Modeling Atmospheric Emissions and Calculating Mortality Rates Associated with High Volume Hydraulic Fracturing Transportation

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Modeling Atmospheric Emissions and Calculating Mortality Rates Associated with High Volume Hydraulic Fracturing Transportation

By

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Abstract

Emissions from the combustion of fossil fuels are a growing pollution concern throughout the global community, as they have been linked to numerous health issues. The freight transportation sector is a large source of these emissions and is expected to continue growing as globalization persists. Within the US, the expanding development of the natural gas industry is helping to support many industries and leading to increased transportation. The process of High Volume Hydraulic Fracturing (HVHF) is one of the newer advanced extraction techniques that is increasing natural gas and oil reserves dramatically within the US, however the technique is very resource intensive. HVHF requires large volumes of water and sand per well, which is primarily transported by trucks in rural areas. Trucks are also used to transport waste away from HVHF well sites. This study focused on the emissions generated from the transportation of HVHF materials to remote well sites, dispersion, and subsequent health impacts. The Geospatial Intermodal Freight Transport (GIFT) model was used in this analysis within ArcGIS to identify roadways with high volume traffic and emissions. High traffic road segments were used as emissions sources to determine the atmospheric dispersion of particulate matter using AERMOD, an EPA model that calculates geographic dispersion and concentrations of pollutants. Output from AERMOD was overlaid with census data to determine which communities may be impacted by increased emissions from HVHF transport. The anticipated number of mortalities within the impacted communities was calculated, and mortality rates from these additional emissions were computed to be 1 in 10 million people for a simulated truck fleet meeting stricter 2007 emission standards, representing a best case scenario. Mortality rates due to increased truck emissions from average, in-use vehicles, which represent a mixed age truck fleet, are expected to be higher (1 death per 341,000 people annually).
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Overview

Emissions from the burning of fossil fuels are a large and growing pollution concern throughout the global community with regard to their potential for adverse health effects. Emissions have been linked to numerous health issues such as asthma, heart disease, and mortality (Smith, Axon, and Darton, 2013; Brook et al., 2010; McCleanor et al., 2007; Sydbom et al. 2001). Transportation accounts for 27% of greenhouse gases emitted in the United States (EPA Office of Transportation and Air Quality, 2013). The freight transportation sector continues to grow, fueled by globalization. Controlling emissions is therefore an environmental health concern, one with multiple approaches, including policy solutions, technological controls, logistical modifications, and lower emission fuel sources.

Within the US, development of energy resources, such as natural gas reserves, are helping to support transportation growth both as an energy source and through the movement of materials and goods needed for energy development. Natural gas has been identified by some as a cleaner fuel source, and with advanced extraction technologies, such as High Volume Hydraulic Fracturing (HVHF or fracking), vast new oil and natural gas reserves have become available, allowing for the extraction of greater amounts of natural shale gas from shale deposits.

The fracking process is very resource intensive, requiring the transportation of drilling equipment and pipe, as well as large volumes of silica sand and water, to well locations and the transport of waste to treatment/disposal facilities. The three primary methods of transport are currently rail, truck, and ship, with truck transport dominating at the local and regional level. This study focused on the emissions generated by the delivery of materials to remote well sites and the removal of waste materials primarily using trucks. The analysis utilized routes, truck counts, and emission totals generated by ArcGIS Network Analyst and the Geospatial Intermodal Freight Transport (GIFT) model to determine locations of high volume traffic along road networks in the Marcellus Shale formation. Coincident route segments with high truck volumes were identified and used as line sources in the US EPA model AERMOD to model emission dispersion around these hotspots in order to ascertain which populations are impacted by the HVHF industry’s freight transport and to evaluate potential community health impacts.
Energy and Transportation Emissions

Air pollution emissions can come from either natural sources, which are typically linked with geological or meteorological effects, or from anthropogenic sources, such as burning fossil fuels. Anthropogenic sources currently account for the majority of pollutant emissions (Reis, 2011). The power generation and the transportation sector account for the largest amount of energy related CO$_2$ emissions, contributing 40.6% and 33.1% respectively in 2008. Coal combustion currently generates approximately 81% of all carbon dioxide emissions from US energy generation. In 2008, about 10.5% of greenhouse gases emitted were methane, the majority of which came from the energy generation sector, which includes petroleum systems and combustion sources (EIA, 2009). It is predicted that the global energy demand will grow by approximately 1.2% each year (Kumar et al. 2011). Transportation emissions related to the energy sector are also expected to grow, as domestic natural gas resources are developed through new technologies, such as horizontal hydraulic fracturing. As such, it is reasonable to conjecture that current emissions inventories may change within the next few decades if natural gas is used more widely.

Transportation is a major focus area in regards to climate change and energy sources. The transportation sector causes 25% of all greenhouse gas emissions in general and about 67% of emissions in the United States (Sperling and Yeh, 2009). One of the most rapidly growing transportation sectors is the freight transportation industry (Winebrake et al., 2008). Transportation also accounts for a significant amount of oil consumption (70%) within the United States (Podesta and Wirth, 2009). Medium and heavy duty trucks are responsible for 21% of oil consumed within the transportation sector, or about 15% of the total US petroleum consumption (Transportation Energy Data Book, 2013). A 49% rise in the energy used by the ground freight industry is anticipated by the year 2020 (Ang-Olson and Schroeer, 2002). Within the transportation sector, medium and heavy-duty trucks account for 22% of greenhouse gas emissions (EPA Office of Transportation and Air Quality, 2013). Factors such as widespread urbanization are leading to a greater demand for transportation (Sydbom et al. 2001), as well as growing demand for mobility in developing countries that are beginning to require and obtain automobiles and other motor vehicles (Kumar et al. 2011). The pattern of freight transportation
contributing the most to the transportation emissions inventory is also consistent for developing
countries (Guttikunda and Calori, 2013). The strong correlation between the economic
development of a country and a rise in the number of motor vehicles (Kabashi et al. 2011),
illustrates how growing emissions from transportation in general, and motor vehicles in
particular, are a growing global problem.

Natural Gas Reserves

Over the past 10 years, the natural gas industry has been helping to stimulate the growth
of freight transport and its associated air emissions as new gas fields are developed through
hydraulic fracturing techniques. The world is currently facing the need for a large scale energy
shift away from decreasing petroleum reserves. A widespread energy transition is both imminent
and vital for the future. Such transitions are often dependent on current economics, as well as
technological capability. A major characteristic of an energy transition is its slow pace, as these
transitions can take several decades or more (Allen, 2012).

Recent technological advances have allowed for a large increase in natural gas
extraction. High volume horizontal hydraulic fracturing (HVHF) is one of the most promising
methods for extracting natural gas yields from tight shale rock and is expanding the technically
recoverable reserves of shale gas in the United States (McKenzie et al. 2012). HVHF, also
known as fracking, allows for increasingly cost effective extraction of natural gas from shale
deposits (Howarth, Ingraffea, and Engelder, 2011), (Argetsinger, 2012). Although hydraulic
fracturing of shale gas has occurred for many years, with the first natural gas well drilled in 1825
(Rotman, 2009), the process only accounted for 14% of the United States’ natural gas supply in
2009 (EIA, 2011). Rising natural gas prices due to current supply and demand dynamics are also
a factor in making hydraulic fracturing economically feasible. Hydraulic fracturing of shale
deposits could provide enough natural gas to help offset the amount of oil that is imported into
the United States (Howarth, Ingraffea, and Engelder 2011). The Energy Information
Administration (EIA) has predicted a large increase in shale gas usage with one of their
projections, estimating that by 2035, 49% of natural gas in the US will be shale gas (EIA,
2011).
In 2009, the US government released a memo (Podesta and Wirth, 2009) suggesting the use of natural gas as a bridge fuel through the energy transition to more sustainable fuels and energy sources. The concept of a bridge fuel would mean introducing more natural gas into the energy fuel mix as coal and oil are phased out, with the eventual goal being that the energy mix will not contain any hydrocarbon-based fuels and instead will be composed of other energy sources such as wind, solar, hydrogen, and biofuels (Pierce, 2012). Part of the appeal of considering natural gas as a transition or bridge fuel is that burning natural gas emits around 50% less greenhouse gases than the combustion of coal, a conventional power-generating fuel (Pierce, 2012).

This statistic, however, can be misleading, as less carbon is emitted by natural gas than coal at the point of combustion, but this does not include the life cycle of natural gas, including its development (Argetsinger, 2012). There are few peer reviewed studies to help determine if global warming will be reduced or enhanced with widespread use of shale gas as a transition fuel (Howarth, Santoro, and Ingraffea, 2011). Some sources say that using natural gas as a bridge fuel may lead to it becoming a fall-back fuel, to be used in conjunction with the creation and market penetration of better green energy technologies such as solar or wind power (Podesta and Wirth, 2009). Other studies suggest that given abundant natural gas reserves, fossil fuels will continue to be a primary energy source until suitable alternatives and their associated infrastructure for implementation are required and made available (Dresselhaus and Thomas, 2001).

Over the past 20 years increased infrastructure, such as natural gas generation plants, has been built, allowing for the increase of utilization of natural gas in the power generation sector. However, this added capacity is currently not being used, despite its availability. This disparity between available natural gas generation capacities verses current use means that there would be less need for initial development of new infrastructure if natural gas use were to increase (Podesta and Wirth, 2009). For example, tens of gigawatts of highly efficient natural gas generation capacity were installed over the past two decades, but only about 40% of this capacity is used at any given time. At little to no additional cost for infrastructure, natural gas generation could easily substitute for existing coal-fired capacity without any new plant or transmission construction. In some parts of the country, a CO\textsubscript{2} price of as little as $7 to $14 per
ton would provide sufficient incentive to prioritize gas-fired electricity over coal-fired electricity (Podesta and Wirth, 2009).

The United States has large reserves of natural gas held in shale deposits, primarily in rural areas looking for economic stimulus. It is estimated that there are 211 trillion cubic feet (Tcf) of proven reserves, and 1744 Tcf of technically recoverable reserves (Kargbo, Wilhelm, and Campbell, 2010). Projections using these numbers show that the current natural gas reservoirs could supply the United States with energy for 90 years or more. The Marcellus Shale (Figure 1) is the largest shale deposit in the US and overlaps New York, Pennsylvania, Maryland, West Virginia, Virginia, and Ohio, two river commissions, and several governmental organizations (Blohm et al. 2012). Each of these entities have different policies and management practices concerning the area (Blohm et al. 2012). Though some estimates suggest that the Marcellus Shale could have reserves as large as 489 Tcf (Kargbo, Wilhelm, and Campbell, 2010), different regulations regarding HVHF and current land use impact fracking reserve estimations (Blohm et al. 2012).

Figure 1: Boundaries of the Marcellus Shale, according to different sources including the EIA, USGS, and Engelder (2009). (Blohm, 2012, Engelder, 2009, Wrightstone, 2009, USGS, 2002)
Hydraulic Fracturing

Hydraulic fracturing begins with a process called slickwater, where an acid treatment is pumped into the wellbore to help the wellbore maintain its permeability. Slickwater fracs are generally required to minimize friction in the wellbore (Harper, 2008, Arthur, Bohm, and Layne, 2008). Highly pressurized water is pumped into the drilled wells to widen the natural fissures within the rock (Kargbo, Wilhelm, and Campbell, 2010). This first round of fracking fluid uses small-grained proppants that can be carried deeper into the fractures than larger-grained proppants. Following this, eight more rounds of fracking fluid are injected into the well, using increasingly coarser proppants, after which the entire well and associated equipment are flushed out with freshwater (Arthur, Bohm, and Layne, 2008).

