EXPOSURES AND HEALTH RISKS DUE TO TRAFFIC CONGESTION

by

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Dedication

This dissertation is dedicated to my wife Xue Chen and my parents Zhao Zhang and Yulan Cui in appreciation of their enduring support and encouragement.

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Abstract

Traffic congestion has increased significantly in urban areas over the past several decades and is associated with significant environmental and health impacts. This research characterizes air pollutant emissions, exposures and health risks due to traffic, particularly when congestion is present. It examines key factors affected by congestion, including time allocation patterns, vehicle emissions, and near-road exposures.

Congestion alters time allocation patterns of commuters since more time is spent in traffic, and thus less time must be spent elsewhere. Time allocation shifts between time spent in a vehicle and other microenvironments were derived using the National Human Activity Pattern Survey and robust regression techniques. Congestion primarily reduced the time spent at home, especially for children and retirees.

Vehicle emissions occurring during traffic congestion, especially in work zones, have received little attention. A field study was conducted to collect data on speed-acceleration profiles in work zone, rush hour and free-flow conditions, and a power demand-based emission model was used to simulate emissions. Acceleration and deceleration significantly increased emission rates. Emission rates differed from those based on average speed, and depended on vehicle type and congestion condition.

Statistical and process-based estimates of traffic impacts on near-road air quality were derived using generalized additive models, the Motor Vehicle Emissions Factor Model 6.2 (MOBILE6.2), and the California Line Source Dispersion Model. The simulation model performed reasonably well for carbon monoxide (CO), but significantly underestimated $PM_{2.5}$ (particulate matter less than 2.5 μm in diameter) concentrations, a likely result of underestimating $PM_{2.5}$ emission factors.

An approach was developed to identify pollutant exposures and health risks associated with traffic congestion. Scenarios for arterial roads and freeways suggest that air pollution and health impacts attributable to congestion are significant, although limitations in the information and models available lead to large uncertainties, particularly with respect to estimating the emissions that are attributable to congestion and the dose-response relationships.

This study highlights the importance of accounting for changes in time allocations, vehicle emissions, and exposures due to traffic congestion. The research results are applicable to air quality, exposure and health risk assessments, as well as transportation planning.

Chapter 1
Introduction[1]

1.1 Background

Urban air quality is a major environmental concern around the world, and its significance is increasing as the world becomes more urbanized. The world's urban population was expected to reach 3.3 billion in 2008 and 5 billion in 2030 (UNFPA, 2007). Urban air pollution has been associated with increased morbidity and mortality (WHO, 2005) and pollutant levels far exceed desired levels or standards in many cities.

Mobile sources are a major contributor to urban air pollution, and include both on- and off-road sources (TRB, 2002; CARB, 2007). On-road sources include passenger cars, motorcycles, trucks, and buses, while off-road sources include heavy-duty construction equipment, recreational vehicles, marine vessels, lawn and garden equipment, and small utility engines (CARB, 2007). These sources emit $PM_{2.5}$ (particulate matter less than 2.5 micrometers in aerodynamic diameter), PM_{10} (particulate matter less than 10 micrometers in aerodynamic diameter), nitrogen oxides (NO_x), hydrocarbons (HC) and carbon monoxide (CO), among other pollutants. In the U.S., mobile source emission and on-road vehicle emissions accounted for 53% and 30% of the national total for criteria pollutants, respectively (U.S. EPA 2003), and on-road emissions contribute a larger share in urban areas where most people live. A recent review (WHO, 2005) of PM apportionment studies in Europe concluded that road transport accounts for one-quarter to one-half of $PM_{2.5}$ in a typical urban area, and that road transport is the most important source of NO_x, CO, benzene and black carbon. Mobile sources also play an important role in tropospheric ozone formation due to emissions of volatile organic compounds (VOCs) and NO_x, which are precursors of ozone (TRB, 2002).

[1] The format of my dissertation follows the guidelines established by the Rackham graduate school at the University of Michigan, Ann Arbor.

Traffic congestion has been increasing dramatically in the U.S. and elsewhere over the past 20 years (World Bank, 2006; Schrank and Lomax, 2009), and poses significant air quality challenges. Traffic congestion is often defined as an excess of vehicles or slower speeds when traffic volume exceeds road capacity (CAMSYS and TTI, 2005). Vehicle and fuel technology improvements, including improved emission controls such as 3-way catalytic converters, have significantly reduced vehicle emissions, but these can be counteracted by rapid growth in vehicle miles traveled (VMT) and congestion (Nam et al., 2002; TRB, 2002; Panis et al., 2006; Smit, 2006). In the US, total urban VMT increased from 0.86 x 10^{12} miles in 1980 to 1.96 x 10^{12} miles in 2005 (BTS, 2006). During the same period, the urban supply or road capacity, as measured by lane miles, grew from 1.40 x 10^{6} to 2.26 x 10^{6} miles (BTS, 2006). Thus, urban VMT grew about twice as fast as the urban capacity. Such growth is reflected by marked increases in traffic congestion, which has become nearly ubiquitous in many parts of the U.S. and elsewhere (U.S. FHWA, 2005; The World Bank, 2006).

Congestion can be caused by physical bottlenecks (40% of cases in the U.S.), traffic incidents (25%), work zones (10%), weather (15%), traffic control devices (5%), special events (5%), and fluctuations in normal traffic (CAMSYS and TTI, 2005). In addition to degrading urban air quality, consequences of congestion include travel delays, wasted fuel, decreased economic competitiveness, and decreased quality of life (Downs, 2004). Congestion in 438 U.S. urban areas in 2007 was estimated to cause approximately 4.2 billion hours of travel delay and waste 2.8 billion gallons of fuel, at a total cost of $87.2 billion (Schrank and Lomax, 2009). Congestion can be divided into recurring congestion and incident congestion, the latter caused by an accident or disabled vehicle (CAMSYS and TTI, 2005).

Concentrations of traffic-related air pollutants show strong spatial patterns (Funasaka et al., 2000; Kingham et al., 2000; Nakai et al., 1995; Roorda-Knape et al., 1998; Zhu et al., 2002). A review by WHO (2005) concluded that concentrations of NO_x, black smoke and $PM_{0.1}$ within 200 to 500 m of roadways far exceeded urban background; $PM_{2.5}$ and PM_{10} had somewhat higher concentrations than urban background; NO_2 had no evident spatial distribution; and higher concentrations of many pollutants were found in street canyons. A few studies have explored temporal patterns of traffic-related air pollution. Temporal patterns can be dramatic since traffic quantities (and congestion), as well as meteorological factors affecting dispersion of pollutants, are substantially related to the time of the day, day of the week, and/or season (Abraham et al., 2002; Beauchamp et al., 2004; Martuzevicius et al., 2004; Roosli et al., 2001).

1.1.1 Time activity patterns and traffic congestion

Understanding time activity patterns (TAPs) is an essential component of exposure estimation, along with the air pollutant concentrations in each microenvironment. TAPs specify where and how people spend their time in various locations called microenvironments, which represent physical spaces that are assumed to have a constant pollutant concentration (EPA, 1992). Shifts in TAPs can either increase an individual's total or cumulative exposure if the concentration and/or exposure time in the congestion microenvironment (e.g., passenger cabin of a vehicle, or roadside playground) increase, or possibly decrease exposure if congestion-related exposure concentrations are lower than levels in the other (displaced) environments. Congestion alters the TAPs of commuters since more time is spent in traffic, and thus less time must be spent in other microenvironments.

A few studies have applied TAPs to air pollutant exposure and health risks since the 1980s, most of which have emphasized inhalation exposure (McCurdy et al., 2000; Klepeis et al., 2001). These studies have mainly used survey methods to understand how much time respondents spent at various locations (McCurdy et al., 2000; Klepeis et al., 2001). Studies on exposures to traffic air pollutants show that personal exposure to PM_{10} and CO can be significantly increased by traffic-related microenvironments (e.g., in a car and outdoor roadside microenvironment), even if little time was spent in them (Chang et al., 2000; Johnson et al., 2000; Marquez et al., 2001; Marshall et al., 2003, 2005; Rea et al., 2001).

Unfortunately, all of the previous work has considered TAPs to be static, i.e., fixed in time, and no study has addressed the question of how time allocations change when time spent in a specific microenvironment increases or decreases. Thus, the previous studies cannot be used to evaluate air pollution exposures resulting from increases in traffic congestion. Moreover, the earlier studies have not separated transport/commuting microenvironments into congestion and non-congestion periods, a potentially important omission since vehicle emissions and concentrations in these modes can differ considerably (Frey et al., 2001; TRB, 2002).

1.1.2 Vehicle emissions and traffic congestion

Vehicle emissions are generated through combustion, fuel evaporation, brake and tire wear, and re-entrainment of dust. However, most attention focuses on engine tailpipe emissions. Gasoline and diesel engines vehicles emit pollutants that include black smoke, carbon monoxide (CO), oxides of nitrogen (NO_x), volatile organic compounds (VOCs), particulates ($PM_{2.5}$ and PM_{10}), and sulfur dioxide (SO_2). Black smoke is mainly composed of carbon particles and is often measured to represent the blackness of particles (WHO, 2005). Ground-level ozone (O_3), a secondary pollutant, is formed in the lower atmosphere (troposphere) from precursors NO_x and VOCs and photochemical reactions by the action of sunlight and warm temperatures.

Vehicle exhaust emissions from fuel combustion include cold start and hot start emissions and running emissions (U.S. EPA, 1994). A cold start occurs when a vehicle is started after being turned off for more than one hour; a hot start occurs when a vehicle engine starts after less than one hour from last operation (U.S. EPA, 1994). Running emissions, the focus of this dissertation, occur during driving and idling (U.S. EPA, 1994).

Many factors affect vehicle emissions (TRB, 1995):

- Travel-related factors: speed, acceleration, deceleration, engine demand, the number of trips, distance traveled, etc;
- Driver behaviors affecting the smoothness and consistency of vehicle speed, e.g., aggressive behavoir (hard stops and quick acceleration) results in high emissions;
- Highway-related factors: signal control, road type, road grade, road conditions, geometry design, etc;
- Vehicle-related and other factors: type and condition of engine, control technology, fuel, ambient temperature, vehicle-to-vehicle and vehicle-to-control interactions.

Among these factors, acceleration, deceleration and engine demand are strongly related to congestion.

The relationship between congestion and vehicle emissions is complex (TRB, 2002). Emission rates are associated with the distributions of speed and acceleration, which depend on road type, traffic flow and other factors (TRB, 2002). Congestion alters driving patterns, specifically causing frequent acceleration and deceleration in stop-and-go traffic, which increases emissions (Cappiello, 2002; Smit, 2006; TRB, 2002). Acceleration increases the load placed on engines, and thus engines are operated in a fuel-rich and high emission mode that can overload catalytic converters (TRB, 1995). CO and VOC emissions are most affected (TRB, 1995). Effects on NO_x emissions are limited because fuel-lean modes cause higher NO_x emissions (TRB, 1995). Deceleration contributes particularly to PM and VOC emissions because unburned fuel can be emitted under fuel enleanment conditions (Cappiello, 2002). However, congestion does not always increase emissions since vehicle emissions may be reduced at low speeds (TRB, 2002).

