factors in the fire inventory equations. Only QFEDv2.4 and FINNv1.5 were utilized in this study. Many other types of fire inventories exist and should be considered when determining which models to use in fire epidemiological models. For instance, FINNv2, which is in beta, has shown that FINNv2 detects higher concentrations of air pollutants in comparison to FINNv1.5. However, before FINNv2 can be incorporated into epidemiological research, validation of its estimation of air pollutants need to be conducted. Future wildfire exposure assessment research should focus on using more recent and updated versions of fire inventories.

Exposure assessment studies such as this one is crucial to increase confidence in measuring accurate estimates of air pollutant emitted from wildfires. Fire inventories not only allow for researchers to acquire information about the pollutants in the atmosphere quickly, but they also allow for the calculation of emissions with more temporal and spatial coverage in comparison to the EPA ground monitor stations.

The results of this study calls for public health researchers to rethink the methods of acquiring emission estimates of air pollutants from wildfires. Not only are more accurate fire inventories needed, but more robust epidemiological studies may be necessary to accurately measure the association between exposure to air pollutants and adverse health outcomes.

6. References

Alman, B. L., G. Pfister, H. Hao, J. Stowell, X. Hu, Y. Liu, and M.J. Strickland (2016), The association of wildfire smoke with respiratory and cardiovascular emergency department visits in Colorado in 2012: a case crossover study, *Environ. Health, 15*, 64, doi: 10.1186/212940-016-0146-8.

Adam, H., D. Hunter, and D. Trichopoulos. 2002 Textbook of cancer epidemiology. Oxford: Oxford University Press.

Ahmadov, R., McKeen, S. A., Robinson, A., Bahreini, R., Middlebrook, A., de Gouw, J., Meagher, J., Hsie, E., Edgerton, E., Shaw, S., and Trainer, M.: A volatility basis set model for summertime secondary organic aerosols over the eastern United States in 2006, J. Geophys. Res., 117, D06301, doi:10.1029/2011JD016831, 2012.

Akagi, S. K., Yokelson, R. J., Wiedinmyer, C., Alvarado, M. J., Reid, J. S., Karl, T., Crounse, J. D., and Wennberg, P. O.: Emission factors for open and domestic biomass burning for use in atmospheric models, Atmos. Chem. Phys., 11, 4039–4072, doi:10.5194/acp-11-4039-2011, 2011.

Chuang, M.-T., Zhang, Y., and Kang, D.: Application of WRF/Chem-MADRID for real-time air quality forecasting over the southeastern United States, Atmos. Environ., 45, 6241–6250, 2011.

Aouizerats B, van der Werf GR, Balasubramanian R, Betha R. Importance of transboundary transport of biomass burning emissions to regional air quality in Southeast Asia. Atmos. Chem. Phys. Discuss. 2014; 14: 11221–48

Battye, W.B., and Battye, R. 2002. Development of emissions inventory methods for wildland fire. Prepared for Thompson G. Pace, D205-01 of the U. S. Environmental Protection Agency, Final report. www.epa.gov/ttn/chief/ap42/ch13/related/firerept.pdf

Darmenov, A., and A. M. da Silva (2014), The Quick Fire Emissions Dataset (QFED) Documentation of versions 2.1, 2.2 and 2.4, NASA TM-2013-104606, vol. 35, 183 pp.

Dennison, P. E., S. C. Brewer, J. D. Arnold, and M. A. Moritz, 2014. Large wildfire trends in the western United States, 1984–2011, Geophys. Res. Lett., 41, 2928–2933, doi:10.1002/2014GL059576.

Dieme, D., M. Cabral-Ndior, et al. (2012). "Relationship between physicochemical characterization and toxicity of fine particulate matter (PM2.5) collected in Dakar city (Senegal)." Environmental Research 113: 1-13.

Dockery D.W., and C.A. Pope. 1994 Acute respiratory effects of particulate air pollution. Annual Reviews of Public Health 15:107-132.

Du Y., Xu X., Chu M., Guo Y., Wang J. Air particulate matter and cardiovascular disease: The epidemiological, biomedical and clinical evidence. J. Thorac. Dis. 2016;8:E8–E19.

Fast JD, Aiken AC, Allan J, Alexander L, et. al.. Evaluating simulated primary anthropogenic and biomass burning organic aerosols during MILAGRO: implications for assessing treatments of secondary organic aerosols. Atmos. Chem. and Phys. 2009; 9: 6191–215.

Fast JD, Gustafson Jr. WI, Easter RC, Zaveri RA, et. al.. Evolution of ozone, particulates, and aerosol direct radiative forcing in the vicinity of Houston using a fully coupled meteorology-chemistryaerosol model. J. Geophys. Res. 2006; 111D21305, doi:10.1029/2005JD006721.

Gego, E., Hogrefe, C., Kallos, G., Voudouri, A., Irwin, J.S., Rao, S.T., 2005. Env. Fluid. Mech. 5, 63–85.

Grell GA, Peckham SE, Schmitz R, McKeen SA, Frost G, Skamarock WC, Eder B. Fully coupled "online" chemistry within the WRF model. Atmos. Environ. 2005; 39: 6957–75.

IPCC, 2013: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 1535 pp, doi:10.1017/CBO9781107415324.

Jang, J.-C.C., Jeffries, H.E., Byun, D., Pleim, J., 1995. Sensitivity of ozone to model grid resolution. I: application of high-resolution regional acid deposition model. Atmos. Environ. 29, 3085–3100.

Jimenez, P., Jorba, O., Parra, R., Baldasano, J.M., 2006. Evaluation of MM5-EMICAT2000-CMAQ performance and sensitivity in complex terrain: high-resolution application to the northeastern Iberian Peninsula. Atmos. Environ. 40, 5056–5072.

Kampa M, Castanas E. Human health effects of air pollution. Environ Pollut. 2007;151:362–7.

Liu, M., Westphal, D.L., 2001. A study of the sensitivity of simulated mineral dust production to model resolution. J. Geophys. Res. 106, 18,099–18,112

Mass, C.F., Ovens, D., Westrick, K., Cole, B.A., 2002. Does increasing horizontal resolution produce more skillful forecasts? Bull. Amer. Meteor. Soc. 407–430

McDonald-Buller, E., Wiedinmyer, C., & Emery, C. 2014. Quality Assurance Project Plan Project 14-011 Targeted Improvements in the Fire INventory from NCAR (FINN) Model for Texas Air Quality Planning.

McKeen, S., Chung, S. H., Wilczak, J., Grell, G., Djalalova, I., Peckham, S., Gong, W., Bouchet, V., Moffet, R., Tang, Y., Carmichael, G. R., Mathur, R., and Yu, S.: Evaluation of several PM2.5 forecast models using data collected during the ICARTT/NEAQS 2004 field study, J. Geophys. Res., 112, D10S20, doi:10.1029/2006JD007608, 2007.