The wells extend both vertically and horizontally. The vertical portion of the well is typically 5,000 to 12,000 feet deep, with the horizontal portion extending outward for approximately another 2,000 feet (Rahm, 2011). Fracturing the shale rock creates greater surface area, which allows the gas to travel more easily from the pores of the shale formation to the wellbore (Harper, 2008). This combined approach is designed to maximize the fissures and natural gas recovery. HVHF wells can contain up to 15 fracturing locations. These fracturing locations branch out horizontally, and require 2 to 10 million gallons of water and additives each (Kargbo, Wilhelm, and Campbell, 2010). The additives to the fracking fluid may be harmful to human health and the environment, but are largely unknown to the public due to loopholes in current legislature (Howarth, Ingraffea, and Engelder, 2011). Drilling in the Marcellus Shale is being modeled after Barnett Shale drilling in Texas, using horizontal wells and hydraulic fracturing (Arthur, Bohm, and Layne, 2008). The Barnett Shale is considered to be the first shale deposit to have undergone high volume hydraulic fracturing (dSGEIS, 2011)

Transportation and HVHF

The silica sand and water resources needed for hydraulic fracturing must be transported to different staging areas and are most often transported by ship, rail, and truck. From the staging areas, most of the actual HVHF wells must be serviced by trucks, as the wells are in rural locations that may not have the transportation infrastructure needed for delivery of materials by
ship or rail. The New York State Department of Environmental Conservation estimates that individual wells within the Marcellus Shale may require 100-623 one way heavy truck trips for sand, water and waste (dSGEIS, 2011). The large amount of required resources will likely lead to increased emissions associated with transportation.

HVHF wells require large amounts of water and sand to effectively obtain the natural gas contained in the shale deposit. A slickwater fracturing system can use 500,000 to 1,000,000+ gallons of water per well. It is expected that slickwater fracturing systems in the Marcellus Shale will likely use several million gallons of water each (Harper, 2008). Abdalla and Drohan (2010) estimate that a horizontal well in the Marcellus Shale may use 4-8 million gallons of water initially, without taking into account that such a well may be refractured throughout its lifetime of 5-20 years. It is estimated that each well also requires anywhere from 1000 tons (Banerjee, 2012) to 10,000 tons of silica sand (Minnesota Department of Natural Resources, 2012). This means that up to 450 trucks may be needed to transport the frac sand to the wells, based on a 22-ton truck hauling capacity.

Additionally, due to the more extensive well bores, HVHF wells have been found to produce up to six times more waste than conventional wells (Lutz, Lewis, and Doyle, 2013). It has been estimated that 200-300 trucks may be required per well to remove flowback wastewater (dSGEIS, 2011), however this may be a conservative estimate, only accounting for 50% of the flowback material. As such, there will potentially be environmental effects related to transport emissions in the local area containing HVHF wells due to the influx of water, sand freight transportation, and waste removal. In Pennsylvania, there have been nearly 2000 permits approved and over 900 wells drilled in the first 9 months of 2013 alone (Pennsylvania Department of Environmental Protection, 2013). Since 2009, there have been over 13000 unconventional and Marcellus permits issued, with over 6000 wells drilled (Pennsylvania Department of Environmental Protection, 2013).

While the industry is working on methods to recycle wastes and materials in the near future and develop multimodal operations long-term, the majority of resources utilized now in the hydraulic fracturing process are transported by truck. In some emissions studies, there is a direct correlation between truck emissions and the prevalence of PM$_{10}$, NO$_x$, and SO$_x$ (Guttikunda and Calori, 2013). The emissions from diesel trucks are primarily made up of
elemental carbon, however organic compounds can also adsorb onto the particles (Lena et al. 2002). Diesel engine exhaust can contain many products as a result of incomplete combustion, such as particulate matter (Ristovski et al., 2012), carbon monoxide and volatile organic compounds (VOCs) (Smith et al., 2009). Diesel particulate matter (PM) has been associated with adverse respiratory health effects (Ristovski et al., 2012) as well as eye, nose, and throat irritation (Wierzbia et al., 2014). Diesel exhaust particles can contain sulfur compounds, as well as nitrogen oxides, and VOCs (Wierzbicka et al., 2014). The different greenhouse gases emitted from the combustion of fuel have varying levels of effect on human health (Smith et al. 2009).

Pollutant emissions can be greater closer to roadways due to traffic, thereby leading to a decrease in air quality (Zhang and Batterman, 2013). Mortality has been associated with excessive PM$_{10}$ pollution, especially deaths due to respiratory disease and deaths from cardiovascular causes. Additionally, PM pollution has also been deemed a probable factor in premature deaths (Litovitz, 2013, Fann, Fulcher, and Baker, 2013, Pope, 2002). There are many categories used to calculate emissions health risk, including cardiopulmonary, respiratory, and all-cause mortality, as well as hospitalization records, and incidences of asthma (Pope, 2002, Ostro, 2004, McEntee and Ogneva-Himmelberger, 2008, Fann, Fulcher, and Baker, 2013). Children and elderly people are thought to be most vulnerable to PM mortality effects (Ostro, 2004, Laumbach, 2010).

Particulate matter emitted by diesel engines can be varied in composition due to the chemical makeup of the fuel as well as adsorption of other compounds (Ristovski et al., 2012). Sulfur oxides are also often emitted by diesel engines, usually in the form of sulfur dioxide (SO$_2$), and may also have negative health effects (Smith et al. 2009). Some studies, however, have suggested that sulfur aerosols do not have a large health impact, especially at the current concentrations being emitted (Smith et al. 2009). The primary emission for heavy-duty vehicles being powered by diesel is carbon dioxide (CO$_2$) (Arteconi et al. 2010), although other components can be present in both gaseous and particulate form (Smith et al. 2009).

Particulate matter has been shown to have spatial variations that correspond to traffic sources (Fruin et al., 2014). As such, it is important to not only know the different types of pollutants emitted by freight transport, but also the locations and routes upon which the transport
is occurring. This is especially important with regards to the rural nature of the growing HVHF industry, as this identifies which communities may be impacted adversely by these emissions. Since many of the wells are located in less populated areas, the road infrastructure required to transport the vast quantities of materials needed by fracking operations may not be in place. These infrastructure limitations have the possibility to create backups and bottlenecks within the freight transport supply chain, thereby exacerbating the atmospheric emissions and potential health impacts caused by traffic.

**Atmospheric Dispersion**

Motor vehicle emissions can affect the spatial distribution of pollutants (Venkatram et al., 2009). High emissions are evident closest to roadways, and concentrations can quickly decrease as distance from the road increases (Misra, Roorda, and MacLean, 2013; Keuken et al., 2013). Atmospheric dispersion models, such as AERMOD (EPA Office of Air Quality, 2013), can be used to calculate pollutant concentrations with regard to heavily trafficked areas (Bhave, Shaikh, and Shaikh, 2013). Using the proper emissions rates for atmospheric dispersion models is vital when predicting pollutant concentrations, as incorrect values can lead to increased error (Misra, Roorda, and MacLean, 2013; Cimorelli et al., 2005). Bhave, Shaikh, and Shaikh, (2013) found that the AERMOD model under-predicted the pollutant concentrations of a busy city intersection, which could have been a result of inaccurate emissions data. Atmospheric parameters can impact the air quality due to road traffic and are important to account for in a traffic air quality analysis (Bhave, Shaikh, and Shaikh, 2013). To get a more comprehensive result, multiple modeling steps, such as predicting traffic data, emissions from the traffic, and the dispersion of the emissions from traffic, can be used in combination (Misra, Roorda, and MacLean, 2013).

By using tools such as atmospheric dispersion models coupled with census data, the number of people affected by elevated emissions at these transportation bottlenecks can be estimated. The bottlenecks, or areas of coincident routes, may be created naturally, such as from terrain or infrastructure limitations, or they may correspond to areas of increased activity, such as the roads leading to a materials staging area. The associated traffic volumes due to these
bottlenecks will likely lead to more emissions exposure in the surrounding communities. The goal of this research is to identify potential bottlenecks resulting from transport activities supporting the HVHF industry in the Marcellus Shale formation and model the atmospheric dispersion of truck emissions in order to determine potential human health impacts.
Methods

This study used the Network Analyst extension in ArcGIS with the Geospatial Intermodal Freight Transportation (GIFT) model to track and calculate the atmospheric emissions totals associated with the transport of HVHF materials to wells in the Marcellus Shale area. The GIFT Model is an ArcGIS extension developed by Rochester Institute of Technology’s Laboratory for Environmental Computing and Decision Making (LECDM) and the University of Delaware. The model works within the ArcGIS framework and uses Network Analyst to determine intermodal or single mode freight routes and compute the associated emissions. The model can compute routes for any combination of truck, rail, or ship transport, and optimize the routes according to a selected parameter such as cost, time, or type of emissions. Each of the different modes can be adjusted and customized depending upon the type of truck, train, or ship being used. An example of the GIFT Model parameters within Network Analyst can be found in Figure 2 below.

![GIFT settings within Network Analyst in ArcGIS. Left: general route and transportation settings. Right: pollutant accumulation settings.](image)

In this study, routes originated from either wells (in the case of waste transport) or resource staging areas, allowing for the generation of sets of origin-destination pairs for the network optimization. Routes were computed between each pair of well and facility points. For
In this study, ArcGIS was used to compute single mode truck routes and high volume (‘hot’) road segments that would likely be used for transporting HVHF materials and resources. Particulate matter (PM$_{10}$) emission data were generated using the GIFT model within ArcGIS, and subsequently used as inputs for the AERMOD model (EPA Office of Air Quality, 2013).

In order to determine the number of trucks per well, several assumptions were made. Databases containing the quantities of waste produced by wells were obtained from open sources, such as the PA Department of Environmental Protection and fractracker.org (see Data Sources). Waste data contained information voluntarily submitted by drilling companies and include the well location and the destination of the waste. Three different truck configurations were computed, varying by the amount of cargo hauled; 10-tons representing a small load, 16-tons representing an intermediate load, and 22-tons representing a large load (Korfmacher, Hawker, and Winebrake, 2015). This was done in an attempt to account for a variety of trucks and to simulate rural road and bridge limitations. Only the 22-ton results were used in this dispersion analysis. The truck configuration of a 22-ton load was derived from load weights from varying sources (Gannet Fleming, 2011; Arthur, Uretsky, and Wilson 2010; Stockdill, 2014; Hart, Adams, and Schwartz, 2013). Highway weight limits and truck tare weights were also consulted (US Federal Highway Administration, 2009; Transportation Energy Data Book, 2013). The other haul weights were obtained using hauling capacity from smaller trucks and accounting for rural infrastructure limits. As the highest truck weight configuration was used for this analysis, the impact estimates produced may be of a more conservative nature. The number of trucks required to transport the waste and other materials such as sand and water away from each well was then calculated. Truck counts were joined to the routes, in order to determine total emissions by route, which were calculated by multiplying truck counts by emissions per mile.

The number of trucks per route was determined based on the amount of materials being hauled. Truck routes can consist of many segments, and some of these segments were used by multiple routes, overlapping and leading to higher emissions and truck counts. The Add Traversal Tool within ArcGIS 10.1 (ESRI, 2013) was used to compute the segments of the routes, based on nodes within the underlying road network. The DISSOLVE command in ArcGIS was then used to merge overlapping segments into one feature. The number of trucks was summed for the merged segments. Multiplying the total number of trucks for each segment
by the emissions generated along each segment created an estimate of total emissions by segment. This process helped identify high volume road segments for use as line sources for the dispersion model and comparisons for dispersion model results.