Information regarding emissions that pertain to congestion is very limited. A few experimental studies have explored the relationship between congestion and emissions. Anderson et al. (1996) found that congestion increased CO, HC and NO_x emissions by 71%, 53% and 4% respectively, compared to free flow conditions. Sjodin et al. (1998) showed a 10-fold increase in CO and HC emissions with congestion (average speed, 20 km/h) compared to uncongested conditions (average speed, 60-70 km/h). De Vlieger et al. (2000) indicated that CO and HC emissions in rush hour increased by 60% and 10%, respectively, compared to smooth conditions, but NO_x emissions were unchanged. Frey et al. (2001) used on-board measurements for CO, NO and HC and found that emissions for all three pollutants increased by 50% in congestion.

1.1.3 Emission modeling and traffic congestion

Mobile emission models can be classified as: (1) macroscopic emission models based on average speed, such as the Motor Vehicle Emissions Factor Model version 6.2 (MOBILE6.2) developed by the U.S. Environmental Protection Agency (EPA) and the Emission Factor Model (EMFAC) developed by the California Air Resources Board (CARB).; and (2) microscopic emission models based on second-by-second vehicle speed profiles and operation conditions, e.g., the Comprehensive Modal Emissions Model (CMEM) (Ahn, 2002).

Macroscopic models utilize emission factors that depend on average speed, vehicle type and age, ambient temperature, fuel, and vehicle operating mode (start, run, idle). Smit (2006) has recently reviewed many of the macroscopic emission models. For example, MOBILE6.2 uses a facility-based methodology (freeway, arterial, ramp and local) to estimate emissions of HC, CO, NO_x, PM and air toxics (Pierce et al., 2008) based on chassis dynamometer measurements and standard driving cycles (e.g., Federal Test Procedure, FTP). These have been criticized as insufficiently representative of actual driving patterns (Joumard et al., 2000). Macroscopic models cannot estimate instantaneous emissions since speed fluctuations are not simulated, thus they do not accurately estimate congestion emissions. Moreover, these models substantially underestimate real emissions because they do not account for acceleration, deceleration and aggressive driving (Joumard et al., 2000).

Microscopic models can be classified as response surfaces or emission maps (e.g., MODEM, an emission model developed by Jost et al., 1992); regression-based models (e.g., the Georgia Institute of Technology Model, the Virginia Polytechnic Institute Model); and load-based models (e.g., CMEM, Cappiello, 2002; and the new EPA Motor Vehicle Emission Simulator, MOVES, EPA, 2009). Emission maps utilize a two-dimensional matrix representing intervals of vehicle speed and acceleration (Cappiello, 2002). Cell values in the matrix are the mean of emission measurements corresponding to the specific speed-acceleration condition (Cappiello, 2002). Emission maps are sensitive to the driving cycles used to calibrate them, and inflexible with respect to their ability to account for road grade, accessory use and other factors (Cappiello, 2002). Regression-based models usually use linear models associating emissions to operational conditions, such as instantaneous vehicle speed and acceleration (Cappiello, 2002). Although they can handle sparseness problems by building an underlying model, they tend to overfit the data, lack clear mechanistic interpretations, and are inappropriate for the cases beyond the calibration data (Cappiello, 2002). Load-based models account for physical mechanisms producing emissions, and simulate steps of the physical and chemical process. These models are calibrated using laboratory measurements and vehicle specifications data (Cappiello, 2002).

Microscopic models estimate emissions under user-specified congested conditions. Smit et al. (2008) recently concluded that macroscopic models do not account for congestion explicitly because these models do not provide input parameters related to congestion. In contrast, microscopic models can account for congestion by specifying dynamic speed and acceleration/deceleration profiles as model inputs. Although microscopic models provide useful tools, they have not been widely applied for congestion scenarios, and no applications for work zones yet exist. Bushman et al. (2008) estimated CO, NO_x and VOC emission rates for cars and trucks due to travel delay caused by a work zone using idling emission factors provided by EPA. These emission rates, however, were neither measured nor based on real speed profiles, and idling emission rates incompletely represented work zone conditions which likely included acceleration, deceleration, idling, and some medium speeds. Moreover, no study has yet compared emissions occurring in work zones, rush hour congestion and free-flow conditions.

1.1.4 Roadway dispersion models

Many dispersion models have been developed to predict near-road concentrations of CO, NO_2, PM and other pollutants. In many applications, these dispersion models use emission factors derived from the emission models discussed above. For example, line source models with Gaussian-plume diffusion equations are widely used to predict pollutant concentrations (Bluett et al., 2004), and models such as the California Line Source Dispersion Model version 4 (CALINE4), have become useful tools for air quality regulatory applications. CALINE4, developed by the California Department of Transportation, simulates dispersion with algorithms that represent vehicle-induced heat flux and mechanical turbulence (Benson, 1989). CALINE4 can predict CO, PM, NO_x and other pollutant concentrations near roadways, intersections, parking areas, bridges and underpasses. Each CALINE4 model execution simulates from 1 to 8 hrs, and predicts mean concentrations at selected “receptor” locations. The emission, meteorological and traffic data are critical inputs to this model. Ausroads, another a line source Gaussian-plume model developed by the Australian EPA, has greater flexibility, although it uses the CALINE4 methodology (Ministry for the Environment New Zealand, 2004). The Hybrid Roadway Model (HYROAD), is another Gaussian plume model developed by

Systems Applications International, Inc., that uses traffic volume to calculate vehicle induced airflows and turbulence (Carr et al., 2002).

Dispersion models have several disadvantages. First, emission factors are required, and are usually taken from the EPA MOBILE model or the California Air Resources Board's EMFAC model (Pierce et al., 2008). Second, these models only simulate emissions from the roadway sources specified, to which “background” concentrations must be added. These can be difficult to estimate, and typically upwind measurements are needed, especially for PM since other regional and urban sources make large contributions. Third, all models have a limited range of applicability, e.g., CALINE4 does not perform well for street canyons and low wind speed conditions (Benson, 1992).

1.1.5 Statistical models for near-road air quality

An alternative approach to the emission/dispersion models discussed above uses statistical models to predict the effect of traffic on air quality. These models can be classified as (1) spatial regression models and (2) non-spatial regression models. Spatial regression models predict traffic’s contribution to pollutant concentrations using environmental variables, generally characterized using a geographic information system (GIS), e.g., land use, traffic intensity, and distance-to-highway (Atten et al., 2005; Jerrett et al., 2005; WHO, 2005). They have been widely used in exposure assessment to assess long term impacts due to traffic (Atten et al., 2005; Jerrett et al., 2005; WHO, 2005).

The non-spatial regression models include linear regression models, mixed models, generalized additive model (GAM), and nonparametric regression models (Abu-Allaban et al., 2003; Aldrin et al., 2005; Levy at al., 2003). Levy at al. (2003) used linear mixed models to link concentrations of $PM_{2.5}$, polycyclic aromatic hydrocarbons (PAHs) and ultrafine particles with traffic counts, GIS-based traffic density scores, wind direction, the percentage of traffic that was diesel-fueled, distance from the road and temporal autocorrelation. Abu-Allaban et al. (2003) modeled PM using vehicle class-specific counts (e.g., cars, light-duty trucks and high-duty trucks). Aldrin et al. (2005) adopted a GAM to relate the concentrations of PM_{10}, $PM_{2:5}$, the difference $PM_{10} - PM_{2.5}$, NO_2 and NO_x to traffic counts, temperature, wind speed, wind direction, precipitation, relative humidity and a snow cover indicator. Most of these studies used concepts from statistical air quality forecasting, e.g., Aldrin et al., 2005; Gardner et al., 1999; Hastie et al., 1990; Kukkonen et al., 2003; Schlink et al., 2003; Thompson et al., 2001. Hastie et al. (1990) compared several approaches in predicting ozone concentrations in Los Angeles and concluded that non-linear methods were superior to linear models, and that additive models with backward selection had the best performance. Neural network models improved upon linear regressions in predicting PM_{10}, NO_2, NO_x and ozone (Gardner et al., 1999; Kukkonen et al., 2003). Schlink et al. (2003) suggested that neural networks and GAMs performed the best because they accounted for non-linear relationships and site characteristics.

Compared to neural networks, GAMs provide more interpretable results since each predictor variable enters the model separately in an additive structure. The core idea of GAM is to characterize non-linear relationships by smoothing confounders using spline smoothing or weighted averaging (Hastie et al., 1990). In adjusting meteorological variables, GAM has been the dominant statistical approach used in air quality epidemiological studies, which investigate associations between air pollutant concentrations and mortality or morbidity outcomes, after controlling for meteorological parameters (Bell et al., 2004; Dominici et al., 2000, 2002).

The main advantage of statistical approaches is that they can capture site-specific characteristics which are difficult to accomplish in air dispersion models. On the other hand, limitations of statistically-based approaches include a lack of physical interpretation, a likely over-fitting of data, the need for extensive data, and a lack of generalizability. In addition, statistical and mechanistic approaches for predicting traffic-related air pollutants have not yet been compared.

1.1.6 Traffic air pollution, congestion and health effects

Traffic-related air pollutants are associated with many adverse health effects, including mortality, non-allergic respiratory morbidity, allergic illness and symptoms, cardiovascular morbidity, cancer, preterm birth, and decreased male fertility (WHO, 2005; HEI, 2010). A growing number of epidemiological studies provide strong evidence between mortality and either exposure to black smoke or $PM_{2.5}$ (Schwartz et al., 2002; WHO, 2005; HEI, 2010). The epidemiological evidence is less consistent for NO_2 (Samet et al., 2000). Most of the epidemiological and experimental studies that have focused on traffic-related air pollutants and respiratory outcomes suggest that black smoke, $PM_{2.5}$ and NO_2 increase the risk of respiratory symptoms (WHO, 2005; HEI, 2010).

A few studies have examined congestion-related impacts on exposure and health risks. Tonne et al. (2008) predicted that congestion charging zone (an area that drivers must pay to enter) in London, UK would extend 183 years-of-life per 100,000 population in the congestion charging zone, and would provide a total of 1,888 additional years of life in the greater London area. Eliasson et al. (2009) suggest that the congestion pricing zone in Stockholm, Sweden would avoid 25-30 deaths annually due to traffic air pollution, in a region with approximately 1.4 million inhabitants. These two studies were conducted in Europe and focused on congestion charging zones' impacts. No study is known that has investigated the impact of rush hour congestion on health in the U.S. population.