Michalakes, J., Chen, S., Dudhia, J., Hart, L., Klemp, J., Middlecoff, J., Skamarock, W., 2001. Development of a next-generation regional weather forecast model, Devel. Teracomputing, pp. 269–276.

Misenis, C., & Zhang, Y. 2010. An examination of sensitivity of WRF/Chem predictions to physical parameterizations, horizontal grid spacing, and nesting options. *Atmospheric Research*, *97*(3), 315-334.

National Research Council (NRC). 2004. Research priorities for airborne particulate matter, IV. Continuing Research Progress. Washington, DC: National Academies Press.

Queen, A., Zhang, Y., 2008. Examining the sensitivity of MM5-CMAQ predictions to explicit microphysics schemes and horizontal grid resolutions. Part III — the impact of horizontal grid resolution. Atmos. Environ. 42, 3869–3881.

Park, M., Emmons, L., and Wiedinmyer, C, 2015. Comparison and Evaluation of Fire Emissions in a Global Chemistry Model with SEAC^{4}RS Observations. National Center for Atmospheric Resesarch. Boulder, CO. https://espo.nasa.gov/missions/sites/default/files/documents/Tu1145_Park_Post.pdf

Reid C E, Brauer M, Johnston F H, Jerrett M, Balmes J R and Elliott C T 2016 Critical review of health impacts of wildfire smoke exposure Environ. Health Persp

Richard B. Schlesinger, 2007. The Health Impact of Common Inorganic Components of Fine Particulate Matter (PM2.5) in Ambient Air: A Critical Review, Inhalation Toxicology, 19:10, 811-832, DOI: 10.1080/08958370701402382

Riley, K. L., J. T. Abatzoglou, T. G. John, C. Isaac, A. E. Klene, and F. A. Heinsch, 2013. The relationship of large fire occurrence with drought and fire danger indices in the western USA, 1984–2008: The role of temporal scale, Int. J. Wildland Fire, 22(7), 894–909.

Ritz B, Yu F, Fruin S, Chapa G, Shaw GM, Harris JA. 2002. Ambient air pollution and risk of birth defects in southern California. Am J Epidemiol 155:17–25.

Schlesinger RB. The Health Impact of Common Inorganic Components of Fine Particulate Matter (PM2.5) in Ambient Air: A Critical Review. Inhalation Toxicology. 2007;19:811–832.

Strickland MJ, Gass KM, Goldman GT, et al. Effects of ambient air pollution measurement error on health effect estimates in time-series studies: a simulation-based analysis [published online ahead of print April 1, 2013]. J Expo Sci Environ Epidemiol. (doi:10.1038/jes.2013.16).

U.S Environmental Protection Agency (EPA), 2016. Air Now: Particle Pollution (PM). [Available at www.airnow.gov/index.cfm?action=aqibasics.particle.]

U.S. Environmental Protection Agency (EPA), 2011. National Ambient Air Quality Standards (NAAQS). [Available at www.epa.gov/air/criteria. html.]

U.S. Environmental Protection Agency (EPA), 2004b. The Particle Pollution Report: Current Understanding of Air Quality and Emissions through 2003. U.S. wEnvironmental Protection Agency, Research Triangle Park, NC (2004) EPA 454-R-04-002

U.S. EPA. Air Quality Criteria for Particulate Matter, Final Report, Oct 2004a.U.S. Environmental Protection Agency, Washington, DC, EPA 600/P-99/002aF-bF, 2004.

Val Martin, M., C. L . Hea ld, B. Ford, A. J. Prenni, a nd C. Wiedinmyer, 2013: A decadal satellite analysis of the origins and impacts of smoke in Colorado. Atmos. Chem. Phy

Westerling, A. L., H. G. Hidalgo, D. R. Cayan, and T. W. Swetnam, 2006. Warming and earlier spring increases western U.S. forest fire activity, Science, 313, 940–943.

Wiedinmyer, C., Tie, X., Guenther, A., Neilson, R., and Granier, C.: Future changes in biogenic isoprene emissions: How might they affect regional and global atmospheric chemistry?, Earth Interactions, 10, 1–19, 2006.

Wiedinmyer, C., and J. C. Neff, 2007. Estimates of CO2 from fires in the United States: Implications for carbon management, Carbon Balance Manage., 2(10), doi:10.1186/1750-0680-2-10.

Wiedinmyer, C., Akagi, S.K., Yokelson, R.J., Emmons, L.K., Al-Saadi, J.A., Orlando, J.J., Soja, A.J., 2011. The Fire INventory from NCAR (FINN): a high resolution global model to estimate the emissions from open burning. Geosci. Model. Dev. 4, 625e641.

Wu, S.-Y., Krishnan, S., Zhang, Y., Aneja, V., 2008. Modeling atmospheric transport and fate of ammonia in North Carolina. Part I. Evaluation of meteorological and chemical predictions. Atmos. Environ. 42, 3419–3436.

Xing, Y.F., Xu, Y.H., Shi, M.H. and Lian, Y.X. (2016). The impact of PM2.5 on the human respiratory system. J. Thorac. Dis. 8: E69–E74.

Zhang, Y., Liu, P., Pun, B., Seigneur, C., 2006a. A comprehensive performance evaluation of MM5-CMAQ for the summer 1999 Southern Oxidants Study Episode—Part I. Evaluation protocols, databases and meteorological predictions. Atmos. Environ. 40, 4825–4838.

Zhang, Y., Liu, P., Queen, A., Misenis, C., Pun, B., Seigneur, C., Wu, S.-Y., 2006b. A comprehensive performance evaluation of MM5-CMAQ for the summer 1999 Southern Oxidants Study Episode—Part II. Gas and aerosol predictions. Atmos. Environ. 40, 4839–4855.

Zhang, Y., Pan, Y., Wang, K., Fast, J. D., and Grell, G. A.: WRF/Chem-MADRID: incorporation of an aerosol module into WRF/Chem and its initial application to the TexAQS2000 episode, J. Geophys. Res., 115, D18202, doi:10.1029/2009JD013443, 2010.

Zhang, Y., Chen, Y., Sarwar, G., and Schere, K.: Impact of gasphase mechanisms on Weather Research Forecasting Model with Chemistry (WRF/Chem) predictions: mechanism implementation and comparative evaluation, J. Geophys. Res., 117, D01301, doi:10.1029/2011JD015775, 2012.