The emission estimates were created from the GIFT Model factor calculator, which takes information, such as the average speed for each mode, the carbon content of the fuel, and how much each mode can carry, and calculates emissions from goods movement by mode, in units of grams per ton equivalent units (TEUs) miles. These estimates were on a per TEU per mile basis of emissions and can be multiplied by the number of trucks, and the distance of the segment, to produce estimates of total emissions along the segment due to HVHF traffic. An example of the edges generated by the Add Traversal Tool can be found in Figure 3, and an example of the factor calculator can be found in Figure 4. The emission rates used in this analysis are included in Table 1 and were provided by the GREET Model version 1.8b from Argonne National Laboratory. The particulate matter and NO\textsubscript{x} rates are from the 2007 Model Year (MY2007) and reflect the new emissions standards implemented that year. It was also assumed that low-sulfur fuel was used. This analysis used the PM\textsubscript{10} emissions rates from MY2007 (Argonne National Laboratory, 2008).

Table 1: Emission rates from 2008, and MY2007 (EPA, 2008; Argonne National Laboratory, 2008).

<table>
<thead>
<tr>
<th>Pollutant</th>
<th>Emission rate (average from 2008)</th>
<th>Model Year 2007 Emissions rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>CO\textsubscript{2}</td>
<td>1740 g/mile</td>
<td>1740 g/mile</td>
</tr>
<tr>
<td>CO</td>
<td>2.311 g/mile</td>
<td>2.311 g/mile</td>
</tr>
<tr>
<td>NO\textsubscript{x}</td>
<td>8.613 g/mile</td>
<td>0.725 g/mile</td>
</tr>
<tr>
<td>PM\textsubscript{10}</td>
<td>0.219 g/mile</td>
<td>0.036 g/mile</td>
</tr>
<tr>
<td>SO\textsubscript{x}</td>
<td>0.012 g/mile</td>
<td>0.012 g/mile</td>
</tr>
<tr>
<td>VOC</td>
<td>0.447 g/mile</td>
<td>0.447 g/mile</td>
</tr>
</tbody>
</table>
Figure 3: Edges of routes generated with the Add Traversal tool.

Figure 4: Example of emissions calculator within the GIFT model, which calculates emissions per TEU mile from fuel and engine inputs. The red circle indicates that a value was changed based on assumptions. For truck the circle indicates that the model calculated emissions based on 22 tons per TEU, with 1 TEU per load for truck. For rail, the model calculated 71 tons per TEU with 1 TEU per well. For ship, the model used the values of 22500 TEUs per ship with 1 ton per TEU. Ship and rail configurations were created, but not used in this analysis, but may be used in future analyses.
One of the goals of this study was to determine how many people may be affected by PM$_{10}$ emissions from HVHF traffic and where these populations were located. The AERMOD model was used to obtain a better idea of the affected areas and provided a clearer picture of the dispersal of the pollutants, giving better information than simply overlaying the high traffic segments with census data. Emissions from areas that were classified as high traffic segments were put through the AERMOD dispersion model to determine which areas might come into contact with the transportation pollutants. The AERMOD model was used to model air quality and predict the concentration of pollutants in the analysis. This study focused exclusively on modeling the dispersion of PM$_{10}$, based on emissions data generated with the GIFT model. Particulate matter was chosen because of its link to heavy duty diesel truck emissions and adverse human health impacts (Fann, Fulcher, and Baker, 2013).

The AERMOD model was chosen for use in this study for multiple reasons. AERMOD is an easy to use atmospheric dispersion model which takes into account multiple factors such as elevation, surface and upper air meteorological data, and line based emissions sources. This study used AERMOD View version 8.5.0, a version of the AERMOD model modified by the Lakes Environmental Company to increase the ease of use and accessibility to support (Lakes Environmental, 2014). Additionally, AERMOD was used by the New York State Department of Conservation (NYSDEC) for their Supplemental Generic Environmental Impact Statement (dSGEIS, 2011), outlining the impact of High Volume Hydraulic Fracturing in the New York portion of the Marcellus Shale. AERMOD was chosen for this study so as to remain consistent with the NYSDEC documentation.

Road segments were used as the source of the emissions and it was necessary to utilize line sources within AERMOD for the analysis. However there were issues when loading the sources into the program. The road segments were in the form of shapefiles, however AERMOD could only import shapefiles as a basemap, rather than emissions sources. Instead of directly importing the line sources and their associated emissions attributes directly into AERMOD, a more roundabout method of inputting the sources had to be devised. Each road segment had at least two nodes. The positions of these nodes had to be determined, and then converted into CSV files for each road segment. The positions of the nodes were calculated by importing road
segments into DNRGPS from the Minnesota Department of Natural Resources (Minnesota DNRGPS, 2012) and exporting to a CSV file.

The AERMOD model uses an analytical approach to model pollutant air dispersion, using physical processes (Cimorelli et al., 2005). AERMOD does not deal with the secondary formation of pollutants in the air (dSGEIS, 2011). The model uses meteorological parameters such as wind speed and direction, temperature, and cloud cover, which can be obtained from the National Weather Service in order to determine the transport of pollutants (dSGEIS, 2011). These were then overlaid with census data obtained from the TIGER database in order to see which areas of the local populace were affected. Figure 5 shows an example of AERMOD pollutant contours that have been influenced by terrain.

Figure 5: Example of AERMOD pollutant contours influenced by terrain

Emissions for each road segment had to be manually loaded into AERMOD. A more detailed guide regarding the AERMOD setup and process can be found in Appendix A. Ideally, the AERMOD model would have more tools to complement GIS functionality, such as importing geographic data with attributes intact, as well as being able to use the geographic locations of the line volume sources to create more accurate receptors. The receptors in AERMOD were the
points at which the concentrations were calculated. Information between receptors was interpolated. A uniform Cartesian grid containing the default value of 441 receptors was used for each case study.

The Williamsport test case was very large, consisting of approximately 600 individual road segments that had to be imported as separate line volume sources. When all of the sources were inputted into a single AERMOD project, the project would not open or run. This led to the assumption that there might be some sort of threshold as to the number of line segments that can be entered into a single project. This was eventually remedied by splitting the segments into three separate AERMOD projects, then exporting the sources to CSV files and reimporting all of them into a single AERMOD project. This allowed for all of the emissions sources to be in one AERMOD project, which then was able to run.

The seven test cases were merged into one dataset in order to choose appropriate threshold values for concentration emissions classes. Based on the model output, five concentration ranges were chosen and emissions classes were created; low emissions, low-moderate emissions, moderate emissions, high-moderate emissions, and high emissions (Table 2).

Table 2: Emission classes determined by PM$_{10}$ concentration and their associated colors.

<table>
<thead>
<tr>
<th>Emissions Class Name</th>
<th>Color</th>
<th>Concentration (µg/m$^3$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>Blue</td>
<td>$\leq0.0004$</td>
</tr>
<tr>
<td>Low-Moderate</td>
<td>Green</td>
<td>0.000401-0.001</td>
</tr>
<tr>
<td>Moderate</td>
<td>Yellow</td>
<td>0.001001-0.002</td>
</tr>
<tr>
<td>High-Moderate</td>
<td>Orange</td>
<td>0.002001-0.004</td>
</tr>
<tr>
<td>High</td>
<td>Red</td>
<td>0.004001-0.006370</td>
</tr>
</tbody>
</table>

Using the contours in combination with 2010 census data, populations living in each emissions class were determined. This was done for each test case individually, as well as with the merged dataset of all of the classes. One of the goals of this project was to determine how many people may be at risk due to the added PM$_{10}$ from increased truck traffic due to HVHF.
Two equations outlined in Ostro (2004) were used for the analysis of increased PM$_{10}$ mortality impacts. In order to assess the health impact from air pollution, several factors were needed, including the elevated transportation emissions concentrations, the population affected by the elevated emissions (in this case each of the populations affected by the five emissions classes), as well as the incidence of PM$_{10}$ mortality. Studies show that an increase of 10 $\mu$g/m$^3$ in PM$_{10}$ concentrations can lead to an increase of 0.5%-1.6% in daily mortality, depending upon the statistical model used as well as other factors, including weather and any potential co-pollutants (Ostro, 2004). The variability in these results may also be accounted for if the study considered lag as a factor instead of exclusively using same-day mortality data.

Relative Risk (RR) of all-cause mortality in the short term as a result of PM$_{10}$ exposure was computed using the mean annual concentration values of the pollutant (Ostro, 2004). The equation for computing the relative risk due to short term PM$_{10}$ exposure is as follows:

$$RR = \exp[\beta(X - X_0)]$$

where $X_0$ was the initial or baseline concentration, $X$ was the current or elevated concentration, and $\beta$ is the coefficient for a 95% confidence interval for estimating mortality risk increase. A value of 0.0008 was used for $\beta$, as per the recommendation of Ostro, 2004. $X_0$ was the baseline concentration data, and $X$ was the new concentration due to HVHF traffic. This subtraction allowed the user to determine the rise or fall of the emissions concentrations. Normally, the baseline concentration is recommended to be pre-anthropogenic concentrations of the chosen pollutants, however this study used the emissions concentrations determined from the AERMOD model analysis which already represent the rise in emissions from HVHF traffic. The categories of emissions risk served as the $X$-$X_0$ value within the relative risk equation. This means that for all seven test cases, the relative risk was constant. Each of the emissions classes had a minimum and maximum value, therefore high and low values of relative risk and attributable fraction were calculated for each emissions class. This also provided high and low estimates of expected deaths for each emissions class. The variables used by this study to calculate Relative Risk are shown below in Table 3.
Table 3: Emissions classes determined from AERMOD output as well as calculated relative risks and a constant Beta value.

<table>
<thead>
<tr>
<th>Emissions Class</th>
<th>Rise in PM$_{10}$ Concentration Low Range (X- $X_o$) (µg/m$^3$)</th>
<th>Rise in PM$_{10}$ Concentration High Range (X- $X_o$) (µg/m$^3$)</th>
<th>$\beta$</th>
<th>RR Low Range</th>
<th>RR High Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>0.00002</td>
<td>0.00004</td>
<td>0.008</td>
<td>1.000000016</td>
<td>1.000000032</td>
</tr>
<tr>
<td>Low-Moderate</td>
<td>0.000401</td>
<td>0.001</td>
<td>0.008</td>
<td>1.000000321</td>
<td>1.0000008</td>
</tr>
<tr>
<td>Moderate</td>
<td>0.001001</td>
<td>0.002</td>
<td>0.008</td>
<td>1.000000801</td>
<td>1.0000016</td>
</tr>
<tr>
<td>High-Moderate</td>
<td>0.002001</td>
<td>0.004</td>
<td>0.008</td>
<td>1.000001601</td>
<td>1.0000032</td>
</tr>
<tr>
<td>High</td>
<td>0.004001</td>
<td>0.00637</td>
<td>0.008</td>
<td>1.000003201</td>
<td>1.000005096</td>
</tr>
</tbody>
</table>

Attributable fraction was used to determine the fraction of deaths from outdoor air pollution and was calculated using the relative risk in the following equation

$$AF = \frac{RR-1}{RR}$$ (Ostro, 2004).

These values were also constant throughout each of the test cases and can be seen below in Table 4.

Table 4: Attributable fractions of each Emissions class. These values were constant across all case studies.