1.2 Research objectives

The overall objective of this research is to understand emissions, exposures and health risks that arise from traffic-related air pollutants, and particularly when traffic congestion is present. Figure 1-1 describes the research framework. The research has four related specific aims. The first is to examine changes in the time allocations occurring between exposure microenvironments when congestion is present. The second characterizes vehicle emissions under different traffic conditions, including work zones, rush hour, and free-flow conditions. The third aim is to compare simulation and statistical models of emission and dispersion processes with the goal of improving near-road air pollutant predictions. Finally, the fourth aim develops and applies a methodology to estimate exposures and health effects resulting from rush hour congestion. These aims and their significance are elaborated below.

Specific aim 1: This aim characterizes shifts in time allocations occurring between microenvironments due to congestion. Data from the National Human Activity Pattern Survey (NHAPS) are used to investigate trade-offs between time spent in vehicles and eight other microenvironments. Statistical models, using robust regression, are used to characterize these trade-offs, and scenarios are developed that demonstrate congestion's effects on total exposures. It is clear that traffic congestion results in more time spent in transit, and specifically vehicles, thus less time elsewhere. As mentioned in the background, previous TAP studies for the purpose of exposure assessment have not considered dynamic trade-offs of time allocations, and thus cannot be used to evaluate time shifts due to traffic congestion. Although a few travel time studies in the transportation field have used linear regression to model travel time as a function of time use (Levinson, 1999; Zhang, 2005), these studies did not account for outliers and results might not be robust. Moreover, previous work has not separated transport related microenvironments into congestion and non-congestion periods, an important omission since vehicle emissions and concentrations in these periods can differ considerably. .

Specific aim 2: Vehicle emissions are characterized under different traffic conditions, including work zone and rush hour congestion, and compared to emissions under free-flow conditions. This aim utilizes a field study to develop typical speed/acceleration profiles, and then predicts emissions using these data in an instantaneous emission model. As noted, few studies have examined emissions under congested conditions, and most of which have used on-board measurements. Such approaches are expensive, and results can vary dramatically from vehicle to vehicle, although they do directly link transient emissions to transient speed, acceleration and deceleration behaviors, and thus can capture emissions resulting from congestion. Emission measurements also are difficult to generalize to the whole fleet of vehicles. The approach taken in this specific aim is to estimate emissions under work zone and rush hour using an instantaneous emission model (CMEM) using the second-by-second speed profiles collected in a field study that uses the vehicle following technique.

Specific aim 3: This aim compares simulation (or process-based) models to statistical models, both of which represent emission and dispersion processes, in order to characterize model capabilities and ultimately to improve model performance. The analysis uses CO and $PM_{2.5}$ pollutant concentrations measured near an interstate freeway in Detroit, MI, traffic counts on the freeway, the MOBILE6.2/CALINE4 simulation model, and a statistical model using generalized additive models (GAM). Although both roadway dispersion models and statistical models can estimate traffic impacts on near-road air quality, few studies have combined or compared process- and statistically-based approaches that potentially can yield more accurate predictions. Differences between these independent approaches can help to highlight model deficiencies, and may lead to approaches that use the models in a complementary or confirmatory manner. As examples, statistical methods have the advantage of deriving empirical emission factors, which can be used in dispersion models to reduce both bias and uncertainty of the emission factors.

Specific aim 4: This aim develops and applies a methodology to estimate exposures and health effects resulting from rush hour congestion. Risk assessment and incremental analysis methods are used, along with site-specific information on travel delay, emission changes, and meteorology. As noted, previous studies have not separated the health impacts due to vehicle emissions into congestion and non-congestion related components. This is a potentially significant omission since vehicle emissions, near-road concentrations, exposures and health risks are likely to differ considerably between congestion and congestion-free periods.

1.3 Importance and novelty

This research addresses several key knowledge gaps in our understanding of the impacts of traffic and congestion. These include the significance of dynamic adjustments to time activity patterns in estimating exposures both on- and near-roadways, the impacts of congestion on emissions and air quality, and the magnitude of health risks associated with traffic and congestion. Despite a growing number of observational studies, the environmental and health effects of traffic and congestion remain poorly understood. There have been relatively few applied or theoretical studies specifically aimed at congestion conditions. Only rarely have pollutant concentrations in traffic-impacted locations under both congestion and free flow conditions been measured, which represents a critical piece of information for exposure assessment purposes (Chan et al., 1991; Riediker et al., 2004; Rodes et al., 1998). While receiving little attention, these factors warrant increasing analysis as congestion increases worldwide. This work represents a fusion of several advanced techniques, including instantaneous emissions models, roadway dispersion models and advanced statistical models.

Work in specific aim 1 increases the understanding of changes of TAPs due to congestion. To date, studies examining TAPs in exposure analysis have considered time allocations to be static, i.e., fixed in time. They have not considered how time allocations would change when time spent in different microenvironment increases or decreases, and thus, cannot be used to evaluate effects of congestion that increase the time spent in traffic. The research conducted for this aim helps to fill this gap by estimating the time allocation shifts due to congestion.

Work in specific aim 2 estimates pollutant emissions under work zones, rush hour and free-flow conditions, and thus helps to quantify congestion's contribution to emissions. In addition, it has applications in evaluating improvement alternatives aimed at managing congestion, an important use since traffic congestion is growing rapidly worldwide.

Work in specific objective 3 compares emission/roadway dispersion models and statistical models. It can improve the understanding of the relationship between traffic and roadway pollutant concentrations. Emissions can be estimated using the statistical models in an inverse manner, which potentially can improve the performance of dispersion models like CALINE4. Emission inputs required by CALINE4 are usually derived from models such as the Motor Vehicle Emissions Factor Model (MOBILE) or the Emission Factor Model (EMFAC). However, such models do not represent actual driving patterns on the roadway links or segments of interest. Many other factors may also bias results of the macroscopic emission models.

Work in specific aim 4, designed to increase the understanding of exposures and health risks of commuters and near-road communities due to traffic and congestion, is relevant to urban areas with increasing levels of congestion. It is anticipated that the research methodologies and results can be used to estimate on- and near-roadway exposures and risks in many areas, and thus can find practical application in health risk assessment. Moreover, improved exposure and risk information makes it possible to account for environmental and health costs, in addition to "agency" costs, in transportation planning decisions. For example, an evaluation of alternative paving materials, specifically engineered cement composites (ECC), shows that one of the major benefits is a greatly reduced frequency of repairs. However, the higher initial costs of ECC are only offset if energy and environmental benefits are factored in (Keoleian et al., 2005). The use of a life cycle approach such as this, and one that includes environmental and health costs, is increasing among transportation agencies.

1.4 Organization of this dissertation

This dissertation is organized into six chapters. This chapter (Chapter 1) has described the background, objectives and specific aims of this research, and has summarized the current literature for the main topics of the research. Chapter 2 investigates the trade-offs of time allocation shifts between time spent in traffic and other microenvironments due to traffic congestion. Chapter 3 estimates emissions under work zones, rush hours and free-flow conditions, and describes field and modeling studies. Chapter 4 compares predictions from emission/dispersion models and statistical models based on a near-road monitoring dataset. Chapter 5 develops a methodology to estimate air pollution and health impacts due to rush hour congestion and applies it to a case study in Detroit, MI. Chapter 6 summarizes the findings and presents conclusions and future research directions.

Chapters 2 through 5, the research chapters, have been written as stand-alone sections, in anticipation of submission to journals as manuscripts. At the time of this writing, Chapter 2 has been published in the journal *Science of the Total Environment* (2009, 407: 5493-5500), and Chapter 4 has been published in *Atmospheric Environment* (2010, 44: 1740-1748).

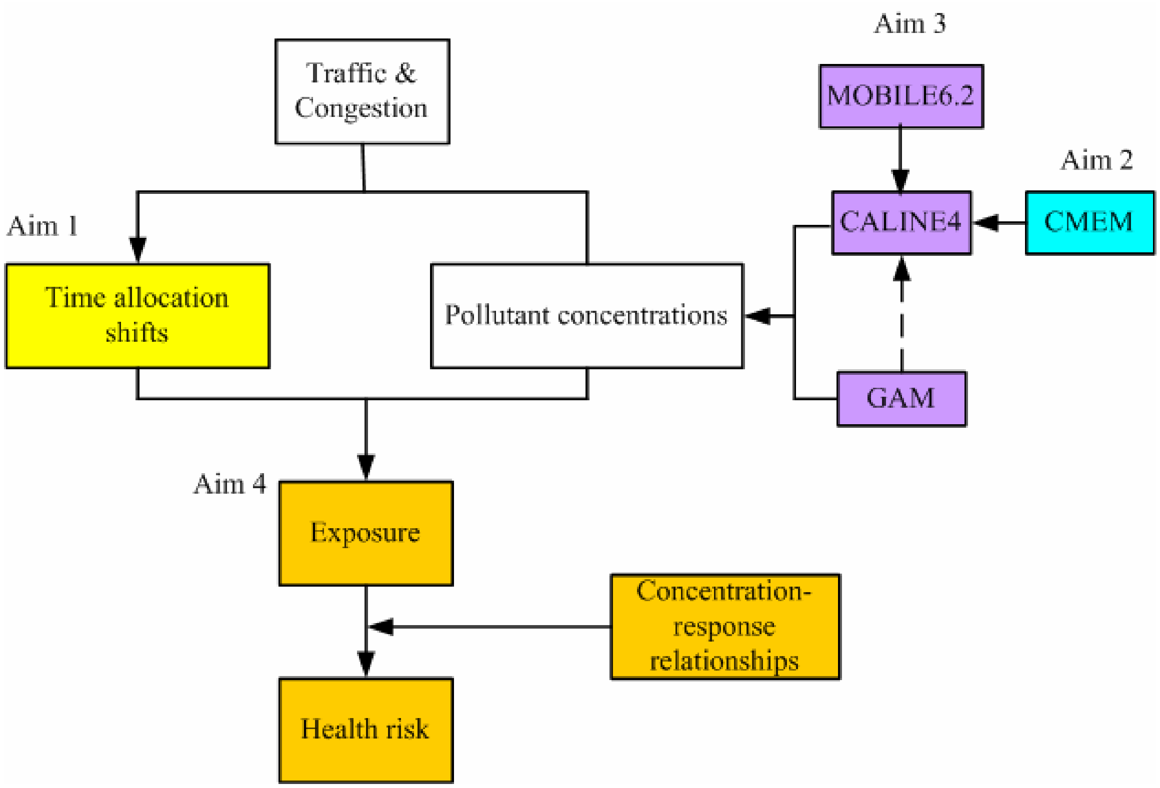

Figure 1-1 Framework of the dissertation research (Different shadings represent different specific aims)

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Chapter 2

Time Allocation Shifts and Pollutant Exposure due to Traffic Congestion: An Analysis using the National Human Activity Pattern Survey

2.1 Abstract

Traffic congestion increases air pollutant exposures of commuters and urban populations due to the increased time spent in traffic and the increased vehicular emissions that occur in congestion, especially "stop-and-go" traffic. Increased time in traffic also decreases time in other microenvironments, a trade-off that has not been considered in previous time activity pattern (TAP) analyses conducted for exposure assessment purposes. This research investigates changes in time allocations and exposures that result from traffic congestion. Time shifts were derived using data from the National Human Activity Pattern Survey (NHAPS), which was aggregated to nine microenvironments (six indoor locations, two outdoor locations and one transport location). After imputing missing values, handling outliers, and conducting other quality checks, these data were stratified by respondent age, employment status and period (weekday/weekend). Trade-offs or time-shift coefficients between time spent in vehicles and the eight other microenvironments were then estimated using robust regression. For children and retirees, congestion primarily reduced the time spent at home; for older children and working adults, congestion shifted the time spent at home as well as time in schools, public buildings, and other indoor environments. Changes in benzene and $PM_{2.5}$ exposure were estimated for the current average travel delay in the U.S. (9 min day^{-1}) and other scenarios using the estimated time shifts coefficients, concentrations in key microenvironments derived from the literature, and a probabilistic analysis. Changes in exposures depended on the duration of the congestion and the pollutant. For example, a 30 min day^{-1} travel delay was determined to account for 21 ± 12 % of current exposure to benzene and 14 ± 8

% of PM2.5 exposure. The time allocation shifts and the dynamic approach to TAPs improve estimates of exposure impacts from congestion and other recurring events.