7. Tables and Figures

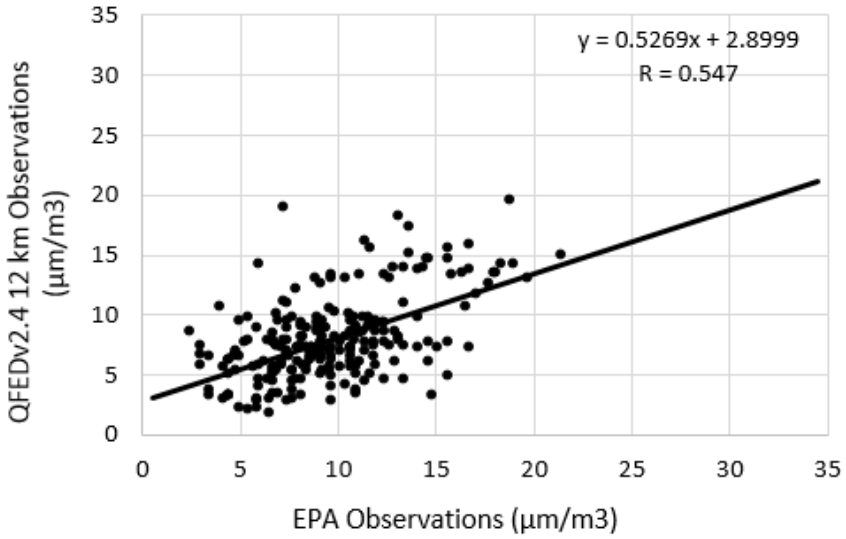

Figure 1. Comparison between QFEDv2.4 and EPA estimates of $PM_{2.5}$

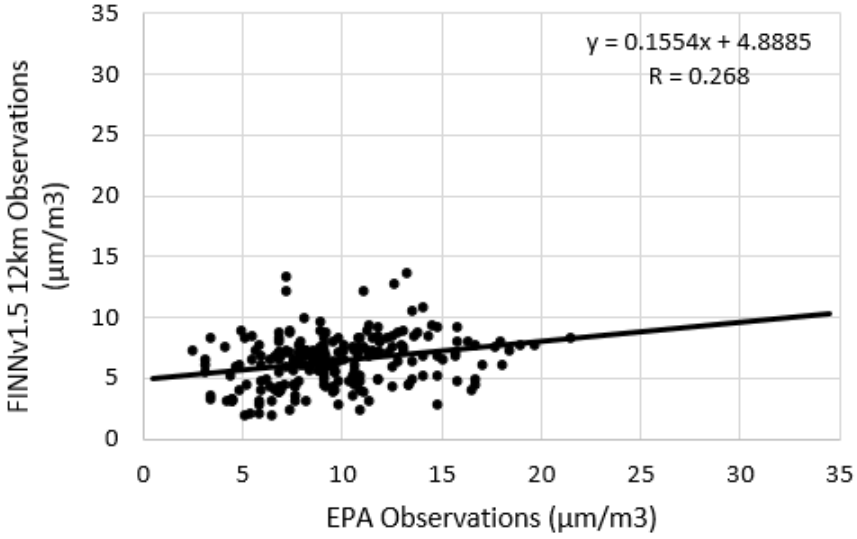

Figure 2. Comparison between FINNv1.5 12 km resolution and EPA estimates of $PM_{2.5}$

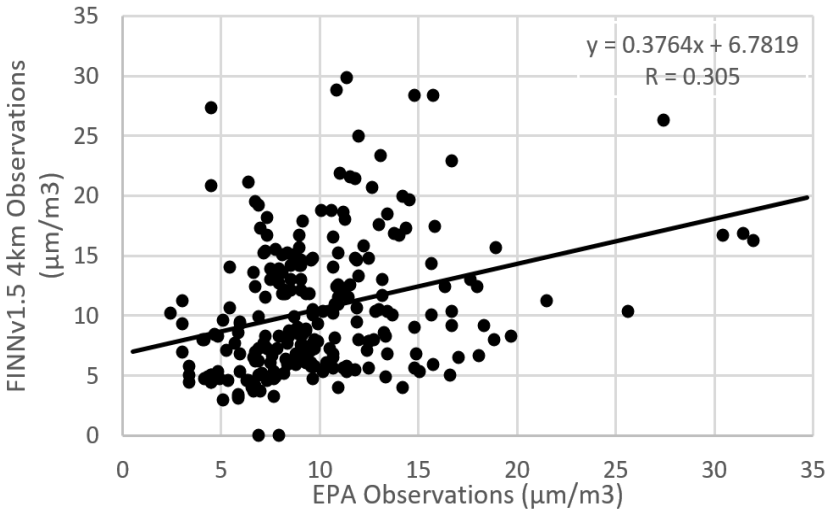

Figure 3. Comparison between FINNv1.5 4 km resolution and EPA Estimates of $PM_{2.5}$

Table 1a. Odds Ratios for respiratory and cardiovascular endpoints for continuous change in 1-h $PM_{2.5}$ concentrations for FINN 4 km resolution.

Health endpoint	Case count	1 h max ORa		
		Lag 0	Lag 0-1b	Lag 0-1-2b
Respiratory				
Asthma & Wheeze (All ages)	1136	0.997 (0.961, 1.033)	1.099 (0.673, 1.795)	1.935 (1.005, 3.726)
(Ages 0–18)	387	0.990 (0.924, 1.060)	1.227 (0.478, 3.148)	3.050 (0.833, 11.158)
(Ages 19–64)	665	0.994 (0.945, 1.045)	0.875 (0.443, 1.728)	1.224 (0.492, 3.047)
(Ages 65+)	84	1.056 (0.914, 1.220)	4.302 (0.590, 31.337)	10.833 (0.740, 158.491)
Upper respiratory infection	3376	0.979 (0.958, 1.000)	0.991 (0.742, 1.324)	1.013 (0.685, 1.499)
Pneumonia	955	0.994 (0.958, 1.032)	0.863 (0.522, 1.428)	0.427 (0.219, 0.835)
Bronchitis	413	0.961 (0.905, 1.022)	0.614 (0.271, 1.392)	1.533 (0.523, 4.491)
COPD	628	1.026 (0.980, 1.075)	0.772 (0.408, 1.462)	0.891 (0.386, 2.058)
Respiratory disease (All ages)	6610	0.988 (0.974, 1.003)	0.928 (0.757, 1.137)	0.928 0.757 ,1.137)
(Ages 0–18)	2710	0.985 (0.960, 1.011)	1.002 (0.711, 1.412)	1.027 (0.637, 1.655)
(Ages 19–64)	2915	0.999 (0.976, 1.024)	0.950 (0.689, 1.310)	1.008 (0.655, 1.549)
(Ages 65+)	985	0.986 (0.942, 1.032)	0.761 (0.424, 1.367)	0.745 (0.344, 1.612)
Cardiovascular				
Acute myocardial infarction	462	1.028 (0.974, 1.084)	1.089 (0.527, 2.252)	0.740 (0.282, 1.943)
Ischemic heart disease	722	1.005 (0.964, 1.049)	0.877 (0.496, 1.550)	0.786 (0.369, 1.675)
Dysrhythmia	1000	1.001 (0.969, 1.034)	0.949 (0.609, 1.477)	0.714 (0.395, 1.292)
Congestive heart failure	510	0.960 (0.910, 1.012)	0.599 (0.297, 1.209)	0.458 (0.179, 1.174)
Ischemic Stroke	576	1.006 (0.960, 1.054)	0.964 (0.506, 1.837)	0.983 (0.419, 2.304)
Peripheral vascular disease	411	1.009 (0.952, 1.070)	0.754 (0.338, 1.682)	0.350 (0.116, 1.053)
Cardiovascular disease	3219	0.998 (0.978, 1.018)	0.851 (0.651, 1.111)	0.669 (0.468, 0.956)

[a] Change per 10 $\mu g/m^3$

[b] Moving average

Table 1b. Odds Ratios for respiratory and cardiovascular endpoints for continuous change in 24-h $PM_{2.5}$ concentrations for FINN 4 km resolution.