<table>
<thead>
<tr>
<th>AF Low Range</th>
<th>AF High Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.600000E-08</td>
<td>3.200000E-08</td>
</tr>
<tr>
<td>3.207999E-07</td>
<td>7.999997E-07</td>
</tr>
<tr>
<td>8.007997E-07</td>
<td>1.599999E-06</td>
</tr>
<tr>
<td>1.600799E-06</td>
<td>3.199995E-06</td>
</tr>
<tr>
<td>3.200795E-06</td>
<td>5.095987E-06</td>
</tr>
</tbody>
</table>
In this analysis, the high and low ranges of each emissions class were used to provide high and low relative risk values for each class. To determine the overall impact of the increased pollution when associated with health risks, it was vital to know the relative risk due to increased concentrations of the pollutant (Attributable Fraction or AF), as well as the incidence of mortality from the pollutant (B), and the affected population (P). The value of P (population) is what causes the number of expected deaths between the seven test cases to change. While the relative risk of PM$_{10}$ exposure per person is low, the large number of people exposed to the pollutant throughout the case study areas resulted in a higher overall health risk from PM$_{10}$ (Ostro, 2004). As there are several emissions classifications within each of the test cases, the population in each of the individual classifications had to be computed. This was accomplished by using definition queries in combination with the ‘select by location’ feature in ArcGIS. The incidence rate (B) is the number of deaths per 1000 people from the chosen pollutant, PM$_{10}$. For this study an incidence rate of 0.234 was used, adjusted from a value of 0.152 (Silva et al., 2013) with the PM$_{2.5}$/PM$_{10}$ ratio of 0.65 from Ostro, 2004. It should be noted that the PM$_{2.5}$/PM$_{10}$ ratio can change depending upon location, sources of emissions, and may vary over time. The value used in this study was based off of the literature.

The overall impact of increased PM$_{10}$ concentrations was calculated using:

$$ E = AF \times B \times P $$

(Winebrake et al., 2009; Ostro, 2004)

where E is the number of deaths expected due to the rise in pollution.

**Calculation example**

This is an example of the calculation process used to obtain the values of expected mortalities due to the increase of PM$_{10}$ emissions from HVHF traffic for the test case in Chemung, New York. The population value is the only variable that differs between test cases. The population affected within each emissions class is shown below in Table 5:
Table 5: Population within each emissions class for Chemung test case.

<table>
<thead>
<tr>
<th>Emission Class Values (10µg/m³)</th>
<th>Emission Class Names</th>
<th>Color of Emission Class in Figures</th>
<th>Chemung Population within Emissions Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>.000020-.0004</td>
<td>Low</td>
<td>Blue</td>
<td>64852</td>
</tr>
<tr>
<td>.000401-.001</td>
<td>Low-Moderate</td>
<td>Green</td>
<td>34963</td>
</tr>
<tr>
<td>.001001-.002</td>
<td>Moderate</td>
<td>Yellow</td>
<td>0</td>
</tr>
<tr>
<td>.002001-.004</td>
<td>High-Moderate</td>
<td>Orange</td>
<td>9344</td>
</tr>
<tr>
<td>.004001-.006370</td>
<td>High</td>
<td>Red</td>
<td>4545</td>
</tr>
</tbody>
</table>

The minimum value of the “Low” emissions class can be used to calculate a conservative estimate of the expected deaths in areas of low PM$_{10}$ emissions from HVHF traffic. This is shown using the values as follows:

\[
E = ((1.60E^{-08}) \times 0.234 \times 64852
\]

\[
E = 0.000486
\]

The rest of the calculations for the Chemung County test case are shown below in Table 6.

Table 6: Number of expected deaths (low and high) calculated for each emissions class for Chemung test case. The zero value is a result of no people living in this emission contour.

<table>
<thead>
<tr>
<th>Chemung Expected Deaths (Low)</th>
<th>Chemung Expected Deaths (High)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.428E-04</td>
<td>4.856E-04</td>
</tr>
<tr>
<td>2.625E-03</td>
<td>6.545E-03</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3.500E-03</td>
<td>6.997E-03</td>
</tr>
<tr>
<td>3.404E-03</td>
<td>5.420E-03</td>
</tr>
</tbody>
</table>
Due to processing limitations within the AERMOD model, the study area needed to be limited to determine the most appropriate sites for the test cases. Using a definition query in ArcGIS, road segments with more than 20,000 annual trucks trips were isolated. Census blocks that intersected the highly trafficked road segments were then selected to obtain the AERMOD areas of interest. Finally, road segments were isolated from the original ‘hot’ segments data set that intersected the areas of interest. These ‘hot’ road segments (which included the highly trafficked segments) were input into AERMOD. This generated assessment areas that would potentially be impacted by increased truck traffic from the fracking industry and allowed for selection of areas to be used as test cases. Seven areas were selected for atmospheric dispersion modeling; six in Pennsylvania and one in New York (Figure 6). Counties overlapping with the test cases are detailed in Table 7. The road segments were loaded into AERMOD View version 8.5.0, a version of the AERMOD model, modified by Lakes Environmental for usability (Lakes Environmental, 2014). Test cases were chosen based on the number and grouping of road segments in a given area, as well as any geographic features or designations (rural areas vs. more urban areas). The resulting AERMOD contour plots were then used in the analysis of health risks from emissions.
Figure 6: A map of the dispersion model areas of interest. Counties that overlapped with the seven test cases are shown.

Table 7: Names of test cases as well as the county or counties that overlap with the test case. The Rural Williamsport test case overlapped with two counties, and the Williamsport test case overlapped with five counties.

<table>
<thead>
<tr>
<th>Test Case</th>
<th>County/Counties</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bradford</td>
<td>Bradford, PA</td>
</tr>
<tr>
<td>Chemung</td>
<td>Chemung, NY</td>
</tr>
<tr>
<td>Clearfield</td>
<td>Clearfield, PA</td>
</tr>
<tr>
<td>Fayette</td>
<td>Fayette, PA</td>
</tr>
<tr>
<td>Rural Williamsport</td>
<td>Clinton, PA; Lycoming, PA</td>
</tr>
<tr>
<td>Tioga</td>
<td>Tioga, PA</td>
</tr>
<tr>
<td>Williamsport</td>
<td>Clinton, Lycoming, Montour, Northumberland, and Union, PA</td>
</tr>
</tbody>
</table>
Results

Trends are revealed by overlaying the emissions concentration contours with other layers in ArcGIS. In the maps of the test cases below, highly trafficked road segments are highlighted in red. Highly trafficked segments correspond to the model predicted areas of highest pollution. This is especially evident in the southwest corner of the Bradford county test case (Figure 7B). In this instance, a highly trafficked road segment led to a localized increase in PM$_{10}$ concentrations, and a clear concentration gradient had been formed. Parts of the Chemung county test case also demonstrate that highly trafficked road segments can lead to higher emissions (Figure 8A). However, while the majority of the road segments in the Chemung test case were highly trafficked, this did not lead to unusually higher emissions in the model results. Higher emissions along the individual segments and differences in total truck counts were responsible for the discrepancy in this case; however, terrain data, census data, and satellite imagery should always be consulted.

In this analysis, the emissions calculated by the GIFT model were based off of MY2007 emissions standards (Table 1), which correspond to an EPA mandate to reduce PM$_{10}$ and NO$_x$ pollution from heavy-duty highway vehicles. As the analysis was conducted using 2011 data four years after the deadline had passed, it was assumed in the analysis that all of the trucks conformed to the 2007 emissions standards. This assumption also took into account that more trucks which conform to MY2007 standards will be on the road in the future. The analysis did not take into account trucks that had been grandfathered in, or older trucks that were kept on the road longer due to an increase in truck prices as a byproduct of the MY2007 standards (Calpin and Plaza-Jennings, 2012). Due to these assumptions, this analysis represents a best case scenario for emissions and their associated mortalities.

The emissions rate used by the GIFT model for these calculations was 0.036 grams of PM$_{10}$ per mile, whereas the average in-use emissions rate in 2008 was 0.219 grams PM$_{10}$ per mile (EPA Office of Transportation and Air Quality, 2008). This means that the emission concentrations produced from this period were likely much higher in reality than what was calculated using AERMOD. The following figures show two types of maps for each of the seven test cases completed in this study. Three of the test cases are discussed in detail in this
section, and the other four can be found in Appendix B. Maximum values and geographic dispersions of PM$_{10}$ emissions computed through the AERMOD model are shown overlaid with other data, such as population and elevation and schools. Health vulnerabilities mentioned in some of the figures are defined as locations that may be more adversely impacted by increased emissions such as nursing homes, hospitals, and ambulatory surgery centers.

**Test Case #1: Bradford County, PA (Figures 7A, 7B and 7C)**

Bradford County is located in the northeast part of Pennsylvania. Figure 7A shows the selected line segments that were input into AERMOD and the resulting emission contours. Census blocks are also shown. Routes of high traffic (greater than 20,000 trucks per road segment annually) are shown in red. There are several geographic areas in this test case which may have elevated health risks, especially near the highly trafficked road segments. This is clearly shown in the southern portion of the map, where a small high traffic road segment corresponds to a relatively steep emissions gradient (Figure 7B). The large high traffic roads to the west and in the east of the map show higher emissions near the highly trafficked routes. The large road segment that parallels a less highly trafficked segment in the eastern portion of the county runs directly through four relatively high population census blocks with a total population of 231 people. The high traffic areas in the northwest portion of the map intersect several relatively high population census blocks and are also close to a city area.

In Figure 7C, the northwest road segments follow a river valley, which could explain why the higher emissions in this corridor are not very widely dispersed. This valley potentially played a part in the formation of the concentration gradient on the northwest high traffic areas. The small high traffic area in the southern part of the contour map is also within the river valley. Because it is such a small segment and along the river, this appears to be a transload facility or an unloading station from the river and nearby railway for any smaller HVHF wells nearby. This assertion was confirmed through aerial imagery. Also on this map are the locations of schools as well as health vulnerabilities (hospitals, nursing homes, hospices, and ambulatory surgery centers). The majority of these locations shown are in areas of lower risk, though there is a school located in an area of high risk in the eastern portion of the map. This school may be more at risk for emission-related health effects than other schools in the region.
Table 8A shows the population affected by each emissions classes and the calculated number of mortalities. Table 8B shows the scaled up population to account for one death, based on the total number of mortalities across all emissions classes.

Figure 7: Road segments overlaid with emissions dispersion clouds and census data (A). Highly trafficked roads are shown in red. (B) Zoomed in section of (A) showing the southern part of the Bradford County test case. A concentration gradient is clearly visible. (C) Shows the PM$_{10}$ concentrations contours overlaid with elevation data.
Table 8: (A) Population within each emissions class, and calculated number of mortalities. (B) Scaled up population to account for one expected death.

<table>
<thead>
<tr>
<th>Emissions Class</th>
<th>Color on Map</th>
<th>Bradford Population</th>
<th>Bradford Expected Deaths (Low)</th>
<th>Bradford Expected Deaths (High)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Least Risk</td>
<td>Blue</td>
<td>36293</td>
<td>0.000135881</td>
<td>0.000271762</td>
</tr>
<tr>
<td>At Risk</td>
<td>Green</td>
<td>3611</td>
<td>0.000271068</td>
<td>0.000675979</td>
</tr>
<tr>
<td>Moderate Risk</td>
<td>Yellow</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>High Risk</td>
<td>Orange</td>
<td>2115</td>
<td>0.000792251</td>
<td>0.001583709</td>
</tr>
<tr>
<td>Severe Risk</td>
<td>Red</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Total:</td>
<td></td>
<td>42019</td>
<td>0.0011992</td>
<td>0.00253145</td>
</tr>
</tbody>
</table>

Scaled Up Population per 1 Expected Death

<table>
<thead>
<tr>
<th></th>
<th>Scaled Up Population per 1 Expected Death</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Low)</td>
<td></td>
</tr>
<tr>
<td>35,039,193 people</td>
<td></td>
</tr>
<tr>
<td>(High)</td>
<td></td>
</tr>
<tr>
<td>16,598,787 people</td>
<td></td>
</tr>
</tbody>
</table>

Test Case #2: Chemung County, NY (Figures 8A and 8B)

Chemung County is located in the southern part of New York State, near the city of Elmira. Figure 8A shows emissions contours overlaid with census block population data and road segments. The road segments make up one primary route. The majority of the road segments in this case study were highly trafficked (greater than 20,000 trucks). This was reflected in the high emissions concentrations along the route. This case study has several areas of high risk concentrations of PM$_{10}$ and two areas of severe risk emissions. The southerly area of severe risk emissions encompasses several high population census blocks. The northerly area of severe risk emissions overlaps with a highly urbanized city area. There are small road segments that are not highly trafficked, which look to be offshoots of the main route.