2.2 Keywords

Activity pattern; air pollutants; congestion; exposure assessment; robust regression; time allocation.

2.3 Introduction

Traffic congestion has increased significantly in the U.S. and elsewhere over the past 20 years (Schrank and Lomax, 2007) and has led to detrimental effects on air quality and health. Congestion not only increases the time individual spend in traffic, but also vehicular emissions, already the most significant urban source of many air pollutants (Rosenbaum et al., 1999; EPA, 2003a). Increase in congestion can thus be linked to increases in exposures to air pollutants of the on-road population (e.g., drivers, commuters), the near-road community (e.g., individuals working or living near major roads), as well as the general urban population. Although time spent in traffic-related microenvironments such as vehicle cabins and near-road activities is relatively short, averaging 97 (in-vehicle) and 80 (near-road) min day^{-1} for the U.S. population (EPA, 1997), traffic can account for a significant fraction of exposure to $PM_{2.5}$ (particulate matter <2.5 μm aerodynamic diameter), carbon monoxide (CO), benzene and other pollutants (Marshall et al., 2003, 2005; WHO, 2005). Congestion will increase an individual's exposure if concentrations in traffic exceed those in the displaced microenvironments.

Traffic-related exposures can be estimated with knowledge of time activity patterns (TAPs), which specify where and how individuals spend their time, along with knowledge of air pollutant concentrations in each microenvironment, defined as a physical space that has a spatially invariant concentration that is constant for a short period (EPA, 1992). Research on time budgets, which dates back to 1920s, generally has used survey data to estimate the time spent among different microenvironments (Klepeis et al., 2001; McCurdy et al., 2000). Several surveys have included commuting and other transport-related microenvironments and, starting in the 1980s, TAPs have been used to estimate air pollutant exposures and health risks (Klepeis et al., 2001; McCurdy et al., 2000). All of this work, however, has considered TAPs to be static, i.e., fixed in time. Thus these studies cannot be used to evaluate shifts in time allocations among microenvironments, specifically when time in one compartment changes. In addition, the previous work has not separated transport-related microenvironments into congestion and non-congestion periods, an important omission since vehicle emissions and concentrations in these periods can differ considerably (TRB, 2002).

This paper examines how traffic congestion changes time allocation patterns and pollutant exposures. The time spent in a vehicle, which would be expected to increase with congestion, as well as the time spent in other microenvironments, are considered as dynamic variables. We separate traffic-related exposures into normal and congestion modes, and estimate the effect of congestion on pollution exposures for several scenarios. The remainder of this paper is organized as follows: In methods, we describe the modeling approach, data sources, microenvironmental classifications, and key variables. The results describe the statistical analyses, and several scenarios. The discussion compares results to the literature, and evaluates the approach's strengths and limitations. We conclude by summarizing the results and suggesting research needs.

2.4 Methods

2.4.1 Approach

Time allocation shifts due to recurring congestion can be estimated in several ways. However, there are advantages in separating the problem into several components for examining incremental changes. First, the overall increase in travel (vehicle) time due to congestion is estimated and represented as $\Delta T_{v,j}$ for the j^{th} individual (min). Next, changes in the time budget among other microenvironments are estimated assuming a linear trade-off with congestion time:

$$\Delta T_{i,j} = \beta_{i,v}\, \Delta T_{v,j} \qquad \forall\, i = 1 \ldots n \qquad (1)$$

where $\Delta T_{i,j}$ = shift in time for microenvironment *i* and individual *j* (min); and $\beta_{i,v}$ = time shift (tradeoff) coefficient between time spent in microenvironment *i* and the transport environment. This equation applies to all *n* microenvironments and assumes that trade-offs are linear in the case of small time shifts, as discussed below. Lastly, the total time spent in microenvironment *i* for individual *j* or $T_{i,j}$ (min) is:

$$T_{i,j} = T_{i,j,nom} + \Delta T_{i,j} = T_{i,j,nom} + \beta_{i,v}\, \Delta T_{v,j} \qquad (2)$$

where $T_{i,j,nom}$ is the nominal or average time spent in microenvironment *i*. The overall time budget forms a constraint that "conserves" time:

$$\Delta T_{v,j} + \Sigma_i \Delta T_{i,j} = 0 \quad (3)$$

i.e., increased travel time must be exactly displaced by changes among other microenvironments. The approach represented by eqs. (1) - (3) is simple and flexible, i.e., it allows analysis of alternative scenarios that change ΔT_v by different amounts. As mentioned, however, it applies to only small changes in ΔT_v. Large increases in congestion may produce nonlinear changes as well as alter the assumption of independence between microenvironments. For example, individuals may combine trips as a result of significant changes in congestion, work longer hours but fewer days, or shift to a different travel mode.

Travel time $\Delta T_{v,j}$ in congestion is estimated using travel delay, which is defined as the travel time above that needed to complete a trip at free-flow speeds (Schrank & Lomax, 2007), and derived using a macroscopic approach as the extra time spent traveling when compared to free flow conditions. Delays on road segments are based on information contained in the Federal Highway Administration's Highway Performance Monitoring System (HPMS) database, traffic volume, and information about link speeds (Schrank and Lomax, 2007). The estimated average annual travel delay for a traveler making trips during rush hours (based on surveys in 437 small to large U.S. urban areas) increased from 30 hours in 1993-94 to an average of 38 hours in 2005 (Schrank and Lomax, 2007). Most reports of travel delay use this method.

The derivation of time shift coefficients $\beta_{i,v}$ representing trade-offs between in-vehicle and other microenvironments is challenging. We could not identify any surveys that tracked time spent in congestion and other microenvironments using a large and representative population. Moreover, many factors can affect time allocations and time shifts, e.g., age, gender, employment status, income, marital status, presence of children, work characteristics, mode to work, and day of the week (weekday/weekends) (Buliung, 2005; Krantz, 2005). The most common methods for examining time allocations in travel behavior analyses are structural equations, discrete choice model and survival models (Bhat and Koppelman, 1999; Buliung, 2005; Zhang, 2005). However, these methods are primarily used to identify factors affecting time use and how individuals choose among different activities and are not appropriate for estimating time shifts. Time shift coefficients might be estimated using longitudinal surveys that track individuals during days with and without congestion, possibly using "natural experiments" that produce periods with (large) differences in congestion, e.g., weekend/weekday, construction/non-construction events, or day/night periods. However, many factors might bias such comparisons. Alternatively, longitudinal studies might use a random sample and attempt to statistical control for factors that might affect results; however, no such study has distinguished time spent in congestion from congestion-free periods.

Time shift coefficients also might be estimated using cross-sectional studies if socio-demographic and other factors that influence TAPs can be sufficiently controlled, and if congestion and congestion-free travel periods can be separated. Again, no known TAP survey has distinguished such periods. This limitation can be addressed, however, if drivers primarily consider the total in-vehicle period in their time allocation decisions, that is, if they do not make major distinctions between time spent in congestion from time spent in "normal" traffic. This follows if driver behavior is aimed at minimizing the overall trip (door-to-door) duration, which appears reasonable since most drivers, for example, will use highways that increase travel distances and trip cost (e.g., due to fuel and vehicle maintenance) if the overall travel time is reduced. The use of cross-sectional analyses to estimate time shifts has not been attempted, although such analyses have been used to examine the dependence of travel time on activity duration (Levinson, 1999; Zhang, 2005).

Here, cross-sectional data are used to construct models that predict time allocation shifts. We incorporate variables known to affect time allocations, and robust estimation is used to improve parameter stability and deal with non-normality, outliers and other statistical issues. A separate linear model is constructed for each of the *n* microenvironments considered (excluding the vehicle compartment):

$$T_{i,j} = \beta_{i,0} + \beta_{i,v} T_{v,j} + \Sigma_k \Gamma_k S_{k,j} \qquad \forall\, i = 1 \ldots n \qquad (4)$$

where $T_{i,j}$ = time spent in microenvironment i for individual j (min); $\beta_{i,0}$ is an intercept constant (min); $\beta_{i,v}$ is the time shift between microenvironment i and the in-vehicle microenvironment as defined earlier; $T_{v,j}$ = time spent in a vehicle for individual j (min); Γ_k are coefficients for the k^{th} covariates; and $S_{k,j}$ are covariates. Table 2-1 defines covariates for the dataset, which include time spent in microenvironments, gender, occupation, education, season, weekday/weekend, and others.

The application of eq. (4) is subject to several limitations. First, only those cases where a minimum amount of time is spent in each microenvironment can be considered since only incremental changes in an existing budget can be determined. Thus, individuals are assumed not to add or remove microenvironments to their time budget or to alter the travel mode. We recognize that some or many individuals will modify behaviors in response to congestion, but much of this will be captured by the desire to minimize travel time, as noted. Second, we focus on a normal commuting population and thus do not consider individuals who report no travel time (thus $T_{v,j} > 0$) or those individuals who report no time at home. We exclude individuals who might be professional drivers since such individuals likely have inelastic work demands. Because such individuals cannot always be identified by occupation, we exclude individuals spending more than 4 h in a vehicle in a 24 h period. Third, we expect that 'true' trade-offs will result in negative coefficients for $\beta_{i,v}$; however, in cross-sectional analyses, positive $\beta_{i,v}$ coefficients may be obtained for discretionary visits to microenvironments such as restaurants. These positive coefficients cannot be considered trade-offs. Fourth, the estimated time shifts may not conserve time, as required in eq. (3), but increases in travel time must be exactly matched by reductions among time spent in all of the other microenvironments. Thus, normalization is used to provide closure on the time budget:

$$\beta'_{i,v} = \beta_{i,v} / \Sigma_i |\beta_{i,v}| \qquad (5)$$

where $\beta'_{i,v}$ = the normalized coefficient. Ideally, normalization will produce only small changes, suggesting that the time shift coefficients capture the major impacts and explain a large fraction of the observed variation.