Health endpoint	Case count	24 h mean ORa		
		Lag 0	Lag 0-1b	Lag 0-1-2b
Respiratory				
Asthma & Wheeze (All ages)	1136	1.040 (0.976, 1.108)	1.304 (0.875, 1.943)	1.653 (0.996, 2.741)
(Ages 0–18)	387	1.024 (0.912, 1.149)	1.567 (0.747, 3.285)	2.177 (0.872, 5.438)
(Ages 19–64)	665	1.051 (0.963, 1.147)	1.217 (0.710, 2.085)	1.400 (0.703, 2.790)
(Ages 65+)	84	1.064 (0.819, 1.382)	2.077 (0.406, 10.608)	3.213 (0.413, 25.027)
Upper respiratory infection	3376	0.963 (0.928, 1.000)	0.859 (0.681, 1.082)	0.856 (0.634, 1.156)
Pneumonia	955	0.996 (0.931, 1.066)	0.991 (0.653, 1.503)	0.685 (0.399, 1.174)
Bronchitis	413	0.970 (0.873, 1.077)	0.856 (0.448, 1.636)	1.144 (0.497, 2.634)
COPD	628	1.020 (0.937, 1.110)	1.003 (0.596, 1.688)	0.935 (0.481, 1.818)
Respiratory disease (All ages)	6610	0.988 (0.962, 1.014)	0.958 (0.813, 1.129)	0.954 (0.772, 1.178)
(Ages 0–18)	2710	0.989 (0.947, 1.033)	1.043 (0.796, 1.366)	1.057 (0.744, 1.502)
(Ages 19–64)	2915	1.008 (0.967, 1.051)	1.069 (0.827, 1.382)	1.115 (0.802, 1.550)
(Ages 65+)	985	0.967 (0.894, 1.046)	0.805 (0.500, 1.298)	0.712 (0.386, 1.313)
Cardiovascular				
Acute myocardial infarction	462	1.017 (0.923, 1.122)	1.059 (0.581, 1.931)	0.784 (0.360, 1.705)
Ischemic heart disease	722	0.993 (0.919, 1.074)	0.949 (0.591, 1.525)	0.832 (0.449, 1.542)
Dysrhythmia	1000	1.054 (0.987, 1.125)	1.373 (0.918, 2.052)	1.232 (0.739, 2.053)
Congestive heart failure	510	0.923 (0.841, 1.013)	0.714 (0.405, 1.258)	0.488 (0.232, 1.029)
Ischemic Stroke	576	1.045 (0.958, 1.139)	1.203 (0.705, 2.053)	1.307 (0.659, 2.591)
Peripheral vascular disease	411	0.964 (0.869, 1.070)	0.655 (0.349, 1.229)	0.518 (0.227, 1.180)
Cardiovascular disease	3219	1.006 (0.969, 1.044)	1.014 (0.810, 1.270)	0.889 (0.665, 1.189)

[a] Change per 5 $\mu g/m^3$

[b] Moving average

Table 2a. Odds Ratios for respiratory and cardiovascular endpoints for continuous change in 1-h $PM_{2.5}$ concentrations for FINN 12 km resolution.

Health endpoint	Case count	1 h max ORa		
		Lag 0	Lag 0-1b	Lag 0-1-2b
Respiratory				
Asthma & Wheeze (All ages)	1136	1.002 (1.001, 1.004)	1.042 (1.026, 1.058)	1.059 (1.038, 1.082)
(Ages 0–18)	387	1.000 (0.983, 1.018)	1.062 (1.023, 1.101)	1.094 (1.042, 1.149)
(Ages 19–64)	665	1.016 (1.004, 1.027)	1.032 (1.007, 1.058)	1.064 (1.023, 1.106)
(Ages 65+)	84	0.995 (0.955, 1.037)	1.074 (0.931, 1.238)	1.118 (0.953, 1.311)
Upper respiratory infection	3376	1.000 (0.999, 1.002)	1.008 (0.992, 1.025)	1.003 (0.982, 1.025)
Pneumonia	955	1.001 (0.999, 1.003)	0.995 (0.962, 1.030)	0.985 (0.944, 1.028)
Bronchitis	413	1.000 (0.996, 1.004)	1.019 (0.987, 1.053)	1.042 (1.006, 1.080)
COPD	628	1.003 (1.001, 1.005)	1.043 (1.020, 1.067)	1.041 (1.010, 1.074)
Respiratory disease (All ages)	6610	1.001 (1.001, 1.002)	1.022 (1.013, 1.031)	1.025 (1.014, 1.037)
(Ages 0–18)	2710	1.000 (0.983, 1.018)	0.998 (0.975, 1.022)	0.998 (0.969, 1.028)
(Ages 19–64)	2915	1.016 (1.004, 1.027)	1.022 (1.009, 1.035)	1.025 (1.008, 1.041)
(Ages 65+)	985	0.995 (0.955, 1.037)	1.007 (0.959, 1.058)	0.999 (0.952, 1.048)
Cardiovascular				
Acute myocardial infarction	462	1.001 (0.999, 1.004)	1.022 (0.995, 1.050)	1.015 (0.977, 1.053)
Ischemic heart disease	722	1.001 (0.998, 1.003)	1.025 (1.001, 1.049)	1.030 (1.000, 1.061)
Dysrhythmia	1000	0.999 (0.996, 1.002)	0.987 (0.951, 1.024)	0.972 (0.929, 1.017)
Congestive heart failure	510	0.996 (0.990, 1.003)	0.952 (0.883, 1.025)	0.944 (0.869, 1.026)
Ischemic Stroke	576	1.000 (0.997, 1.003)	0.978 (0.922, 1.037)	0.936 (0.861, 1.017)
Peripheral vascular disease	411	1.000 (0.996, 1.004)	0.997 (0.948, 1.048)	0.983 (0.921, 1.050)
Cardiovascular disease	3219	1.000 (0.998, 1.001)	0.999 (0.981, 1.017)	0.989 (0.967, 1.012)

[a] Change per 10 $\mu g/m^3$

[b] Moving average

Table 2b. Odds Ratios for respiratory and cardiovascular endpoints for continuous change in 24-h $PM_{2.5}$ concentrations for FINN 12 km resolution.