Figure 8B overlays PM$_{10}$ concentration contours with elevation data and schools. Road segments (both normal and highly trafficked) are also included. Road segments in this case study also follow a river valley. The contours show the emissions spreading within the river valley, but not going far beyond it, being contained by the topography. This is especially evident near the southern emissions hotspot. There is a large orange (high-moderate) area, of which the eastern part extends farther along the river valley rather than spreading out in all directions. This
helps account for the higher concentrations along the road segment. There are several schools displayed on the map, all of which are within the emissions contours. One school in the northern portion of the region is within the high-moderate/high emissions contours, indicating that there may be higher risks of adverse health effects at that location.

Table 9A displays affected population per emissions class and the corresponding number of mortalities. Table 9B shows the scaled up population to account for one death, based on the total number of mortalities across all emissions classes.

Figure 8: Road segments overlaid with emissions data. (A) Emissions data and census data. Areas of higher population are shown in darker colors. (B) Emissions data and road segments over elevation data. Schools are also displayed
Table 9: (A) Population within each emissions class, and their calculated mortalities. (B) Scaled up population to account for one expected death.

<table>
<thead>
<tr>
<th>Emissions Class</th>
<th>Color on Map</th>
<th>Chemung Population</th>
<th>Chemung Expected Deaths (Low)</th>
<th>Chemung Expected Deaths (High)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Least Risk</td>
<td>Blue</td>
<td>64852</td>
<td>0.000242806</td>
<td>0.000485612</td>
</tr>
<tr>
<td>At Risk</td>
<td>Green</td>
<td>34963</td>
<td>0.002624574</td>
<td>0.006545071</td>
</tr>
<tr>
<td>Moderate Risk</td>
<td>Yellow</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>High Risk</td>
<td>Orange</td>
<td>9344</td>
<td>0.00350014</td>
<td>0.006996776</td>
</tr>
<tr>
<td>Severe Risk</td>
<td>Red</td>
<td>4545</td>
<td>0.003404141</td>
<td>0.005419735</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>113704</td>
<td>0.009771661</td>
<td>0.019447194</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Scaled Up Population per 1 Expected Death (Low)</th>
<th>Scaled Up Population per 1 Expected Death (High)</th>
</tr>
</thead>
<tbody>
<tr>
<td>11,636,097 people</td>
<td>5,846,808 people</td>
</tr>
</tbody>
</table>

Test Case #3 Williamsport, PA (Figures 9A, 9B, and 9C)

Williamsport is a city in central Pennsylvania. It is the most populated of all of the test cases, with a population of over 200,000 people. There is a large area of emissions within the map of the test case, with several areas of higher emissions in the central region. There are also large high traffic roads. Figure 9A shows the entire area of the test case with associated emissions, census data, and roads. The areas of higher emissions appear to correspond spatially to the high traffic road segments. In the central part of the map (Figure 9B), the census blocks show where some of the highly populated locations are. There are also three areas of emissions that fall into the orange (high-moderate) category. These areas are intersected by census blocks containing 3640 people, or about 1.6% of the population in the area.

Figure 9C shows emissions contours and elevation data. There are also schools and medical locations in this map, which can be expected from such a highly populated area. Many of these vulnerable locations are located within the emissions contours, and there are several within areas of high emissions as well. There appear to be several rivers and elevation changes within the region, and some of the emissions follow these changes. This is especially apparent in the southwestern part of the map, where the emissions contours stretch along the river valley.
Figure 9: (A) Road segments, population data, and census data of the largest test case in Williamsport, PA. Many of the road segments in this test case are considered highly trafficked. (B) Zoomed in portion of the Williamsport test case, where there are many highly trafficked segments and higher PM$_{10}$ emissions. (C) Emissions and road segments on top of elevation data. Also shown are schools and potentially vulnerable locations.

Table 10A details the number of people affected by each emissions class and the corresponding value of calculated mortalities. Table 10B shows the scaled up population to account for one death, based on the total number of mortalities across all emissions classes.
Table 10: (A) The number of expected deaths as well as the population impacted by each emissions class. (B) Scaled up population to account for one expected death.

<table>
<thead>
<tr>
<th></th>
<th>Williamsport Population</th>
<th>Williamsport Expected Deaths (Low)</th>
<th>Williamsport Expected Deaths (High)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Least Risk</td>
<td>Blue</td>
<td>182668</td>
<td>0.000683909</td>
</tr>
<tr>
<td>At Risk</td>
<td>Green</td>
<td>37907</td>
<td>0.002845572</td>
</tr>
<tr>
<td>Moderate Risk</td>
<td>Yellow</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>High Risk</td>
<td>Orange</td>
<td>3640</td>
<td>0.001363496</td>
</tr>
<tr>
<td>Severe Risk</td>
<td>Red</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>224215</td>
<td>0.004892977</td>
</tr>
</tbody>
</table>

Scaled Up Population per 1 Expected Death

<table>
<thead>
<tr>
<th></th>
<th>Scaled Up Population per 1 Expected Death</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Low)</td>
<td>(High)</td>
</tr>
<tr>
<td>45,823,841 people</td>
<td>20,037,744 people</td>
</tr>
</tbody>
</table>

The total number of expected deaths across each of the seven test cases is shown in Table 11. This table shows the number of expected deaths (both low and high) per test case, and also shows the sum of the expected mortalities, providing an idea of the total number of calculated deaths obtained by this study.

Table 11: Expected deaths from all seven test cases, as well as the totals. Populations of each test case are also displayed.

<table>
<thead>
<tr>
<th>Test Case</th>
<th>Total Population of Test Case</th>
<th>Expected Deaths (Low)</th>
<th>Expected Deaths (High)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bradford</td>
<td>42,019</td>
<td>1.199E-03</td>
<td>2.531E-03</td>
</tr>
<tr>
<td>Chemung</td>
<td>113,704</td>
<td>9.772E-03</td>
<td>1.945E-02</td>
</tr>
<tr>
<td>Williamsport</td>
<td>224,215</td>
<td>4.893E-03</td>
<td>1.119E-02</td>
</tr>
<tr>
<td>Clearfield</td>
<td>63,926</td>
<td>6.511E-04</td>
<td>1.478E-03</td>
</tr>
<tr>
<td>Fayette</td>
<td>2,222</td>
<td>8.320E-06</td>
<td>1.664E-05</td>
</tr>
<tr>
<td>Rural Williamsport</td>
<td>1,338</td>
<td>7.655E-05</td>
<td>1.576E-04</td>
</tr>
<tr>
<td>Tioga</td>
<td>37,657</td>
<td>5.586E-03</td>
<td>1.077E-02</td>
</tr>
<tr>
<td>Total</td>
<td><strong>471,815</strong></td>
<td><strong>2.219E-02</strong></td>
<td><strong>4.560E-02</strong></td>
</tr>
</tbody>
</table>

35
Discussion

Diesel truck emissions can be composed of multiple pollutants such as particulate matter, volatile organic compounds, carbon monoxide, and nitrogen oxides (EPA, 2008). There are multiple health effects that can be related to diesel truck emissions such as stroke (Sørenson et al., 2014), hospitalization, and mortality (Zhang and Batterman, 2013). This study focused on a small portion of health effects from elevated emissions due to truck traffic, namely the emission of diesel particulate matter from truck traffic and the calculation of number of anticipated acute mortalities associated with these emissions. This study did not focus on morbidity outcomes associated with diesel exhaust, such as hospitalization, exacerbation of asthma, or other effects, nor did it focus on mortalities from long-term chronic health effects. Other pollutants such as ozone, nitrogen oxides, volatile organic compounds, and sulfur oxides are associated with air pollution and can lead to health effects of their own (De Kok et al., 2006). This study focused on primary pollutants of PM\textsubscript{10} emitted by diesel powered trucks.

Using the formulas detailed in the WHO document to compute the additional mortality rates due to HVHF traffic in the seven test cases produced a conservative sum of 0.02218 deaths and a higher sum of 0.0456 deaths for the study attributed to additional emissions from fracking trucks. These numbers mean that for all of the test cases conducted in this study, a high value of 0.0456 total deaths can be expected in 2011. Although the sum of the test case mortalities is not a whole number, or even a large fraction, it does not mean that this should be discounted. The expected deaths calculated are a function of population, which can lead to non-integer values. Fractional deaths as a function of population are interpreted as an increased risk of dying in actuarial life-tables (Wei, 2008). In some cases, the expected number of deaths are simply rounded to a whole number (Ostro, 2004), but the probabilities are calculated before the rounding occurs (Thatcher, 1992). The number of expected deaths can also be used as part of the calculations to determine Disability-Adjusted Life Years (DALYs), which accounts for the decrease in healthy years of life (Ostro, 2004). Adjusting the population so that the expected deaths equals 1 gave a value of 1 death per 10,347,878 people in 2011 as a result of increased truck emissions from the HVHF industry under the emission standards of the 2007 MY trucks. This represents a best case scenario, with EPA reductions in PM\textsubscript{10} fully implemented in the truck fleet.
The emissions that were loaded into AERMOD used a 22-ton load configuration; the largest configuration that was run through GIFT during this analysis (other configurations included 10-ton and 16-ton loads). This means that the overall emissions impact and mortality rates may be higher than the 0.045595 expected deaths detailed in these results, as it would take fewer trucks with a 22-ton carrying capacity to move the same amount of materials. These numbers represent mortality over an annual time span, as the emissions data were only from 2011. Health effects from emissions can be both acute and/or chronic (Guo, 2010) and some of the effects might not present on a shorter time span, such as a single year. Longer cohort studies may be useful in conducting a more comprehensive health impact analysis (Guo, 2010).

The overall sum of the deaths calculated for the seven test cases (Table 9) in this study was very small, but may in fact be representative of a best case scenario. The truck configurations used in the GIFT model for this study were based on a fleet of trucks complying with 2007 emissions standards. In reality, the truck fleet would be a mixture of older and newer trucks, with emission rates similar to EPA reported emission rates for the average in-use fleet in 2008 (EPA, 2008). Multiplying our emission values for PM_{10} by 6.4 would provide a rough estimate of the 2008 in-use emission estimates.

Additionally, this study did not account for temporal resolution of truck traffic. AERMOD is capable of simulating emissions in several temporal scales such as hourly, daily, and monthly, however this study did not have access to real traffic pattern data, so the annual model configuration was deemed to be the best option. The AERMOD model requires an emissions input in units of grams per second or pounds per hour. The emissions data generated from the GIFT model are annual total values. In order to convert annual totals to emissions rate units for AERMOD, these emissions totals were divided by the number of seconds in a year. While this allowed for the emissions rates to be imported into AERMOD, it assumed uniform rates for the whole year and did not take into account diurnal, seasonal, or other circumstances where truck traffic may not be uniform. Assuming uniform truck traffic throughout the year is not realistic, and may lead to the impression that the emissions are not serious, as they appear to be dispersed over a longer period of time. However, attempting to account for an appropriate temporal resolution, the truck emissions can increase greatly.
For example, assuming that HVHF truck traffic will occur five days a week, then the number of deaths can be multiplied by a factor of 1.4 (365 days/260 days), bringing the total to 0.064 deaths. Similarly, it can also be assumed that trucks are not driving for 24 hours a day as a constant rate. If it is assumed that the trucks are driving for 8 hours a day, then 0.064 deaths can be multiplied by 3, giving a new total of 0.19 deaths. This means that of the population in the area of interest, one person experiences an increased risk of death by 19%. Scaling the expected deaths up to 1 gives a value of 1 death per 2,463,780 people. This is still assuming that the truck fleet is comprised exclusively of trucks that conform to 2007 emissions standards, so the likely number of deaths could be even higher. Meteorological fluctuations could also contribute greatly to the number of deaths expected from the truck traffic. For example, a large inversion layer would not allow for much emission dispersion and could lead to more deaths than a period of higher wind shear.