2.4.2 Data sources, cleaning and aggregation

TAP data collected in the National Human Activity Pattern Survey (NHAPS), a portion of the Consolidated Human Activity Database (CHAD) developed by the U.S. Environmental Protection Agency (McCurdy et al., 2000), was used to estimate time shift coefficients. Conducted from 1992 to 1994, this nationwide survey included 9,386 randomly selected participants drawn from 48 states using a standard two-stage random digit dial (RDD) sample design. Respondents were asked to record their locations and activities in a diary for a 24 h period. Respondent locations were coded into 83 microenvironments (Klepeis et al., 1996). This information, along with basic socio-demographic data, e.g., age, gender, employment status (full time, part time work, not employed), education (less than high school, high school graduate, less than college, college graduate and post-graduate), and race (White, Black, Asian, Hispanic, other), was recorded using a computer-assisted telephone interview instrument (Klepeis et al., 1996).

To reduce the number of compartments and increase sample size, the original 83 microenvironments were grouped into 9 microenvironments following Klepeis et al. (1996). We further combined two outdoor locations (residence-outdoors and other-outdoor). The final set included six indoor microenvironments (home, workplace, shopping, bar/restaurant, school/public building, and other indoor), two outdoor microenvironments (near road, other outdoor), and one transport category (in-vehicle). The school/public building includes school, hospital, church and public building/library/museum/theatre. Our in-vehicle, near-road and outdoor compartments differed slightly from Klepeis et al. (1996): (1) In-vehicle groupings included car, truck (pick-up/van), truck (other), bus and motorcycle/moped/scooter (n=6762), but not train/subway/rapid transit, airline and boat (n = 395), due to our focus on roadway congestion. (2) The near-road grouping included walking, bicycle/skateboard/roller-skates, in a stroller/carried by an adult, sidewalk/street/neighborhood, parking lot, and service station/gas station, but excluded motorcycle/moped/scooter (moved to the in-vehicle microenvironment). (3) The outdoor grouping included "residence-outdoors" and "other-outdoor".

Data checking and cleaning for the NHAPS dataset included the following: Cases (individuals) were eliminated that were missing, repeated or invalid, including cases where (1) age or gender was missing (n=191 or 2% of the sample); (2) time spent at home was equal to 0 (n=41 or 1%); (3) travel time exceeded 4 h (n=425 or 5%); (4) travel time was spent in airline, transit, boat, other transportation modes not included in in-vehicle microenvironment defined above (n=195 or 2%); (5) records were duplicated (n=298 or 3%); and (6) the time in all nine microenvironments for each individual was verified to sum to 1440 min (24 h; n=8297). These steps left 8,297 valid and complete cases. The number of deletions represented a small fraction of the total cases, thus deletions seem unlikely to significantly affect results.

Outliers were identified (but not removed) using Tukey's 1.5 interquartile range (IQR) method, i.e., values that exceeded 1.5 IQR plus the 75th percentile value or fell below 1.5 IQR minus the 25th percentile value (Moore and McCabe, 2002).

Several of the statistical methods required complete datasets. Many cases (n=1773, 19%) were missing employment and education information, a potentially significant omission since employment status can affect time allocations (Klepeis et al., 1996). Missing observations for these two variables were replaced using "hot deck" imputation (Little and Rubin, 2002), e.g., persons from 18 and 64 years of age had 53 and 11% chances of having a full- or part-time job, respectively, and these probabilities were used to replace missing values of this variable. For children (≤17 years of age), employment status was assigned to non-employed.

2.4.3 Parameter estimation

Time shift coefficients between the time spent in vehicle and time in other microenvironments (in eq. 4) were first estimated using ordinary least squares (OLS) regression, primarily as an exploratory analysis based on the original dataset, and also using the 10% trimmed dataset (omitting the lowest and highest deciles). Second, robust regression was used to obtain final estimates. We used the MM method, a maximum likelihood procedures that combines Huber M estimation (addressing outliers in the dependent variable) and high breakdown value methods (handling high leverage or influential points) (Chen, 2002). This technique addresses outliers in both the dependent and independent variables, and is more efficient and reliable than OLS with outlier deletions (Faraway, 2004).

In part to address interactions between age, gender and employment, data were stratified by respondent age (<4, 5-17, 18-64, and >64 years of age) and employment status (working/nonworking; only for adults). Additionally, older children and working adults were divided into weekday and weekend groups. We assumed that few individuals <17 years of age would have jobs, thus occupation-vehicle time shift coefficients were not estimated for this group.

Variable selection used backward elimination. Sensitivity analyses were used to compare final and full models (including all covariates) in order to check to what extent variable selection affected the estimated time allocation shifts.

2.4.4 Scenario analysis

Exposures to benzene and $PM_{2.5}$ were simulated as follows. Based on the national survey (Klepeis et al.,1996), a typical working adult in weekdays spent an average of 45 min day^{-1} in transit and experienced total annual travel delay of 38 h (Schrank and Lomax, 2007). Distributing this delay over the 255 working days in a year is equivalent to 9 min day^{-1}. Although estimates of travel times without and with travel delays, 36 and 45 min day^{-1}, respectively, are quite robust, the amount of time spent in congestion is unknown. Congestion periods could range from just slightly more than the travel delay (9 min day^{-1}) to the entire transit duration (currently 45 min day^{-1}). A reasonable "midpoint" estimate might assume that travel delays result from congestion in which the average speed falls by half from free flow conditions. In this case, the current travel delay of 9 min day^{-1} would represent congestion lasting 18 min day^{-1}. We recognize that this estimate is uncertain and subjective, and that the boundary between free flow and congested conditions is continuous and variable. For the purpose of the scenario analysis, we tested three limiting cases: (1) trips without delays, i.e., no congestion, in which the total travel duration = free flow duration = 36 min day^{-1}; (2) current conditions with a travel time delay of 9 min day^{-1} and associated 50% speed reduction, i.e., total duration = 45 min day^{-1}, free flow = 27 min day^{-1}, and congestion = 18 min day^{-1}; and (3) high and possible future travel delay of 30 min day^{-1} (total duration = 66 min day^{-1}, free flow = 6 min day^{-1}, congestion = 60 min day^{-1}). These three scenarios, which represent a limited sensitivity analysis, can be regarded as ideal, current, and worst-case conditions.

Inhalation exposure was calculated as:

$$E_{total} = 1/1440\ \Sigma_i\ C_i\ T_{i,nom}\ BR_i \qquad (6)$$

where E_{total} = total exposure (μg person-day^{-1}); C_i = pollutant concentration in microenvironment i (μg m^{-3}); $T_{i,nom}$ = time in microenvironment i (min); and BR_i = breathing rate (m^3 min^{-1}). The time budgets used the average values in NHAPS normalized to arrive at a 24 h budget. Breathing rates for each microenvironment used recommended values (EPA, 1997). The rate for sitting/standing activities (0.008 m^3 min^{-1} for adults) was used for traffic and congestion. The incremental exposure attributable to congestion, ΔE (μg person-day^{-1}), was calculated as:

$$\Delta E = \Sigma_i\ C_i\ \Delta T_i\ BR_i \qquad (7)$$

where ΔT_i is the estimated time allocation shift from eq. (1) after normalization.

In urban areas, benzene is largely emitted from transport-related sources (WHO, 2005). Benzene is considered a carcinogen (EPA, 2003b) and thus long-term exposure is important. Mobile sources also are a major emission source of $PM_{2.5}$, which has both acute and chronic morbidity and mortality effects (WHO, 2005). Due to both the difficulty of locating concentration data for all nine microenvironments and for simplicity, we further collapsed the analysis to six microenvironments: congestion-free transport; transport with congestion; near-road; outdoor; workplaces; and a new group called home and other indoors that combined home, shopping places, bar/restaurant, school/public building and indoor-other microenvironments (discussed in the data cleaning section). Concentrations in these microenvironments were considered to be independent.

Benzene and $PM_{2.5}$ concentrations were based on recent literature, and Monte Carlo (MC) analyses were used to address both the variation and uncertainty in the available data. Our goal was to estimate the current range of concentration ranges found in the major microenvironments in urban settings in the U.S. Concentrations were assumed to be log-normally distributed. The geometric mean μ_g was derived from the median or mean values (if medians were unavailable) among the selected studies, and a geometric standard deviation (GSD) σ_g was taken from the literature or our judgment. For benzene, a weighted mean was calculated from 25 recent studies using sample size as weights (Table S2-2). For $PM_{2.5}$, many outdoor and residential measurements are available, but little information exists regarding representative levels in vehicles, most workplaces and near-road environments. Instead, we used typical concentrations, indoor/outdoor concentration ratios, and near-road/ambient concentration ratios, again weighting the means by sample size. We also conducted sensitivity analyses that examined effects of concentration in vehicle cabins and increases in GSDs.

The regression and robust analyses used SAS 9.1 (SAS Institute Inc., Cary, NC, U.S.). The MC and sensitivity analyses used Crystal Ball software (Decisioneering Inc., Denver, CO, U.S.).

2.5 Results and discussion

2.5.1 Descriptive statistics and exploratory data analysis

The NHAPS respondents reported a daily travel time of 76 ± 52 min (mean ± standard deviation), and statistically significant differences were seen by respondent age, e.g., travel times averaged 62 ± 49, 65 ± 47, 80 ± 52 and 73 ± 53 min for the 0–4, 5–17, 18–64, and >64 year old age groups, respectively (Kruskal-Wallis test, $p<0.0001$). Differences by gender were small and not statistically significant, e.g., travel times for men and women in the 18–64 yr group were 82 ± 54 min and 79 ± 51 min, respectively (Kruskal-Wallis $p=0.35$). Time distributions were right-skewed, especially for microenvironments that had relatively low durations, e.g., near-road and shopping activities. The dataset contained many outliers (21% of the total observations across the nine microenvironments), and the roadside microenvironment had the largest fraction (17%). Time allocations and outliers are summarized in Table S2-1.

2.5.2 Time shifts due to traffic and congestion

Initial analyses using OLS regression models showed large differences between full and trimmed datasets, indicating that outliers strongly influenced results. Analysis using MM-type robust regression provided more stable estimates of time shifts, and results are displayed in Table 2-2. Estimated time shifts were mostly negative, reflecting trade-offs between travel time and time in other microenvironments. Overall, increased travel time was primarily associated with reductions in time at home, although smaller shifts were seen for workplaces and school/public buildings. The travel/home trade-off is reasonable since most people spend the largest share of their time at home (71 ± 19% for the NHAPS population) and since time at home is likely to be more elastic than time spent in other microenvironments. The following summarizes results by age group.