Health endpoint	Case count	24 h mean ORa		
		Lag 0	Lag 0-1b	Lag 0-1-2b
Respiratory				
Asthma & Wheeze (All ages)	1136	1.011 (1.004, 1.018)	1.118 (1.067, 1.171)	1.177 (1.106, 1.253)
(Ages 0–18)	387	0.981 (0.923, 1.043)	1.181 (1.038, 1.344)	1.324 (1.119, 1.567)
(Ages 19–64)	665	1.032 (1.005, 1.059)	1.085 (1.013, 1.164)	1.179 (1.053, 1.320)
(Ages 65+)	84	1.015 (0.899, 1.146)	1.342 (0.870, 2.071)	1.474 (0.883, 2.463)
Upper respiratory infection	3376	1.002 (0.994, 1.011)	1.009 (0.955, 1.065)	0.998 (0.932, 1.068)
Pneumonia	955	1.003 (0.987, 1.019)	0.964 (0.857, 1.084)	0.964 (0.844, 1.100)
Bronchitis	413	0.999 (0.975, 1.023)	1.045 (0.942, 1.159)	1.113 (0.996, 1.245)
COPD	628	1.019 (1.009, 1.029)	1.131 (1.056, 1.210)	1.134 (1.037, 1.239)
Respiratory disease (All ages)	6610	1.008 (1.004, 1.012)	1.060 (1.032, 1.090)	1.075 (1.039, 1.113)
(Ages 0–18)	2710	0.981 (0.923, 1.043)	0.974 (0.899, 1.055)	0.992 (0.901, 1.092)
(Ages 19–64)	2915	1.032 (1.005, 1.059)	1.046 (1.009, 1.085)	1.058 (1.009, 1.109)
(Ages 65+)	985	1.015 (0.899, 1.146)	1.049 (0.908, 1.213)	1.024 (0.889, 1.180)
Cardiovascular				
Acute myocardial infarction	462	1.009 (0.999, 1.020)	1.063 (0.987, 1.146)	1.056 (0.953, 1.171)
Ischemic heart disease	722	1.008 (0.998, 1.019)	1.075 (1.007, 1.148)	1.098 (1.011, 1.193)
Dysrhythmia	1000	0.993 (0.974, 1.013)	0.953 (0.845, 1.073)	0.912 (0.790, 1.053)
Congestive heart failure	510	0.984 (0.949, 1.020)	0.840 (0.665, 1.063)	0.824 (0.635, 1.070)
Ischemic Stroke	576	0.996 (0.970, 1.023)	0.913 (0.746, 1.117)	0.843 (0.657, 1.082)
Peripheral vascular disease	411	1.000 (0.978, 1.023)	0.985 (0.839, 1.157)	0.926 (0.740, 1.158)
Cardiovascular disease	3219	1.000 (0.992, 1.009)	0.998 (0.945, 1.055)	0.978 (0.913, 1.047)

[a] Change per 5 $\mu g/m^3$

[b] Moving average

Table 3a. Odds Ratios for respiratory and cardiovascular endpoints for continuous change in 1-h $PM_{2.5}$ concentrations for QFED 12 km resolution.

Health endpoint	Case count	1 h max ORa		
		Lag 0	Lag 0-1b	Lag 0-1-2b
Respiratory				
Asthma & Wheeze (All ages)	1136	1.004 (1.002, 1.005)	1.056 (1.039, 1.073)	1.065 (1.046, 1.085)
(Ages 0–18)	387	1.041 (1.015, 1.068)	1.066 (1.026, 1.106)	1.096 (1.050, 1.144)
(Ages 19–64)	665	1.032 (1.012, 1.051)	1.054 (1.029, 1.080)	1.065 (1.035, 1.095)
(Ages 65+)	84	1.045 (0.979, 1.116)	1.136 (1.046, 1.234)	1.110 (1.007, 1.223)
Upper respiratory infection	3376	1.000 (0.999, 1.002)	1.001 (0.987, 1.016)	0.998 (0.981, 1.015)
Pneumonia	955	0.999 (0.997, 1.002)	0.988 (0.962, 1.016)	0.987 (0.958, 1.017)
Bronchitis	413	1.001 (0.999, 1.004)	1.014 (0.983, 1.046)	1.025 (0.992, 1.060)
COPD	628	1.002 (1.001, 1.004)	1.029 (1.007, 1.052)	1.037 (1.011, 1.063)
Respiratory disease (All ages)	6610	1.001(1.00,1 1.002)	1.017 (1.009, 1.026)	1.020 (1.010, 1.030)
(Ages 0–18)	2710	0.998 (0.983, 1.012)	0.994 (0.975, 1.013)	0.997 (0.975, 1.019)
(Ages 19–64)	2915	1.013 (1.003, 1.022)	1.021 (1.008, 1.033)	1.023 (1.009, 1.037)
(Ages 65+)	985	1.006 (0.981, 1.031)	1.008 (0.979, 1.038)	1.002 (0.969, 1.036)
Cardiovascular				
Acute myocardial infarction	462	0.999 (0.996, 1.002)	0.994 (0.962, 1.027)	0.990 (0.954, 1.028)
Ischemic heart disease	722	1.000 (0.998, 1.002)	1.005 (0.980, 1.031)	1.007 (0.979, 1.036)
Dysrhythmia	1000	0.998 (0.995, 1.001)	0.970 (0.939, 1.001)	0.980 (0.950, 1.010)
Congestive heart failure	510	0.997 (0.993, 1.002)	0.965 (0.920, 1.013)	0.951 (0.901, 1.005)
Ischemic Stroke	576	1.000 (0.997, 1.003)	0.997 (0.963, 1.032)	0.991 (0.952, 1.031)
Peripheral vascular disease	411	0.999 (0.994, 1.003)	0.979 (0.931, 1.029)	0.969 (0.917, 1.023)
Cardiovascular disease	3219	0.999 (0.998, 1.000)	0.986 (0.970, 1.001)	0.985 (0.968, 1.002)

[a] Change per 10 μg/m^3

[b] Moving average

Table 3b. Odds Ratios for respiratory and cardiovascular endpoints for continuous change in 24-h $PM_{2.5}$ concentrations for QFED 12 km resolution.