Diesel exhaust is classified as a carcinogen by the United States Environmental Protection Agency and there is limited published research of the health impacts of particulate matter from diesel combustion with regards to unconventional natural gas development (Adgate, 2014). Particulate matter released due to primary sources, such as the point of combustion, or secondary formation, due to chemical reactions in the atmosphere, can vary in both makeup and toxicity (Thurston, 2011). Excluding point of combustion emissions, some primary sources of particulate matter include crustal/soil particles from wind or re-suspension of road dust (Thorpe, 2008), emissions from metals and steel processing, and salts, which can originate from marine sources or from winter road salt. Combustion of biomass is also a contributing factor to particulate matter emissions. Traffic emissions are often tracked using elemental carbon (EC) and NO₂ concentrations (Thurston, 2011). Particulate matter originating from road traffic contributes greatly to the total amount of primary particulate matter within an area, however non-exhaust sources can play a significant role (Thorpe, 2008). Non-exhaust sources of particulate matter associated with traffic can include brake wear, tire wear, and general scraping of the surface of the road (Thorpe, 2008). Some studies have shown that traffic particulate matter can be attributed in nearly equal parts to both exhaust and non-exhaust sources (Lenschow, 2001, Harrison et al., 2001).
There are different metrics used to evaluate health impacts of PM$_{10}$ emissions across both mortality and morbidity. For example, a change of PM$_{10}$ concentrations by 10µg/m$^3$ has been used to compute increases in mortality (associated with a rise in concentration) or decreases in life expectancy (associated with a decrease in concentration) across multiple studies (Laden et al, 2000; Pope, 2002; Pope, 2009; Gronlund, 2014). These data can subsequently be used to calculate the number of lives lost. A rise in PM$_{10}$ concentrations by 10µg/m$^3$ can lead to a short term mortality increase of 0.08%, which is the basis of the β value used in the equations in this study (Ostro, 2004).

Another metric often used to help quantify health and disease impact is the Disability-Adjusted Life Year (DALY). DALYs are the sum of Years of Life Lost (YLL) and Years Lost due to Disability (YLD). YLL is a metric accounting for mortality, and YLD accounts for morbidity, therefore DALY takes both into account (WHO, 2002). DALY values account for the differences between an ideal life expectancy without negative health effects and the current situation, and can be thought of as a loss of healthy years of a person’s life. Other values can be calculated using DALY values, such as the burden of disease, which is a DALY value over the course of a year (Gronlund, 2014).

An additional metric is Loss of Life Expectancy (LLE), which has been suggested to be of more useful than the number of lives lost. Rabl (2003), uses the example of a car accident versus air pollution. Both may lead to a loss of life, however a car accident can lead to decreased life expectancy of 30 or more years whereas air pollution may decrease life expectancy by a matter of months (Rabl, 2003). The use of LLE can help to put health impacts from air pollution into context in relation to mortality from other causes.

Mortality and morbidity impacts are measured using multiple factors, which reflect different causes of health deterioration over age and geographic region. The US EPA BenMAP model uses a combination of incidence rates and prevalence rates for health impact calculations. Examples of this include incidences of acute myocardial infarction (heart attack), emergency room visits, hospital admissions and mortalities based on different counties and age groups. Prevalence data can include factors such as asthma exacerbation and chronic bronchitis.
(BenMAP, 2014). Both mortality and morbidity outcomes are measured to provide as clear a picture as possible for health impacts caused by pollution.

During the course of this assessment it was necessary to compare the results of the GIFT model output with traffic data collected by governmental sources. The traffic data were obtained through the Pennsylvania Department of Transportation (PA DOT, 2011). It is essential to find how much truck traffic there is in an area, and then to determine how much traffic from the HVHF industry is contributing to the total. Doing this gives an idea of where fracking truck traffic may have the largest additive impact. Additionally, going through the road networks and traffic counts to collate them into a cohesive product allowed for a rudimentary analysis of the GIFT model output.

The road segments produced by the study were compared to the PA DOT road segments. The PA DOT road segments did not line up exactly with the road segments produced by the study, so steps had to be taken to make sure that only the relevant PA DOT segments were used. To directly compare the two road networks in order to determine the percentage of truck traffic due to HVHF, a one to one comparison is needed. To narrow down the number of road segments to be compared, a 250-meter buffer was created around the ‘hot roads’ segments produced by the study, and PA DOT segments that intersected this buffer were chosen. Finally, the clip tool in ArcGIS was used to clip the PA DOT segments to the 250 meter buffer, to remove extraneous segments. This process was also done with other sized buffers, however a 250 meter buffer proved to be the best at capturing the majority of the overlapping roads. This process narrowed down the number of roads that had to be looked at to complete a visual analysis. The visual analysis showed that there were many rural roads that had the vast majority of their traffic coming from the HVHF industry. Some roads appeared to be used exclusively by the fracking industry. A road segment within the Tioga County test case appeared to have over 16 times more traffic from HVHF than from the PA DOT truck counts.

In the future, it may be better to use a geographic boundary such as a grid, or census blocks, to conduct traffic comparisons throughout a region. This would allow for both road networks to be included with repeatable results that aren’t able to be accomplished through a subjective visual analysis. The valuation of the economic impact from emissions is an important
factor to consider, as it allows for a broader context of the analysis. Although health effects are not necessarily defined within the scope of the HVHF industry itself, there are still health impacts, damages, and other externalities that can be monetarily defined. Such damages can include cost of illness and subsequent treatment, and loss of wages due to illness (Brown, Henze, and Milford, 2014). In terms of emissions, monetary damages are dependent on spatial locations due to factors like population density (Brown, Henze, and Milford, 2014), as well as topography and weather.

There are several models that can be used to compute the financial impact of emissions health effects, including the Air Pollution Emissions Experiments and Policy (APEEP) model, and the Environmental Benefits Mapping and Analysis Program (BenMAP). The APEEP model computes damages using values and information from literature in both the air quality and epidemiological fields (Litovitz, 2013). The APEEP model computes these damages with the units of dollar per ton for criterion air pollutants (Muller and Mendelsohn, 2006). There are several different types of damage computed by the APEEP model, ranging from human health, to agricultural yields, to impacted visibility (Muller and Mendelsohn, 2006). The APEEP model computes damage per ton of a particular pollutant on a county-wide basis, while also accounting for population exposure (Muller and Mendelsohn, 2006). The APEEP model breaks down valuations of marginal damages by pollutant and county (Muller and Mendelsohn, 2006). Shown below in Table 12 are the marginal damages from PM$_{10}$ ground source emissions broken down by test case, calculated by the APEEP model and obtained from the APEEP website.
Table 12: Total marginal damages from PM$_{10}$ ground emissions per test case. In the case of the Rural Williamsport and Williamsport test cases, the marginal damages were summed. This table serves as an example of APEEP data that may be used in future work.

<table>
<thead>
<tr>
<th>Test Case Name</th>
<th>Number of Overlapping Counties</th>
<th>Sum of Marginal PM$_{10}$ Damages by County (dollars/ton)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bradford</td>
<td>1</td>
<td>311.8</td>
</tr>
<tr>
<td>Chemung</td>
<td>1</td>
<td>300.4</td>
</tr>
<tr>
<td>Clearfield</td>
<td>1</td>
<td>341.5</td>
</tr>
<tr>
<td>Fayette</td>
<td>1</td>
<td>408.9</td>
</tr>
<tr>
<td>Rural Williamsport</td>
<td>2</td>
<td>627.9</td>
</tr>
<tr>
<td>Tioga</td>
<td>1</td>
<td>268.2</td>
</tr>
<tr>
<td>Williamsport</td>
<td>5</td>
<td>2129.5</td>
</tr>
</tbody>
</table>

The BenMAP model was developed in order to evaluate air quality standards and regulations to quantify health benefits from a policy standpoint (BenMAP, 2012). BenMAP does not include factors outside of health effects, but does compute the financial effect of health impacts from air quality policy changes (BenMAP, 2012). BenMAP uses the Value of Statistical Life, which is ‘the monetary value that people are willing to pay to slightly reduce the risk of premature death’ to compute the economic impact of a health effect (BenMAP, 2012). The willingness to pay for a decrease of mortality rate is assigned a monetary value and then divided by the mortality rate decrease decimal value (BenMAP, 2012). Monetary damages will vary from location to location based on the amount of emissions and population size, and must be calculated as such (Litovitz, 2013). The BenMAP model is able to calculate valuation for both mortality and morbidity effects.

This study focused on particulate matter emissions from diesel powered trucks in the HVHF industry leading to higher incidences of mortality. To validate the results found in this study, it was important to use observational studies as they reflect reality rather than predicted impacts. Some observational studies have shown that there are multiple health effects that can be associated with elevated traffic. Black carbon has been used as a surrogate for diesel particulate emissions (Maynard et al., 2007) and has been associated with coronary heart disease
mortality in cohort studies (Gan et al., 2011). Diesel exhaust has been associated with both pulmonary and systemic inflammation, and effects from exposure have been noticed in as little as one hour (Salvi, 1999).

Fine particulate matter has been strongly associated with increased risk of mortality (Smith, Axon, and Darton, 2013). A study performed by Maynard et al. (2007) found an association between increased chances of mortality and traffic particles in the Boston area, using hospital death data in combination with daily traffic emissions concentration from a spatial land use regression model. Additionally, roadway emissions of NO$_x$ (which has also been used as a surrogate for overall traffic emissions) as well as traffic noise have been associated with adverse health effects such as fatal strokes (Sørenson et al., 2014). A reduction of lung function in people with asthma has been observed when exposed to diesel traffic emissions, and were more pronounced in those with more severe cases of asthma (McCreanor et al., 2007). These studies support the conclusion reached in this study that diesel vehicle emissions can lead to increased risks of mortality, and can help serve as validation.
Future Work Recommendations

A uniform Cartesian grid was used within the AERMOD portion of the analysis; however there are some inherent disadvantages when using this process, such as the fact that a uniform grid gives equal spacing to each of the receptors. A multi-tiered receptor scheme would have been preferable, as it allows the user to place more receptors in areas that are closer to the pollution, thus reducing interpolation in the immediate areas near the sources. A multi-tiered grid is possible in AERMOD, however it was impractical to use in this analysis due to its rectangular shape, as demonstrated in Figure 10. To include multiple emissions sources within a rectangular multi-tiered receptor placement would mean that the first tier would likely have to be the size of the entire study area; making it comparable to the uniform Cartesian grid used in this analysis. Subsequent tiers outside of the area of emissions would simply lead to extraneous calculations, increasing computational demand. Moreover the multi-tiered grid would have to have been so large to cover the test case areas that the resulting receptor placement would not have been better than that of a uniform grid. However, if there were a way to create a multi-tiered receptor placement scheme based on the geographic area of interest, this would allow for greater detail and less interpolation in the locations closest to the emissions sources (Figure 11). For example, being able to create multiple buffer zones around the emissions road segments and then determining the density of the receptors within those zones would allow the user to have more control of the amount of interpolation vs. calculation that would occur within the model run and is something to be considered for future works.
Figure 10: A Multi-tiered rectangular grid currently available in AERMOD. In order to include all emission sources within the first tier of higher receptor density (red box), the whole area must be included in the first tier. The first tier becomes like a uniform Cartesian grid over the whole area of the test case. The second and third tiers (yellow and blue boxes) don’t serve much of a purpose, and would just increase computational demand and the size of the test case.
Other researchers are currently simulating 2008 emission rates for in-use vehicles, and a preliminary check suggests that a linear conversion factor of 6.4 may be applied to the mortality rates calculated by this study. This conversion factor, coupled with previous assumptions (trucks driving 5 days a week, 8 hours a day) yields a new mortality rate of 1 death per 340,906 people.