Children. For children ≤4 yrs of age, the home/travel time shift coefficient was large (-1.76 ± 0.21) and no other microenvironment was associated with travel time. The models explained a modest proportion of variance (R^2 = 0.24). Children spend most of their time at home (1219 ± 211 min in NHAPS). Why the coefficient exceeded one by such a large amount is puzzling. One possible reason was misclassification: adults completed the child's TAP survey and may have under-reported travel times to day care, preschool, and other locations. If so, the difference was absorbed by the home microenvironment. A comparison between final models (containing only statistically significant covariates) and "full" models (including all covariates) showed little change (<1%) in the estimated coefficients, suggesting that the results are stable and robust. Given that only one microenvironment is involved, the normalized travel time/home coefficient is simply -1, i.e., each additional minute of travel time reduces time at home by the same amount.

For children 5 to17 yrs of age, increased travel time on weekdays was associated with shifts at home (-1.05 ± 0.17), bars/restaurant (+0.30 ± 0.06) and school/public building (-0.23 ± 0.10). The fit (R^2) for these microenvironments was low, especially for school/public buildings. As shown by Levinson (1999) and Zhang (2005), the positive coefficient for bars/restaurants likely reflects trips that represent deliberate choices of the subject (or the subject's family), and thus does not represent a trade-off due to congestion. Time spent in school/public buildings was only slightly elastic, possibly because much of the school day is fixed, although there may be some trade-offs with extracurricular school activities, e.g., sports. Normalization for the home and school/public microenvironments yielded coefficients of -0.82 and -0.18 respectively. On weekends, travel time was associated with less time at home (-1.65 ± 0.20) and more time for shopping (0.23 ±0.14) and near-road (0.15 ±0.05) activities. The positive coefficient for shopping again represents a deliberate choice, not a trade-off. The positive coefficient for near-road activities might represent time waiting for rides, and also does not to appear to be a travel or congestion trade-off. As seen earlier, trade-off coefficients estimated for final and full models were close (changes<3%). Overall, additional travel time for children on weekends appeared to be displaced solely with time at home, and normalization again leads to a -1 coefficient.

Adults. Travel time shifts for adults were distributed among many microenvironments. The primary shift was between travel time and time spent at home, and estimated trade-off coefficients depended on weekend/weekday period and employment status (range from -0.68 ± 0.07 to -1.70 ± 0.21; Table 2-2). No other microenvironments were affected for working individuals on weekends, or for non-working individuals on weekdays. The other adult groups had more complex situations. For working individuals and weekday periods, travel time was associated with five microenvironments: home, workplace, school/public buildings, shopping, and other indoor microenvironments. The positive association for shopping indicates a preference choice and not a trade-off, as discussed above. The association with workplaces was consistent with Schwanen and Dijst (2002), who showed an inverse relationship between commuting time and work duration. Earlier, Kitamura et al. (1992) suggested that travel time for working individuals was proportional to the amount of non-working time. Although we obtained a negative time shift for work, these two studies suggest that this should not be attributed to travel time or congestion. The time shifts for school/public buildings and other indoor environments might be a direct trade-off because time spent in these environments is likely to be more flexible than that in mandatory activities (e.g., work, sleep and lunch/dinner), thus, these shifts are allocated to congestion. For non-working adults on weekends, travel time was associated with three microenvironments, but only the time shift with the home was a trade-off since positive coefficients for shopping and school/public buildings indicate preference choices. The coefficients of final (reduced) and full models were similar (changes were <1.5%, except for school/public buildings-travel trade-off among working adults on weekdays where the change was 10.5%).

In summary, increased travel time or congestion alters the time adults spend at home, as well as weekday activities for working adults, specifically, time spent at school and in other indoor activities. For working adults on weekends and non-working individuals on weekdays and weekends, normalized coefficients were -1 for the home. For working individuals on weekdays, normalized coefficients were -0.23 for home, -0.49 for school/public buildings and -0.28 for other indoor microenvironments.

Older adults. Only two trade-offs were seen for this group: The coefficient for the home microenvironment showed a nearly 1:1 trade-off and modest fit ($R^2 = 0.25$). Older adults spend most of their time at home (83 ± 15% in NHAPS), thus this trade-off appears reasonable. This group also showed time shifts with the near-road microenvironment, but the effect was small and marginally significant (-0.08 ± 0.04; $p = 0.06$) and may have reflected less time walking on roads due to a disability or other factor, thus this time shift seems unlikely to be due to congestion. Again, results of final and full models were similar (coefficients within 1%). Normalization gave a 1:1 travel/home trade-off for this group.

2.5.3 Benzene exposures

A recent review of benzene concentrations in a variety of microenvironments (HEI, 2007) was updated, focusing on homes, vehicle cabins (with and without congestion), workplaces, near-road and outdoor microenvironments. The existing literature is not comprehensive and often inconsistent, thus some judgment was needed to estimate hopefully realistic but not necessarily representative concentration distributions in each microenvironment.

In vehicle cabins, benzene levels from 1 to 43 $\mu g\ m^{-3}$ have been reported (Table S2-2). Many factors affect concentrations. Moderate to heavy traffic can increase benzene levels (Chan et al., 1991; Lawryk et al., 1996; Rodes et al., 1998), while a higher intake location for cabin air (away from the road and tailpipe locations) tends to decrease concentrations (Batterman et al., 2002; Fitz et al., 2003). In vehicles with defective fuel or exhaust systems, self-pollution due to vehicle emissions leaking into the cabin can cause high concentrations (Lawryk et al., 1996). Concentrations are affected by fuel composition and vehicle technology, e.g., earlier studies used non-reformulated gasoline and often older and high emitting vehicles (Chan et al. 1991; Lawryk et al., 1996), while newer studies reflect reformulated gasoline and newer emission standards (Fedoruk et al., 2003; EPA, 2007a). Other factors include traffic mix, fuel type (diesel, gasoline, ethanol, etc.), vehicle maintenance, urban background concentrations, and meteorology (Rodes et al., 1998). Overall, benzene concentrations have been decreasing (HEI, 2007).

Benzene concentrations in vehicle cabins were estimated as follows. First, the selected studies were grouped into congestion and non-congestion periods based on routes and sampling periods. Measurements taken in heavy traffic or during rush hour were considered to represent congestion conditions; those taken off-peak or with low or moderate traffic were considered to represent non-congestion conditions. The study with evident self-pollution (Lawryk et al., 1996) was eliminated. The overall weighted averages for non-congestion and congestion periods were 8.3 and 12.8 $\mu g\ m^{-3}$, respectively, and a GSD of 1.9 was taken from Loh et al. (2007).

In the near-road environment, benzene concentrations can be influenced by the distance to the road, traffic volume and composition, wind direction and speed, and other factors (Chan et al., 1991; Riediker et al., 2003; Rodes et al., 1998; Sapkota et al., 2003). A study near a tunnel entrance (Sapkota et al., 2003) was eliminated because it was not typical situation. Concentrations typically range from 1 to 7 $\mu g\ m^{-3}$ (Chan et al., 1991; Riediker et al., 2003; Rodes et al., 1998), and the weighted average was 2.8 $\mu g\ m^{-3}$. Again, the GSD of 1.9 from Loh et al. (2007) was used.

Many investigators have measured benzene in residences, as summarized by Jia et al. (2008) for several of the more recent and larger studies. Concentrations depend on many factors, including the presence of smokers, whether the residence has an attached garage, the contents of the garage, and the degree of urbanization. Typically, benzene levels in the studies averaged from 1 to 4 $\mu g\ m^{-3}$, although much higher concentrations in individual homes have been measured, e.g., benzene levels in non-smoker residences ranged from 0.5 to 10 $\mu g\ m^{-3}$ (HEI, 2007). The weighted average concentration (among studies in Table S2-2) was 2.2 $\mu g\ m^{-3}$, which is assumed to be representative. Loh et al. (2007) derived a GSD of 3.1 for benzene from studies that included residences with smokers or that were close to industrial sources. We use a GSD of 2.0 as a more typical value for non-smokers' homes.

Benzene concentrations reported for offices have typically ranged from 1 to 4 μg m^{-3}. A median concentration of 3.7 μg m^{-3} was reported by Girman et al. (1999) in the largest office building study (n > 200); an average level of 1.0 μg m^{-3} was reported by Daisey (1994). Another workplace study reported an average level of 1.0 μg m^{-3} in San Francisco (Daisey et al., 1994). Because the sample sizes of the latter two studies were unclear, we used an unweighted average which gave 2.4 μg m^{-3}. A GSD of 1.8 for this microenvironment was taken from Loh et al. (2007). These office building studies are older than most of the other studies in the scenario analysis, and the derived average concentration may slightly overestimated.

Very few studies have provided representative statistics on benzene levels in public buildings, shopping areas, bars/restaurants, and other indoor microenvironments. We assumed the same distribution as in homes (mean = 2.2 μg m^{-3}, GSD = 2.0).

Outdoors, benzene levels tend to be elevated in urban areas, primarily due to mobile source emissions (HEI, 2007), although levels can also reflect proximity to sources such as gasoline stations. Typical levels ranged from 0.5 to 3 μg m^{-3}, and a weighted average of 1.7 μg m^{-3} was calculated. A 1.6 of GSD was used, selected to match the variation at ambient monitoring sites, which shows a 10^{th} to 90^{th} percentile range of 0.5 to 2.8 μg m^{-3} (EPA, 2007b).

Table 2-3 summarizes the Monte Carlo exposure analysis and gives benzene apportionments by microenvironment for ideal, current and worst-case conditions. Typical concentrations in six microenvironments were taken from recent key studies with judgment as discussed above. The dominant exposure source in each scenario was homes and other indoor environments, which accounted for about half of the total exposure. For the congestion-free scenario, vehicle cabin exposures accounted for 10 ± 7% of the total benzene exposure; the current congestion scenario increased the share to 15 ± 8%; and the worst-case congestion scenario led to a share of 23 ± 12%. The simulation results depend on the time shift trade-offs, time allocations, concentration distributions, and breathing rates in each compartment. The sensitivity analysis showed that each 1.0 μg m^{-3} increase in cabin concentration during congestion will increase the total benzene exposure by an average of 0.5 and 1.6% for the current and worst-case scenarios, respectively. Increasing the GSD by 0.1 in each microenvironment only slightly affected results. Probabilistic and deterministic approaches (the latter considering only average concentrations) gave similar results.