Health endpoint	Case count	24 h mean ORa		
		Lag 0	Lag 0-1b	Lag 0-1-2b
Respiratory				
Asthma & Wheeze (All ages)	1136	1.017 (1.011, 1.024)	1.130 (1.083, 1.179)	1.161 (1.104, 1.221)
(Ages 0–18)	387	1.092 (1.007, 1.184)	1.139 (1.018, 1.274)	1.253 (1.108, 1.417)
(Ages 19–64)	665	1.082 (1.032, 1.134)	1.123 (1.054, 1.196)	1.139 (1.061, 1.223)
(Ages 65+)	84	1.125 (0.949, 1.334)	1.387 (1.114, 1.727)	1.322 (1.014, 1.725)
Upper respiratory infection	3376	1.002 (0.996, 1.008)	0.995 (0.955, 1.036)	0.984 (0.938, 1.031)
Pneumonia	955	1.000 (0.989, 1.011)	0.979 (0.910, 1.054)	0.990 (0.915, 1.072)
Bronchitis	413	1.008 (0.996, 1.020)	1.041 (0.959, 1.129)	1.076 (0.984, 1.177)
COPD	628	1.013 (1.005, 1.021)	1.078 (1.019, 1.141)	1.093 (1.022, 1.169)
Respiratory disease (All ages)	6610	1.008 (1.004, 1.011)	1.042 (1.018, 1.065)	1.052 (1.025, 1.079)
(Ages 0–18)	2710	0.989 (0.950, 1.029)	0.979 (0.928, 1.031)	0.988 (0.930, 1.049)
(Ages 19–64)	2915	1.032 (1.007, 1.056)	1.042 (1.009, 1.075)	1.048 (1.011, 1.086)
(Ages 65+)	985	1.023 (0.953, 1.098)	1.031 (0.948, 1.122)	1.013 (0.922, 1.112)
Cardiovascular				
Acute myocardial infarction	462	1.000 (0.987, 1.014)	0.980 (0.897, 1.072)	0.991 (0.902, 1.089)
Ischemic heart disease	722	1.004 (0.994, 1.015)	1.018 (0.955, 1.085)	1.029 (0.960, 1.102)
Dysrhythmia	1000	0.989 (0.975, 1.004)	0.931 (0.856, 1.013)	0.958 (0.882, 1.040)
Congestive heart failure	510	0.989 (0.967, 1.011)	0.882 (0.771, 1.009)	0.830 (0.708, 0.973)
Ischemic Stroke	576	1.000 (0.985, 1.014)	1.001 (0.917, 1.092)	0.997 (0.903, 1.102)
Peripheral vascular disease	411	0.994 (0.971, 1.017)	0.935 (0.817, 1.071)	0.901 (0.773, 1.050)
Cardiovascular disease	3219	0.997 (0.990, 1.004)	0.966 (0.926, 1.007)	0.967 (0.924, 1.011)

[a] Change per 5 $\mu g/m^3$

[b] Moving average

Table 4a. Odds Ratios for respiratory and cardiovascular endpoints for continuous change in 1 h $PM_{2.5}$ concentrations for FINN 4 km resolution.

Health endpoint	Case count	1 h max ORa		
		Lag 0	Lag 0-1b	Lag 0-1-2b
Respiratory				
Asthma & Wheeze (All ages)	1136	0.997 (0.961, 1.033)	1.029 (0.886, 1.196)	1.224 (1.001, 1.496)
(Ages 0–18)	387	0.990 (0.924, 1.060)	1.065 (0.798, 1.421)	1.407 (0.946, 2.092)
(Ages 19–64)	665	0.994 (0.945, 1.045)	0.960 (0.779, 1.182)	1.064 (0.805, 1.406)
(Ages 65+)	84	1.056 (0.914, 1.220)	1.563 (0.851, 2.870)	2.074 (0.912, 4.715)
Upper respiratory infection	3376	0.979 (0.958, 1.000)	0.997 (0.913, 1.090)	1.004 (0.891, 1.132)
Pneumonia	955	0.994 (0.958, 1.032)	0.956 (0.820, 1.115)	0.771 (0.62,8, 0.946)
Bronchitis	413	0.961 (0.905, 1.022)	0.861 (0.671, 1.107)	1.139 (0.820, 1.583)
COPD	628	1.026 (0.980, 1.075)	0.924 (0.760, 1.123)	0.965 (0.747, 1.247)
Respiratory disease (All ages)	6610	0.988 (0.974, 1.003)	0.977 (0.918, 1.040)	0.994 (0.914, 1.080)
(Ages 0–18)	2710	0.985 (0.960, 1.011)	1.001 (0.901, 1.111)	1.008 (0.871, 1.167)
(Ages 19–64)	2915	0.999 (0.976, 1.024)	0.984 (0.892, 1.086)	1.002 (0.879, 1.143)
(Ages 65+)	985	0.986 (0.942, 1.032)	0.920 (0.769, 1.100)	0.914 (0.721, 1.157)
Cardiovascular				
Acute myocardial infarction	462	1.028 (0.974, 1.084)	1.027 (0.822, 1.282)	0.912 (0.679, 1.225)
Ischemic heart disease	722	1.005 (0.964, 1.049)	0.961 (0.807, 1.144)	0.929 (0.737, 1.171)
Dysrhythmia	1000	1.001 (0.969, 1.034)	0.984 (0.859, 1.127)	0.902 (0.752, 1.081)
Congestive heart failure	510	0.960 (0.910, 1.012)	0.855 (0.690, 1.060)	0.787 (0.590, 1.050)
Ischemic Stroke	576	1.006 (0.960, 1.054)	0.989 (0.812, 1.205)	0.995 (0.767, 1.291)
Peripheral vascular disease	411	1.009 (0.952, 1.070)	0.917 (0.717, 1.173)	0.725 (0.518, 1.016)
Cardiovascular disease	3219	0.998 (0.978, 1.018)	0.952 (0.877, 1.033)	0.884 (0.793, 0.986)

[a] Change per 3.06108 $\mu g/m^3$

[b] Moving average

Table 4b. Odds Ratios for respiratory and cardiovascular endpoints for continuous change in 24-h $PM_{2.5}$ concentrations for FINN 4 km resolution.

Health endpoint	Case count	24 h mean ORa		
		Lag 0	Lag 0-1b	Lag 0-1-2b
Respiratory				
Asthma & Wheeze (All ages)	1136	1.040 (0.976, 1.108)	1.101 (0.953, 1.273)	1.200 (0.999, 1.443)
(Ages 0–18)	387	1.024 (0.912, 1.149)	1.177 (0.899, 1.541)	1.328 (0.952, 1.852)
(Ages 19–64)	665	1.051 (0.963, 1.147)	1.074 (0.883, 1.306)	1.130 (0.880, 1.452)
(Ages 65+)	84	1.064 (0.819, 1.382)	1.304 (0.721, 2.360)	1.529 (0.725, 3.225)
Upper respiratory infection	3376	0.963 (0.928, 1.000)	0.946 (0.870, 1.029)	0.945 (0.847, 1.054)
Pneumonia	955	0.996 (0.931, 1.066)	0.997 (0.857, 1.160)	0.871 (0.716, 1.060)
Bronchitis	413	0.970 (0.873, 1.077)	0.945 (0.747, 1.196)	1.050 (0.775, 1.422)
COPD	628	1.020 (0.937, 1.110)	1.001 (0.828, 1.210)	0.976 (0.766, 1.243)
Respiratory disease (All ages)	6610	0.988 (0.962, 1.014)	0.985 (0.928, 1.045)	0.983 (0.910, 1.061)
(Ages 0–18)	2710	0.989 (0.947, 1.033)	1.015 (0.920, 1.120)	1.020 (0.898, 1.159)
(Ages 19–64)	2915	1.008 (0.967, 1.051)	1.025 (0.933, 1.125)	1.040 (0.923, 1.173)
(Ages 65+)	985	0.967 (0.894, 1.046)	0.924 (0.777, 1.099)	0.884 (0.707, 1.104)
Cardiovascular				
Acute myocardial infarction	462	1.017 (0.923, 1.122)	1.021 (0.821, 1.271)	0.915 (0.690, 1.214)
Ischemic heart disease	722	0.993 (0.919, 1.074)	0.981 (0.826, 1.166)	0.936 (0.748, 1.171)
Dysrhythmia	1000	1.054 (0.987, 1.125)	1.122 (0.970, 1.299)	1.079 (0.896, 1.299)
Congestive heart failure	510	0.923 (0.841, 1.013)	0.885 (0.720, 1.087)	0.771 (0.587, 1.011)
Ischemic Stroke	576	1.045 (0.958, 1.139)	1.070 (0.881, 1.299)	1.102 (0.859, 1.414)
Peripheral vascular disease	411	0.964 (0.869, 1.070)	0.857 (0.682, 1.078)	0.787 (0.583, 1.062)
Cardiovascular disease	3219	1.006 (0.969, 1.044)	1.005 (0.926, 1.091)	0.958 (0.862, 1.065)