The mortality equations applied in this analysis calculated all-cause mortality from PM$_{10}$, however the incidence rate for this data was only available for a large geographic area (North America). Other incidence rates that detail deaths from respiratory or cardio pulmonary effects may also be used, and should be available for a more specific geographic region. Using different incidence rates, reflecting different causes of death should be explored in future studies.

Future work that may use portions of this study may include further exploration into the health risks and more robust calculations of mortality rates and expected deaths on a larger scale.
The APEEP model has valuation data already calculated, which is good for rapid analysis, however the BenMAP model appears to be more robust and considers more human health and morbidity factors. The BenMAP model would provide a more comprehensive analysis than the APEEP model and is thereby the recommended model to use for future analysis. A step-by-step version of the methodology used to create and run the AERMOD test cases is provided in Appendix A.

Additionally, other factors should be addressed in order to decrease the number of assumptions made throughout the modeling processes. Incorporating real traffic data patterns within AERMOD would allow for a more accurate output, and may allow for a smaller temporal resolutions to be created and used effectively. Within ArcGIS, taking into account factors such as bridge loads can change the number of trucks used as well as the routes generated by network analyst, which subsequently change emissions data calculated by the GIFT model. Bridges not able to be used in the analysis due to low load limits can be blocked off using point barriers in Network Analyst, and show where bottlenecks and areas of higher traffic may occur. See Appendix C for an example. Bridge data were obtained from the National Bridge Database to be used within this project, however as there were many bridges that did not have load limits assigned, point barriers were ultimately not used. Additionally, bridges have been recently classified as critical infrastructure, so data may not be readily available for future work.
Conclusions

This study is part of a larger set of projects within the Laboratory for Environmental Computing and Decision Making (LECDM) revolving around intermodal freight transport with regards to the High Volume Hydraulic Fracturing industry. This study was determined to be a pilot project meant to test out methodology for atmospheric dispersion modeling using emissions data generated by the GIFT model. This analysis used multiple models in combination and denotes a methodological approach for determining communities impacted by emissions resulting from elevated traffic as well as basic mortality calculations due to these increased emissions.

This study used AERMOD to compute atmospheric PM$_{10}$ dispersion for seven test cases in Pennsylvania and New York. The PM$_{10}$ concentrations were divided into 5 different emissions classes used across all test cases. Mortality rates were computed for each of the test cases and each of the emissions classes within the individual test cases. The total expected deaths calculated was equal to approximately 1 death per 10 million people. However because of the assumptions used in this analysis (a fleet of trucks meeting 2007 Model Year emission rates), the mortality rates calculated represented a best case scenario, and the actual deaths from emission from additional HVHF truck traffic may be higher. Refining the calculations to estimate truck traffic during typical business hours increased the probability of death to 1 in approximately 2.5 million people. Other factors, such as refining the composition of the fleet to use average in-use emission rates from 2008, instead of emission standards, would also lead to increases in the calculated number of expected deaths (1 in 340,906 people). This work provides methodological contributions for integrating multiple models to assess health impact of increased truck traffic.
References


**Data Sets:**

[Destinations of PA waste shipped to NYS in 2011]. (2013). Data provided by The FracTracker Alliance on FracTracker.org. Original data source: PA DEP.

[Destinations of PA waste shipped to NYS in 2012]. (2013). Data provided by The FracTracker Alliance on FracTracker.org. Original data source: PA DEP.


[Sources of PA waste shipped to NYS in 2011]. (2013). Data provided by The FracTracker Alliance on FracTracker.org. Original data source: PA DEP.

[Sources of PA waste shipped to NYS in 2012]. (2013). Data provided by The FracTracker Alliance on FracTracker.org. Original data source: PA DEP.


Appendix A: AERMOD Guide

AERMET:

AERMET is the meteorological preprocessor for AERMOD. It takes care of all of the meteorological data and produces both a surface file and a sounding file (vertical atmospheric profile).

Preprocessing:

I used this PDF in order to help with the downloading and preprocessing of the data for AERMET.


Use Section 1 in order to get the appropriate surface data.

You want ISH data (AKA TD-3505 data). It’s from the National Climactic Data Center.


click on the desired year

need to find the appropriate file for the desired location


use control f to search for the place of interest

Ex: Williamsport

Associated file number is 14778⇒use this number to get the file you want⇒note that you may have to unzip the file.

AERMET:

Start a new project using the icons at the top of the screen.

Bring in the ISH file

Click on open folder icon under ‘Hourly Surface Data File’

Open file you just downloaded

The ISH file will not be reported in local standard time (LST), so you have to change it. For EST the adjustment is 5 hours, but there’s a tool to help with that (‘Tip’).

Make sure that the dates to be retrieved line up with the actual dates you want.
Hit Next

You want to include the 1-minute ASOS Wind Data files Replay at a later time.

Click on the AERMINUTE button, then download the files and load the 1-minute ASOS files

Select ‘Process’

Option to view output files pops up, you can close that window

QA Surface Variables:

- TMPD, WSPD, RHUM, PRCP, DPTP

Defaults selected in AERMET guide

Surface Variable Ranges:

- Check modify ranges, select Default and All

Onsite Data

- Not necessary for this analysis

Upper Air Data

I used Buffalo (72528) Upper Air Data, however there is also Pittsburgh (72520) Upper Air Data, which you may want to try as well.

Use Valley Air PDF again (Section 5).


- Upper Air Data will be in FSL format and should be reported in GMT

No QA for Upper Air Data

Sectors

Get Anemometer Height from Wunderground.com (use ‘station height’ for your station of choice)

Leave defaults

Click Next

Use the AERSURFACE Output file (check the checkbox)

Click on AERSURFACE

Use default file format, download the files and process
Hit Next ➔ make sure everything looks good: especially check the dates

Run the model

*The model will tell you if your project is complete or not.

AERMOD: This is the actual atmospheric dispersion model

New Project ➔ specify project name

Select Coordinate System (I’ve been using the defaults.) WGS1984

We’re in UTM zone 18

Choose a reference point to make sure your project in the correct location

Choose ‘center’ for the reference point

Use Google Earth for this

Specify the radius of the modeling area (I use either 35km or 50km depending upon the case study)

Hit Finish

Open the Control Window

Select Concentration

Select the Pollutant to be modelled and the averaging time options

I chose 1 hour, 1 month, and annually, but you may want to do 24 hours in the future

Select Elevated Terrain

This is because we’re assuming the terrain will have hills and other elevation changes.

You may want to experiment with the ‘Flat and Elevated’ setting later

Select Re-Start Files

This ensures that if something goes wrong while the model is running, you’re files and will be saved. The default setting says that these files will be saved every 5 days, but if your model runs take less time than that, you may want to choose a smaller number.
Open the Source Window

The sources are the road segments that are emitting pollution.
You need to input each individual road segment by hand
Make sure that the correct Pollutant is selected at the top
Close the Source Window

For Sources: I used line volume segments. The tool is the black line segment on the side of the workspace (directly above the red line segment).

Select the line volume segment tool and create any line (it doesn’t matter where). This is the dummy line. The Source inputs window will come up. For Configuration select Adjacent (because our sources are continuous roads). Plume Height is 7.259 and Plume Width is 13.32 (from the Haul Roads calculator to the right). To use the Haul Road calculator, you need to know vehicle height and width, which must be found through other sources. The emission rate you’ll get from the attribute table in ArcGIS. Finally, you need to import the nodes for the line segment. The nodes are geographic locations, and importing them will override the dummy line you created earlier with actual locations. Once the nodes are imported, you can close the Source Inputs window.

*Note: there will be the occasional segment that does not work. This is usually because it is too small, and Line Volume is not the best option for that particular segment or because there are no emissions. Ignore the segment and move on.

Getting Source nodes:

Use the DNR GPS Application (from the Minnesota Department of Natural Resources)

Load from File ➔ select ESRI Shapefile

Select the shapefile you want to load

Select SourceOID ➔ this is the field with the track names you want
The tracks will then load.

Select File ➔ Save to File ➔ Text file, comma delimited (CSV file)
Go to Excel ➔ open the CSV file you just created (specify that you want all files or text files shown, not just Excel workbooks)

The Text Import Wizard window will open

Select Delimited

Comma

Make sure not to accidentally select ‘tab’

Leave the defaults

Select Finish

These are the headings you want for your Excel CSV file. This is also the order they must be in. Any other fields can be deleted.

Type  tident  ident  X  Y  Base_Elevation  Release_Height

You’ll need to create the Base_Elevation and Release_Height fields and populate them both with zeroes. You’ll also need to rename y_proj to Y and x_proj to X and switch them (they’re in the wrong order in the unprocessed Excel CSV file). X needs to be first, followed by Y.

The field labelled tident should contain a 7 digit number. This is the sourceOID from ArcGIS. Use this to get the emission data from the attribute table in ArcGIS.

The field labelled ident should contain values such as T1, T7, T9, etc. These are the track numbers. All of T1 is one road segment, but there are multiple nodes within the road segment. Each of these Track numbers need to be saved to their own Excel CSV file (So all of the T1 values go into 1 Excel file, all of the T7 values go into another excel file, all of the T9 values go into yet another Excel file and so on).

*These are the nodes that you import into AERMOD.

Receptors in AERMOD:

Once all of your sources are inputted, you need receptors, which are places that will track and read the data. All of the dispersion data between the receptors will be interpolated. Use the Uniform Cartesian Grid tool on the sidebar (Under the plus sign that says ARC). For this, there isn’t a good way to set a buffer about how far away the receptor grid should stretch. You need to
stretch the grid outside of where the sources are located. The receptor grid will determine the geographic bounds of your results (you can cutoff some of your results if you don’t stretch it far enough).

Meteorological Data:

Load in your results from AERMET here, input the base elevation of the anemometer, and make sure that the data period is still ok.

Output:

Tabular outputs:

Select the top three highest values for all of the averaging periods. This will give you results and contours based on the three largest average values for each receptor.

Max Values:

Type in 50. This will give you the 50 maximum concentration values for the whole year.

Close the Output window

Terrain:

This is where we get elevation data for the region we’re working with. The program will provide the data you need. Select WebGIS data, and select the 1 degree DEM data. There are higher spatial resolutions available, however they may not work.

Selecting the region to import

You can either choose ‘Set to Model Extent’ or ‘Set to Map Extent’. This will determine how far your elevation data will go. Look at both options, and select which one is larger.

Select the ‘Process and run AERMAP’ button. The AERMAP model will now run. Once it is finished a new window will appear. Select ‘import all’.

Now you should be able to run your project. Again AERMOD will tell you if your project is complete or not, and it will tell you what (if anything) you’re missing. Also, it may take a couple of days to run, so enjoy!
Appendix B: Additional Test Cases

Test Case #4 Clearfield County, PA (Figures 12A, 12B, and 12C)

Clearfield County is located in central Pennsylvania, west of State College, Pennsylvania. Figure 12A shows emissions contour overlays of PM$_{10}$ concentrations with census data. Road segments input into AERMOD are also shown, with the red line segments representing highly trafficked roads. There are fluctuations within the emissions in the area, but when the general emissions classes are applied, the area appears to mostly be within the ‘least risk’ or blue category. This is likely because all of the roads inputted for this test case are in a centralized region, so that the area outside that region has lower emissions. The areas near the highly trafficked road segments have higher emissions, as expected. These higher emissions cross into the ‘moderate risk’ category. Census blocks that intersect the areas of moderate risk contain a total population of 394 people. The primary area of moderate risk (Figure 12B) is near a more populated area with approximately 10,000 people.