2.5.4 $PM_{2.5}$ exposures

$PM_{2.5}$ concentrations in vehicle cabins depend on fuel type, vehicle characteristics (e.g., engine type, age, maintenance, and controls), air exchange rate, traffic composition and volume, meteorology, urban and background levels, and other factors. (Table S2-3 summarizes several of the larger U.S. studies and one U.K. study, included given the scarcity of U.S. studies.) Adam et al. (2001) found that $PM_{2.5}$ levels during non-congestion periods ranged from 20 to 26 μg m^{-3} and during congestion periods from 31 to 46 μg m^{-3}. Riediker et al. (2003) reported an average concentration of 23.0 μg m^{-3} in non-rush hour periods. Rodes et al. (1998) indicated that $PM_{2.5}$ levels in congestion increased slightly compared to non-congestion periods in Sacramento, but the opposite trend was seen in Los Angeles. These studies may reflect differences in the vehicle mix. The U.K. and Europe have a higher fraction of diesel-powered vehicles (many cars and most trucks), while at present there are few diesel cars in the U.S. Additionally, the volume of heavy duty trucks, nearly all of which are diesel-powered, tends to decrease during rush hour periods. Possibly the Los Angeles' results are due to the relative scarcity of (highly emitting) diesel vehicles during congestion periods. The weighted average concentrations for free-flow and congestion periods was 28.5 and 35.4 μg m^{-3}, respectively. A representative GSD could not be derived from the available studies. We chose a GSD of 1.8 both because of the measured concentration range (Table S2-3) and because the variation of in-cabin levels should exceed that of ambient levels since the former should reflect both the variation in background levels as well as on-road emissions. Given the lack of information, however, the $PM_{2.5}$ cabin concentrations are considered to be highly uncertain and not representative.

Near-road $PM_{2.5}$ levels exceed background levels by 1.1 to 1.3 times, depending on the distance to the highway and other factors (Table S2-3; WHO, 2005). Most $PM_{2.5}$ arises from background (distant) sources, e.g., power plants, and the variation among studies can be explained by urban background and varying distances to the highway. A factor of 1.2 represents a typical ratio and gives a near-road concentration of 14.3 μg m^{-3} (based on the average ambient concentration, see below). A GSD of 2.0 was chosen given the variation in the available near-road measurements.

In residences, $PM_{2.5}$ levels depend on smoking, cooking, vacuum cleaning, human activity, ventilation, season, and other factors (Monn, 2001). EPA (1996) and Monn (2001) suggest indoor/outdoor (I/O) ratios of 1 for homes without smokers, 2 for homes in areas of low ambient $PM_{2.5}$ concentrations, and 0.9 for homes in areas of high ambient $PM_{2.5}$ concentrations. Turpin et al. (2007) also found I/O ratio of 0.9 ratio using median indoor and outdoor $PM_{2.5}$ measurements in Los Angeles, CA, Houston, TX, and Elizabeth, NJ. An I/O ratio of 0.9 was selected, and a GSD of 1.9 was taken from Meng and Turpin et al. (2005).

In workplaces, $PM_{2.5}$ levels are affected by smoking, ventilation, window status (open/closed), human activity, and other indoor sources, including sources specific to the workplace. It was difficult to generalize typical levels or ratios from the literature. Many workplaces, such as offices, often have better filtration than that found in residences and fewer internal sources. Thus, we assumed an I/O ratio of 0.8 for workplaces, schools/public buildings and shopping malls. A GSD of 1.9 was chosen, matching the value for homes.

Ambient $PM_{2.5}$ concentrations in the U.S. in 2007 averaged 11.9 $\mu g\ m^{-3}$, and the 10th and 90th percentiles were 7.5 and 15.4 $\mu g\ m^{-3}$, respectively (EPA, 2008). The national annual average was considered typical; a GSD of 1.6 matched the stated range.

Table 2-4 summarizes the $PM_{2.5}$ exposure analysis for working adults. Typical $PM_{2.5}$ levels in each microenvironment reported in the literature were taken with judgment as discussed above. For the ideal, current, and worst-case congestion scenarios, exposures in vehicles accounted for 7 ± 5%, 10 ± 5%, and 15 ± 9% of the total $PM_{2.5}$ exposure, respectively. The sensitivity analysis shows that each 1 $\mu g\ m^{-3}$ increase in cabin concentration increases exposures by 0.1 and 0.4%, respectively, for the current and worst-case scenarios. Overall, traffic's contribution to $PM_{2.5}$ exposure is smaller than that for benzene, a result of the many other $PM_{2.5}$ sources that contribute to the exposure. Nonetheless, the time spent in traffic and congestion accounts for a disproportionate share of exposure, a conclusion that applies to both benzene and $PM_{2.5}$. Importantly, this analysis does not consider that vehicle exposure includes 'fresh' exhaust particles and specifically ultrafine PM of potentially greater toxicity than the 'aged' aerosols that constitute most of the $PM_{2.5}$ mass found in other microenvironments (Wang et al., 2008). Unfortunately, the literature does not yet permit a parallel assessment of ultrafine PM exposure.

2.5.5 Discussion

This paper makes two primary contributions in exposure science. It is the first study to investigate dynamic trade-offs in time allocations among different microenvironments, specifically those that arise due to traffic and congestion, which are important for understanding time budgets, behavioral changes, and pollutant exposures. Individuals compensate for an increase in travel time by spending less time at home, and sometimes at school, public buildings, and indoor-other microenvironments. These environments are selected because their time allocations are elastic. In this study, these trade-offs were derived in an indirect manner using an existing TAP dataset. Time shifts might also be derived using surveys that specifically note time spent in congestion, and that quantify differences between actual (congested) and free flow commuting time. Such 'direct' approaches must account for multipurpose trips, which constitute over half of vehicle trips during rush hour (DOT, 2006), and they must address issues of confidentiality, since respondents' homes and workplace addresses are needed to estimate free flow commuting time. Time shifts might also be estimated using longitudinal and panel sampling designs, conjoint analysis and other advanced survey techniques, although responses may not reflect actual behavior. An intriguing and potentially accurate approach that is emerging would use advanced technology (global positioning systems, cellular phones) to track the location and travel behavior of a large number of individuals. Studies specifically investigating congestion would help to validate our results.

Time shifts were estimated in a cross-sectional analysis and results were assumed to apply to small changes in transport times. While this assumption is unlikely to apply at the individual level, we assumed that it was relevant for the population and small time shifts. Clearly, this analysis is subject to a number of limitations. It implies that adaptations to avoid congestion were not utilized. Individuals often can and do alter commuting patterns (routes, mode and time of travel) to minimize travel time or to avoid congestion, although such adaptations are not always possible. In our derivation of trade-offs, individuals were assumed not to differentiate between the time spent in free flow and congestion periods, a necessity for the analysis since available TAP studies have not distinguished between these periods. While justifiable if individuals minimize total travel time, this assumption clearly has limits and is unlikely to apply to large changes. We did not consider effects from different types or severities of congestion (e.g., recurring versus unexpected congestion due to accidents), which might alter individual driving/routing decisions. We excluded several groups of individuals who did not appear to belong to a 'normal' commuting population (e.g., individuals who spent no time at home, and who have travel times exceeding 4 hrs day^{-1}).

The paper's second major contribution is to help understand the significance of traffic and, in particular, congestion, to an individual's total exposure. The benzene and $PM_{2.5}$ scenarios used fairly simple probabilistic techniques to apportion exposures among the major microenvironments. On average, travel accounts for 15 and 10% of the total benzene and $PM_{2.5}$ exposure, respectively. Long periods of congestion, e.g., 30 min day^{-1}, can significantly increase exposures due to the higher concentrations and because the compensating environments typically have lower concentrations. The high-end exposures, e.g., 90th percentile, can be considerably greater. Results depend on the pollutant, and the analysis highlighted large data gaps that preclude precise – much less representative – results. Still, results illustrate general trends. If concentrations among the different microenvironments differ markedly, even relatively small time shifts will alter exposure.

There is surprisingly little information regarding pollutant concentrations in vehicles and other microenvironments, and the lack of population-based samples may limit the generalizability of results. Many of the available studies were conducted before 2000 and may reflect higher pollutant levels than current conditions. The analysis likely underestimated the true variability of exposures since it used typical or average parameters for concentrations, durations, time shifts, and breathing rates. Further, emissions attributable to congestion will increase ambient, near-road and indoor concentrations, effects ignored in the present analysis which assumed that congestion altered time spent in different compartments, not the concentration. Accounting for increased emissions, a second order effect, would increase the significance of congestion emissions (though it may not greatly affect exposures in vehicle cabins, as shown in Tables 2-3 and 2-4).

2.5.6 Recommendations

This study highlights several limitations in the information available for estimating time allocations and exposures. First, both time allocation and exposure studies should separate transit activities into congestion and non-congestion periods. Second, longitudinal surveys and other analyses are needed to validate the travel trade-offs derived here. Third, the time trade-off and exposure models should be validated, which would increase their value to policy makers and others. This would require collecting simultaneous personal exposure and time activity data to monitor and quantify the impacts of both congestion and non-congestion periods, especially for key pollutants like benzene and $PM_{2.5}$. Finally, it would be worthwhile to examine ultrafine particles and other pollutants that are strongly associated with traffic and for which current data gaps preclude analysis.

2.6 Conclusions

A dynamic trade-off analysis was used to quantify effects of congestion on time allocations and pollutant exposures, which appears to be the first such analysis in the literature. Increased traffic and congestion alters time allocations and increases exposures to the two traffic-related air pollutants examined. Time shifts depend on an individual's age and employment status, and also show weekend/weekday effects, but most individuals adjust for time in traffic by spending less time at home. Exposures of benzene and $PM_{2.5}$ calculated for several traffic/congestion scenarios show that traffic- and congestion-related exposures can account for a significant fraction of the cumulative exposure. The analyses presented in this paper can be used to help evaluate interventions designed to reduce congestion, determine the cost-effectiveness of low-maintenance roadway and infrastructure materials that reduce congestion, and for other applications in exposure and risk assessment.

Table 2-1. Definitions of variables and percentage of respondents answering in the affirmative. Sample size = 8,297.

Variable Name	Definitions		Percent (%)
Time in microenvironment	Minutes in microenvironments		NA
Age	Individual age:	0-4 years	5.8
		5-17 years	14.5
		18-64 years	64.9
		>64 years	14.9
Sex	Male=1; Female=0		46.1
Employment	Full-time =1; other=0		44.1
status	Part-time=1; other=0		8.6
Education	High School =1; other=0		28.3
	Less than college =1; other=0		19.6
	College or Post College =1; other=0		23.6
Summer	Summer=1; other=0		26.3
Fall	Fall=1; other=0		23.0
Winter	Winter=1; other=0		25.2
Day type	Weekend=1; Weekday=0		33.7

Table 2-2. Time shift coefficients between the vehicle and other microenvironments. Results from robust regression without normalization.