[a] Change per 1.81817 $\mu g/m^3$

[b] Moving average

Table 5a. Odds Ratios for respiratory and cardiovascular endpoints for continuous change in 1 h $PM_{2.5}$ concentrations for FINN 12 km resolution.

Health endpoint	Case count	1 h max ORa		
		Lag 0	Lag 0-1b	Lag 0-1-2b
Respiratory				
Asthma & Wheeze (All ages)	1136	1.002 (1.001, 1.004)	1.011 (1.007, 1.015)	1.015 (1.010, 1.021)
(Ages 0–18)	387	1.008 (1.001, 1.014)	1.016 (1.006, 1.026)	1.024 (1.011, 1.037)
(Ages 19–64)	665	1.004 (0.999, 1.009)	1.008 (1.002, 1.015)	1.016 (1.006, 1.027)
(Ages 65+)	84	0.997 (0.959, 1.036)	1.019 (0.982, 1.057)	1.029 (0.987, 1.073)
Upper respiratory infection	3376	1.000 (0.999, 1.002)	1.002 (0.998, 1.006)	1.001 (0.995, 1.006)
Pneumonia	955	1.001 (0.999, 1.003)	0.999 (0.990, 1.008)	0.996 (0.985, 1.007)
Bronchitis	413	1.000 (0.996, 1.004)	1.005 (0.996, 1.014)	1.011 (1.002, 1.020)
COPD	628	1.003 (1.001, 1.005)	1.011 (1.005, 1.017)	1.011 (1.003, 1.019)
Respiratory disease (All ages)	6610	1.001 (1.001, 1.002)	1.006 (1.003, 1.008)	1.007 (1.004, 1.010)
(Ages 0–18)	2710	1.000 (0.996, 1.005)	1.000 (0.993, 1.006)	0.999 (0.992, 1.007)
(Ages 19–64)	2915	1.004 (1.001, 1.007)	1.006 (1.002, 1.009)	1.006 (1.002, 1.011)
(Ages 65+)	985	0.999 (0.988, 1.010)	1.002 (0.989, 1.015)	1.000 (0.987, 1.012)
Cardiovascular				
Acute myocardial infarction	462	1.001 (0.999, 1.004)	1.006 (0.999, 1.013)	1.004 (0.994, 1.014)
Ischemic heart disease	722	1.001 (0.998, 1.003)	1.006 (1.000, 1.013)	1.008 (1.000, 1.016)
Dysrhythmia	1000	0.999 (0.996, 1.002)	0.997 (0.987, 1.006)	0.993 (0.981, 1.004)
Congestive heart failure	510	0.996 (0.990, 1.003)	0.987 (0.968, 1.007)	0.985 (0.964, 1.007)
Ischemic Stroke	576	1.000 (0.997, 1.003)	0.994 (0.979, 1.010)	0.983 (0.962, 1.004)
Peripheral vascular disease	411	1.000 (0.996, 1.004)	0.999 (0.986, 1.012)	0.996 (0.979, 1.013)
Cardiovascular disease	3219	1.000 (0.998, 1.001)	1.000 (0.995, 1.004)	0.997 (0.991, 1.003)

[a] Change per 2.61467 μg/m^3

[b] Moving average

Table 5b. Odds Ratios for respiratory and cardiovascular endpoints for continuous change in 24-h $PM_{2.5}$ concentrations for FINN 12 km resolution.

Health endpoint	Case count	24 h mean ORa		
		Lag 0	Lag 0-1b	Lag 0-1-2b
Respiratory				
Asthma & Wheeze (All ages)	1136	1.011 (1.004, 1.018)	1.038 (1.022, 1.055)	1.057 (1.035, 1.080)
(Ages 0–18)	387	1.025 (0.994, 1.057)	1.058 (1.013, 1.106)	1.100 (1.039, 1.165)
(Ages 19–64)	665	1.011 (0.996, 1.027)	1.028 (1.004, 1.053)	1.058 (1.018, 1.099)
(Ages 65+)	84	0.940 (0.782, 1.129)	1.105 (0.954, 1.281)	1.141 (0.958, 1.358)
Upper respiratory infection	3376	1.002 (0.994, 1.011)	1.003 (0.985, 1.022)	0.999 (0.976, 1.023)
Pneumonia	955	1.003 (0.987, 1.019)	0.988 (0.949, 1.028)	0.988 (0.944, 1.033)
Bronchitis	413	0.999 (0.975, 1.023)	1.015 (0.980, 1.051)	1.037 (0.999, 1.077)
COPD	628	1.019 (1.009, 1.029)	1.043 (1.019, 1.067)	1.044 (1.013, 1.076)
Respiratory disease (All ages)	6610	1.008 (1.004, 1.012)	1.020 (1.011, 1.030)	1.025 (1.013, 1.037)
(Ages 0–18)	2710	0.994 (0.973, 1.014)	0.991(0.964, 1.018)	0.997 (0.965, 1.030)
(Ages 19–64)	2915	1.011 (1.002, 1.020)	1.015 (1.003, 1.028)	1.019 (1.003, 1.036)
(Ages 65+)	985	1.005 (0.965, 1.047)	1.017 (0.968, 1.068)	1.008 (0.961, 1.058)
Cardiovascular				
Acute myocardial infarction	462	1.009 (0.999, 1.020)	1.021 (0.995, 1.047)	1.019 (0.984, 1.055)
Ischemic heart disease	722	1.008 (0.998, 1.019)	1.025 (1.002, 1.048)	1.032 (1.004, 1.062)
Dysrhythmia	1000	0.993 (0.974, 1.013)	0.984 (0.945, 1.024)	0.969 (0.923, 1.018)
Congestive heart failure	510	0.984 (0.949, 1.020)	0.943 (0.870, 1.021)	0.936 (0.857, 1.023)
Ischemic Stroke	576	0.996 (0.970, 1.023)	0.970 (0.905, 1.038)	0.944 (0.867, 1.027)
Peripheral vascular disease	411	1.000 (0.978, 1.023)	0.995 (0.942, 1.051)	0.974 (0.903, 1.051)
Cardiovascular disease	3219	1.000 (0.992, 1.009)	0.999 (0.981, 1.018)	0.992 (0.970, 1.016)

[a] Change per 1.69876 μg/m^3

[b] Moving average

Table 6a. Odds Ratios for respiratory and cardiovascular endpoints for continuous change in 1 h $PM_{2.5}$ concentrations for QFED 12 km resolution.