Figure 12C is a map of emissions contours atop elevation data. Schools and areas of health vulnerabilities are also shown. It is difficult to determine from a visual assessment if the elevation of the region plays any large part in the dispersion of the particulate matter in the more at risk areas. However, looking at the vulnerable locations in the area, there are many schools and medical locations that are close to the areas of higher elevation. While not all of these locations may be directly within a region of higher emission concentrations, they may be close enough that factors such as meteorological conditions could make them susceptible to higher concentrations. Table 13A shows the population within each emissions class in the Clearfield County test case as well as the expected calculated deaths. Table 13B shows the scaled up population to account for one death, based on the total number of mortalities across all emissions classes.
Figure 12: (A) Emissions data, roads, and census data. (B) Zoomed in image of the eastern end of the Clearfield County Test Case. (C) Vulnerable locations such as hospitals, nursing homes, and schools. Elevation data are also displayed.
Table 13: (A) The number of expected deaths in Clearfield and population impacted by each emissions class. (B) Scaled up population to account for one death.

<table>
<thead>
<tr>
<th>Risk Level</th>
<th>Population</th>
<th>Clearfield Expected Deaths (Low)</th>
<th>Clearfield Expected Deaths (High)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Least Risk</td>
<td>Blue</td>
<td>58773</td>
<td>0.000220046</td>
</tr>
<tr>
<td>At Risk</td>
<td>Green</td>
<td>4759</td>
<td>0.000357245</td>
</tr>
<tr>
<td>Moderate Risk</td>
<td>Yellow</td>
<td>394</td>
<td>0.000738305</td>
</tr>
<tr>
<td>High Risk</td>
<td>Orange</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Severe Risk</td>
<td>Red</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>63926</td>
<td>0.00651121</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Scaled Up Population per 1 Expected Death</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Low)</td>
</tr>
<tr>
<td>98,181,539 people</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Scaled Up Population per 1 Expected Death</th>
</tr>
</thead>
<tbody>
<tr>
<td>(High)</td>
</tr>
<tr>
<td>43,251,691 people</td>
</tr>
</tbody>
</table>
Test Case #5 Fayette County, PA (Figures 13A and 13B)

Fayette County is located in Southwestern Pennsylvania, near Pittsburgh. Figure 13A shows the emissions in the area from HVHF truck traffic as well as roads and census data. In this map, there is not much variation in the concentrations of PM$_{10}$ emitted. The entire region is within the blue, ‘least risk’ category, seemingly because there are very few road segments and only a small portion are categorized as ‘heavy traffic’. Additionally, there is only one small road segment that is highly trafficked in the area. It can be surmised that this small segment may be some sort of loading or well facility, which is be confirmed via aerial imagery. The total population of the census blocks displayed is approximately 3000 people. It can also be noted that the highly trafficked road segment does not contribute enough emissions to place it into a higher emissions category. Figure 13B shows the elevation of the region as well as the vulnerable locations, schools, and emissions distribution. The elevation data reveals that the entire region is at a relatively high elevation in the range of approximately 524 meters to 820 meters, which may account for the seemingly uniform distribution of the emissions in all directions. While hilly, there are not any notable elevation features that constrain the emissions, although there is a river to the east of the affected area. Figure 13B also shows nursing homes, hospitals, and other health related locations as well as schools. There are several schools and a medical location within the emissions dispersal which may be affected. Table 14A shows the population within each emissions class in the Fayette County test case as well as the expected calculated deaths. Table 14B shows the scaled up population to account for one death, based on the total number of mortalities across all emissions classes.
Figure 13: (A) Road segments, their associated census blocks and emissions data. (B) Elevation data with road segments and emissions data output.

Table 14: (A) The number of expected deaths in Fayette and population impacted by each emissions class. (B) Scaled up population to account for one death

<table>
<thead>
<tr>
<th>Emissions Class</th>
<th>Fayette Population</th>
<th>Fayette Expected Deaths (Low)</th>
<th>Fayette Expected Deaths (High)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Least Risk Blue</td>
<td>2222</td>
<td>8.31917E-06</td>
<td>1.66383E-05</td>
</tr>
<tr>
<td>At Risk Green</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Moderate Risk Yellow</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>High Risk Orange</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Severe Risk Red</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>2222</td>
<td>8.31917E-06</td>
<td>1.66383E-05</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Scaled Up Population per 1 Expected Death (Low)</th>
<th>Scaled Up Population per 1 Expected Death (High)</th>
</tr>
</thead>
<tbody>
<tr>
<td>267,067,308 people</td>
<td>133,533,654 people</td>
</tr>
</tbody>
</table>
Test Case #6 Rural Williamsport (Figures 14A, 14B, and 14C)

Williamsport, PA is located in the central part of Pennsylvania. Williamsport is a highly populated area of PA (2010 population = 29381), (US Census Bureau, 2010), however for this project, the region was divided in two; one for the rural area of Williamsport, and one for the more urban parts.

Figure 14A shows the rural portion of Williamsport. This area is west of the city, but still in the greater Williamsport area. From the census data, it is evident that there is not a high population in the area, with the vast majority of census blocks falling into the 0-50 people category. The total population shown on this map is just over 2700 people. There is one group of road segments of interest in this map. The eastern and western edges of the main road segment are not categorized as highly trafficked, but the central portion is. There are four areas of higher PM$_{10}$ concentrations originating from the highly trafficked segment, which can be viewed in more detail in Figure 14B. The western areas of higher emissions are similar in shape to the underlying high traffic road. This particular area is also interesting because the areas of high emissions are not confined exclusively to the highly trafficked roads, and actually spread along some of the other roads of interest.

Figure 14C shows the Rural Williamsport area with emissions contours and elevation data. Also displayed are vulnerable points of interest. There is one school and one health vulnerability within an area of low emissions. It is also apparent in this map that there are two gaps in the emissions coverage. The reasoning for these gaps is not apparent from the underlying elevation data, however the western area of higher elevations seems to follow the curve of the river. The eastern part of the emissions contours also go along the river in the northeast part of the map.

Table 15A shows the population within each emissions class in the Rural Williamsport test case as well as the expected calculated deaths. Table 15B shows the scaled up population to account for one death, based on the total number of mortalities across all emissions classes.
Figure 14: (A) Road segments, census data based on population, and the atmospheric emissions output from AERMOD. (B) Zoomed in figure of the Rural Williamsport region, highlighting the areas of higher emissions concentrations. (C) Emissions data over elevation data. Also visible are health vulnerabilities and schools, however there are not any in the areas of emission concentrations.
Table 15: (A) The number of expected deaths in Rural Williamsport and population impacted by each emissions class. (B) Scaled up population to account for one death

<table>
<thead>
<tr>
<th></th>
<th>Rural Williamsport Population</th>
<th>Rural Williamsport Expected Deaths (Low)</th>
<th>Rural Williamsport Expected Deaths (High)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Least Risk</td>
<td>Blue</td>
<td>967</td>
<td>3.62045E-06</td>
</tr>
<tr>
<td>At Risk</td>
<td>Green</td>
<td>133</td>
<td>9.98394E-06</td>
</tr>
<tr>
<td>Moderate Risk</td>
<td>Yellow</td>
<td>142</td>
<td>2.6609E-05</td>
</tr>
<tr>
<td>High Risk</td>
<td>Orange</td>
<td>95</td>
<td>3.55858E-05</td>
</tr>
<tr>
<td>Severe Risk</td>
<td>Red</td>
<td>1</td>
<td>7.48986E-07</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>1338</td>
<td>7.65481E-05</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Scaled Up Population per 1 Expected Death (Low)</th>
<th>Scaled Up Population per 1 Expected Death (High)</th>
</tr>
</thead>
<tbody>
<tr>
<td>17,478,772 people</td>
<td>8,489,848 people</td>
</tr>
</tbody>
</table>
Test Case #7 Tioga County, PA (Figures 15A, and 15B).

Tioga County, PA is located just south of the New York border. This area has a relatively high population of approximately 29,400 people. Figure 15A shows emissions dispersions as well as truck routes. Many of the road segments in this map are highly trafficked, leading to areas of elevated PM$_{10}$ emissions. The spatial distribution of particulate matter corresponds well with the highly trafficked road segments. There are several areas that fall into the orange ‘high risk’ category and the red ‘severe risk’ category. About 8900 people or approximately 29% of the population of the case study reside in census blocks that intersect these orange and red areas. This means that a large number of people may be impacted by the elevated emissions in the area.

Figure 15B shows emissions contours in Tioga county as well as vulnerable locations and elevation data. There are several medical facilities that are within the orange and red areas in the western part of the region. There are also several schools within the green ‘at risk’ areas. These locations might be susceptible to adverse effects due to the elevated emissions. This map also shows that there are several rivers in the Tioga area. In the southern part of the map, the PM$_{10}$ emissions appear to follow the river, likely being ‘funneled’ through the river valley. Depending upon meteorological conditions, it may be possible for emissions to linger in these valleys, which may be a concern for people living in those areas. Table 16A shows the population within each emissions class in the Tioga County test case as well as the expected calculated deaths. Table 16B shows the scaled up population to account for one death, based on the total number of mortalities across all emissions classes.
Figure 15: (A) a map of the Tioga County Test Case showing roads in the area of interest as well as atmospheric PM$_{10}$ emissions and population data. (B) Atmospheric emissions and roads overlaid with elevation data. Also visible are schools and locations of potential health vulnerabilities.
Table 16: (A) The number of expected deaths in Tioga and population impacted by each emissions class. (B) Scaled up population to account for one death

<table>
<thead>
<tr>
<th>Risk Level</th>
<th>Color</th>
<th>Tioga Population</th>
<th>Tioga Expected Deaths (Low)</th>
<th>Tioga Expected Deaths (High)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Least Risk</td>
<td>Blue</td>
<td>16662</td>
<td>6.23825E-05</td>
<td>0.000124765</td>
</tr>
<tr>
<td>At Risk</td>
<td>Green</td>
<td>11120</td>
<td>0.000834747</td>
<td>0.002081663</td>
</tr>
<tr>
<td>Moderate Risk</td>
<td>Yellow</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>High Risk</td>
<td>Orange</td>
<td>7230</td>
<td>0.002708263</td>
<td>0.005413815</td>
</tr>
<tr>
<td>Severe Risk</td>
<td>Red</td>
<td>2645</td>
<td>0.001981068</td>
<td>0.003154059</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>37657</td>
<td>0.005586461</td>
<td>0.010774303</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Scaled Up Population per 1 Expected Death (Low)</th>
<th>Scaled Up Population per 1 Expected Death (High)</th>
</tr>
</thead>
<tbody>
<tr>
<td>6,741,318 people</td>
<td>3,496,472 people</td>
</tr>
</tbody>
</table>
Appendix C: Bridges and Infrastructure

Infrastructure should be considered as it may influence or create limitations on routes. As some bridges are not designed to carry 40 tons, either smaller trucks will have to be used to cross these bridges, or these bridges will not be able to be included in future route analyses. Both of these scenarios have the possibility to change the generated routes. Data from the national bridge inventory (NBI) can be used to help determine which bridges are viable, and which bridges would act as barriers, forcing trucks to reroute from optimal routes. This will influence truck counts on other segments and influence emissions and emission dispersion. Within the NBI datasets, it may be good to choose bridges that have design loads less than 20 tons as possible barriers for the generated routes. This designation was close to the 22 ton maximum truck load limit used in this analysis. All bridges with a load limit less than 20 tons or unknown should be treated as a point barrier within the bridge reroute analysis. Figure 15 shows an example of waste removal routes with bridge point barriers.

Figure 15: Transportation routes showing the sum of trucks on each route segment and bridges designed to carry less than 20 tons.