Health endpoint	Case count	1 h max ORa		
		Lag 0	Lag 0-1b	Lag 0-1-2b
Respiratory				
Asthma & Wheeze (All ages)	1136	1.004 (1.002, 1.005)	1.026 (1.018, 1.034)	1.030 (1.021, 1.039)
(Ages 0–18)	387	0.999 (0.992, 1.006)	1.030 (1.012, 1.049)	1.044 (1.023, 1.066)
(Ages 19–64)	665	1.006 (1.001, 1.011)	1.025 (1.014, 1.037)	1.030 (1.017, 1.044)
(Ages 65+)	84	1.003 (0.991, 1.015)	1.062 (1.021, 1.104)	1.051 (1.003, 1.100)
Upper respiratory infection	3376	1.000 (0.999, 1.002)	1.001 (0.994, 1.008)	0.999 (0.991, 1.007)
Pneumonia	955	0.999 (0.997, 1.002)	0.995 (0.982, 1.007)	0.994 (0.980, 1.008)
Bronchitis	413	1.001 (0.999, 1.004)	1.007 (0.992, 1.021)	1.012 (0.996, 1.028)
COPD	628	1.002 (1.001, 1.004)	1.014 (1.003, 1.024)	1.017 (1.005, 1.029)
Respiratory disease (All ages)	6610	1.001 (1.001, 1.002)	1.008 (1.004, 1.012)	1.009 (1.005, 1.014)
(Ages 0–18)	2710	1.019 (1.007, 1.032)	0.997 (0.988, 1.006)	0.998 (0.988, 1.009)
(Ages 19–64)	2915	1.015 (1.006, 1.024)	1.010 (1.004, 1.016)	1.011 (1.004, 1.017)
(Ages 65+)	985	1.021 (0.990, 1.053)	1.004 (0.990, 1.018)	1.001 (0.985, 1.017)
Cardiovascular				
Acute myocardial infarction	462	0.999 (0.996, 1.002)	0.997 (0.982, 1.012)	0.995 (0.978, 1.013)
Ischemic heart disease	722	1.000 (0.998, 1.002)	1.002 (0.990, 1.015)	1.003 (0.990, 1.017)
Dysrhythmia	1000	0.998 (0.995, 1.001)	0.986 (0.971, 1.001)	0.990 (0.976, 1.005)
Congestive heart failure	510	0.997 (0.993, 1.002)	0.984 (0.962, 1.006)	0.977 (0.952, 1.002)
Ischemic Stroke	576	1.000 (0.997, 1.003)	0.998 (0.982, 1.015)	0.996 (0.977, 1.014)
Peripheral vascular disease	411	0.999 (0.994, 1.003)	0.990 (0.967, 1.013)	0.985 (0.960, 1.011)
Cardiovascular disease	3219	0.999 (0.998, 1.000)	0.993 (0.986, 1.001)	0.993 (0.985, 1.001)

[a] Change per 4.72214 $\mu g/m^3$

[b] Moving average

Table 6b. Odds Ratios for respiratory and cardiovascular endpoints for continuous change in 24-h $PM_{2.5}$ concentrations for QFED 12 km resolution.

Health endpoint	Case count	24 h mean ORa		
		Lag 0	Lag 0-1b	Lag 0-1-2b
Respiratory				
Asthma & Wheeze (All ages)	1136	1.017 (1.011, 1.024)	1.067 (1.043, 1.092)	1.083 (1.054, 1.112)
(Ages 0–18)	387	0.994 (0.973, 1.015)	1.071 (1.009, 1.137)	1.127 (1.056, 1.204)
(Ages 19–64)	665	1.017 (1.004, 1.030)	1.064 (1.028, 1.100)	1.072 (1.032, 1.113)
(Ages 65+)	84	1.012 (0.975, 1.051)	1.190 (1.059, 1.337)	1.160 (1.007, 1.336)
Upper respiratory infection	3376	1.002 (0.996, 1.008)	0.997 (0.976, 1.019)	0.991 (0.967, 1.017)
Pneumonia	955	1.000 (0.989, 1.011)	0.989 (0.951, 1.028)	0.995 (0.954, 1.038)
Bronchitis	413	1.008 (0.996, 1.020)	1.021 (0.978, 1.067)	1.040 (0.992, 1.090)
COPD	628	1.013 (1.005, 1.021)	1.041 (1.010, 1.072)	1.048 (1.012, 1.086)
Respiratory disease (All ages)	6610	1.008 (1.004, 1.011)	1.022 (1.010, 1.034)	1.027 (1.013, 1.041)
(Ages 0–18)	2710	1.048 (1.004, 1.094)	0.989 (0.961, 1.017)	0.993 (0.962, 1.026)
(Ages 19–64)	2915	1.043 (1.017, 1.069)	1.022 (1.005, 1.039)	1.025 (1.006, 1.045)
(Ages 65+)	985	1.065 (0.973, 1.165)	1.017 (0.972, 1.063)	1.007 (0.958, 1.058)
Cardiovascular				
Acute myocardial infarction	462	1.000 (0.987, 1.014)	0.990 (0.944, 1.038)	0.995 (0.947, 1.046)
Ischemic heart disease	722	1.004 (0.994, 1.015)	1.010 (0.976, 1.044)	1.015 (0.979, 1.053)
Dysrhythmia	1000	0.989 (0.975, 1.004)	0.963 (0.921, 1.007)	0.977 (0.936, 1.021)
Congestive heart failure	510	0.989 (0.967, 1.011)	0.935 (0.871, 1.005)	0.906 (0.832, 0.985)
Ischemic Stroke	576	1.000 (0.985, 1.014)	1.000 (0.955, 1.048)	0.999 (0.947, 1.053)
Peripheral vascular disease	411	0.994 (0.971, 1.017)	0.965 (0.898, 1.037)	0.946 (0.872, 1.026)
Cardiovascular disease	3219	0.997 (0.990, 1.004)	0.982 (0.960, 1.004)	0.982 (0.959, 1.006)

[a] Change per 2.65656 μg/m^3

[b] Moving average