Population group	Category	Home	Workplaces	Shopping	BarsRes	School/Public Bldg.	Indoor-other	Near-road	Outdoors-other
Young children[a]	Coef.	-1.76 (0.21)	-[j]	-	-	-	-	-	-
	N[i]	319	-	-	-	-	-	-	-
	R^2	0.24	-	-	-	-	-	-	-
Weekday old children[b]	Coef.	-1.05 (0.17)	-	-	0.30 (0.06)	-0.23 (0.10)	-	-	-
	N	687	-	-	112	545	-	-	-
	R^2	0.07	-	-	0.07	0.01	-	-	-
Weekend old children[c]	Coef.	-1.65 (0.20)	-	0.23 (0.14)[k]	-	-	-	0.15 (0.05)	-
	N	303	-	112	-	-	-	102	-
	R^2	0.17	-	0.05	-	-	-	0.03	-
Weekday working adults[d]	Coef.	-0.68 (0.07)	-0.51 (0.07)	0.14 (0.05)	-	-1.44 (0.20)	-0.82 (0.22)	-	-
	N	2540	1251	709	-	726	443	-	-
	R^2	0.05	0.02	0.01	-	0.1	0.16	-	-
Weekend working adults[e]	Coef.	-1.55 (0.13)	-	-	-	-	-	-	-
	N	1175	-	-	-	-	-	-	-
	R^2	0.14	-	-	-	-	-	-	-
Weekday non-working adults[f]	Coef.	-1.44 (0.14)	-	-	-	-	-	-	-
	N	620	-	-	-	-	-	-	-
	R^2	0.18	-	-	-	-	-	-	-
Weekend non-working adults[g]	Coef.	-1.68 (0.20)	-	0.27 (0.11)	-	0.47 (0.21)	-	-	-
	N	310	-	119	-	115	-	-	-
	R^2	0.18	-	0.03	-	0.03	-	-	-
Older adults[h]	Coef.	-1.12 (0.11)	-	-	-	-	-	-0.08 (0.04)[l]	-
	N	808	-	-	-	-	-	214	-
	R^2	0.25	-	-	-	-	-	0.02	-

a. Younger children (0-4 yrs of age); b. Older children (5-17 yrs of age) on weekdays;
c. Older children (5-17 yrs of age) on weekends; d. Working adults (18-64 yrs of age) on weekdays;
e. Working adults (18-64 yrs of age) on weekends; f. Non-working adults (18-64 yrs of age) on weekdays;
g. Non-working adults (18-64 yrs of age) on weekends; h. Retirees above 64; i. sample size;
j. Not statistically significant at 0.05 significant level; k.p=0.09; l.p=0.06.

Table 2-3. Estimated benzene exposures (mean and standard deviation in parentheses) for working adults on weekdays for three scenarios: no travel delay, 9 min of travel delay, and 30 min of travel delay.

Microenvironment	Concentrations	Without travel delay			With 9 min travel delay			With 30 min travel delay		
		Duration	Exposure		Duration	Exposure		Duration	Exposure	
	($\mu g\ m^{-3}$)	(min)[a]	(μg person-day $^{-1}$)	(%)	(min)	(μg person-day $^{-1}$)	(%)	(min)	(μg person-day $^{-1}$)	(%)
In-cabin - Free flow	8.3 (5.9)	36.3	2.4 (1.7)	10.5 (7.4)	27.3	1.8 (1.3)	7.5 (5.6)	6.3	0.4 (0.3)	1.6 (1.3)
In-cabin - Congestion	12.8 (9.3)	0.0	0.0	0.0	18.0	1.8 (1.3)	7.6 (5.5)	60.0	6.1 (4.4)	21.5 (12.3)
Near-road	2.8 (2.2)	61.3	1.4 (1.0)	6.1 (4.9)	61.3	1.4 (1.0)	5.8 (4.6)	61.3	1.4 (1.0)	5.3 (4.2)
Home & other Indoors	2.2 (1.6)	980.1	16.3 (12.5)	57.2 (16.8)	971.1	16.2 (12.4)	54.2 (16.6)	950.1	15.8 (12.2)	49.0 (17.0)
Workplaces	2.4 (1.5)	254.8	4.7 (3.0)	19.8 (11.5)	254.8	4.7 (3.0)	18.8 (10.9)	254.8	4.7 (3.0)	17.2 (10.1)
Outdoor	1.7 (0.8)	107.5	1.4 (0.7)	6.4 (4.0)	107.5	1.4 (0.7)	6.1 (3.7)	107.5	1.4 (0.7)	5.5 (3.4)
Total	-	1440.0	26.2 (13.1)	100.0	1440.0	27.2 (13.1)	100.0	1440.0	29.7 (13.5)	100.0

a. Average durations of each microenvironment were normalized to meet time budget of 1440 min.

Table 2-4. Estimated $PM_{2.5}$ exposures. Otherwise as Table 2-3

Concentrations	Without travel delay			With 9 min travel delay			With 30 min travel delay		
	Duration	Exposure		Duration	Exposure		Duration	Exposure	
($\mu g\ m^{-3}$)	(min)[a]	(μg person-day $^{-1}$)	(%)	(min)	(μg person-day $^{-1}$)	(%)	(min)	(μg person-day $^{-1}$)	(%)
28.5 (12.0)	36.3	8.0 (5.2)	7.3 (5.1)	27.3	6.0 (3.9)	5.4 (3.9)	6.3	1.4 (0.9)	1.2 (0.9)
35.4 (15.5)	0.0	0.0	0.0	18.0	5.0 (3.2)	4.5 (3.2)	60.0	16.7 (10.6)	13.7 (8.4)
14.3 (11.3)	61.3	6.8 (5.4)	6.2 (5.0)	61.3	6.8 (5.4)	6.0 (4.8)	61.3	6.8 (5.4)	5.7 (4.5)
10.7 (7.8)	980.1	82.5 (61.4)	60.5 (15.6)	971.1	81.7 (60.9)	58.8 (15.6)	950.1	79.9 (59.5)	55.2 (15.9)
9.5 (7.1)	254.8	19.3 (14.4)	16.7 (10.6)	254.8	19.3 (14.4)	16.2 (10.3)	254.8	19.3 (14.4)	15.5 (9.9)
11.9 (5.9)	107.5	10.0 (5.0)	9.3 (5.6)	107.5	10.0 (5.0)	9.1 (5.4)	107.5	10.0 (5.0)	8.6 (5.1)
-	1440.0	126.7 (63.8)	100.0	1440.0	128.9 (63.3)	100.0	1440.0	134.2 (62.8)	100.0

a. Average durations of each microenvironment were normalized adjusted to meet time budget of 1440 min.

Table S2-1. Descriptive statistics of time allocations for NHAPS by age groups.

Continuous Variables	No. of Response[a]	Mean	SD[b]	Min[c]	P25[d]	Median	P75[e]	Max[f]	No. of Outliers[g]
The total population									
Home (min)	8297	1018.8	269.5	30.0	810.0	1005.0	1250.0	1440.0	5
Workplaces (min)	1697	401.6	228.5	1.0	210.0	495.0	555.0	1037.0	0
Shopping (min)	2391	116.5	143.5	1.0	30.0	60.0	135.0	1080.0	241
Bars or restaurants (min)	1926	113.5	135.8	1.0	40.0	60.0	120.0	925.0	210
School/public bldg. (min)	2624	277.9	202.0	1.0	100.0	235.0	435.0	1015.0	7
Indoor-other (min)	982	209.8	216.6	1.0	55.0	120.0	337.0	1040.0	107
Near road (min)	2437	80.3	141.5	1.0	10.0	30.0	65.0	985.0	411
Outdoor-other (min)	3508	190.4	186.3	1.0	60.0	125.0	275.0	1290.0	378
In a vehicle (min)	6762	76.4	51.8	1.0	35.0	64.0	105.0	240.0	460
Age less than 4 (inclusive)									
Home (min)	478	1219.4	211.2	285.0	1080.0	1265.0	1410.0	1440.0	3
Workplaces (min)	10	26.9	19.6	5.0	10.0	22.5	40.0	60.0	0
Shopping (min)	106	91.0	78.7	5.0	40.0	65.0	110.0	420.0	9
Bars or restaurants (min)	57	62.8	48.8	4.0	35.0	55.0	80.0	330.0	1
School/public bldg. (min)	96	212.3	195.8	1.0	59.0	149.5	352.5	900.0	1
Indoor-other (min)	25	95.3	77.1	10.0	25.0	85.0	160.0	270.0	0
Near road (min)	96	45.5	59.2	1.0	10.0	30.0	60.0	420.0	6
Outdoor-other (min)	223	202.5	170.3	1.0	85.0	145.0	300.0	980.0	7
In a vehicle (min)	319	61.6	49.4	1.0	30.0	45.0	80.0	240.0	20
Age between 5 and 17 (inclusive)									
Home (min)	1199	995.2	229.7	190.0	835.0	970.0	1165.0	1440.0	4
Workplaces (min)	29	132.8	179.0	1.0	10.0	40.0	195.0	625.0	3
Shopping (min)	246	84.0	88.8	1.0	20.0	60.0	120.0	530.0	12
Bars or restaurants (min)	188	68.0	65.3	2.0	30.0	45.0	85.0	360.0	16
School/public bldg. (min)	708	361.9	152.7	1.0	275.0	400.0	440.0	935.0	16
Indoor-other (min)	118	131.9	147.7	1.0	40.0	93.5	160.0	910.0	7
Near road (min)	507	47.3	70.7	1.0	10.0	22.0	50.0	540.0	58
Outdoor-other (min)	701	193.5	177.0	1.0	65.0	145.0	265.0	1250.0	33
In a vehicle (min)	990	65.3	47.0	1.0	30.0	55.0	90.0	240.0	24
Age between 18 and 64 (inclusive)									
Home (min)	5385	965.8	268.7	30.0	765.0	917.0	1185.0	1440.0	3
Workplaces (min)	1548	427.3	215.3	1.0	300.0	505.0	561.5	1037.0	2
Shopping (min)	1681	128.4	159.7	1.0	30.0	60.0	150.0	1080.0	188
Bars or restaurants (min)	1449	124.6	148.0	1.0	40.0	65.0	135.0	925.0	160
School/public bldg. (min)	1478	271.4	218.2	1.0	90.0	195.0	460.0	1015.0	0
Indoor-other (min)	739	236.4	230.8	1.0	60.0	125.0	432.0	1040.0	1
Near road (min)	1529	97.7	166.3	1.0	10.0	30.0	75.0	985.0	228
Outdoor-other (min)	2072	191.7	192.5	1.0	50.0	120.0	280.0	1130.0	82
In a vehicle (min)	4645	80.3	52.2	1.0	40.0	70.0	110.0	240.0	90
Age greater than 65 (inclusive)									
Home (min)	1235	1195.3	212.4	60.0	1060.0	1230.0	1380.0	1440.0	5
Workplaces (min)	110	144.7	196.1	1.0	10.0	32.5	210.0	705.0	6
Shopping (min)	358	90.5	91.4	1.0	30.0	60.0	120.0	655.0	19
Bars or restaurants (min)	232	93.8	93.6	3.0	45.0	60.0	105.0	750.0	21
School/public bldg. (min)	342	150.5	127.4	5.0	60.0	115.5	195.0	710.0	24
Indoor-other (min)	100	134.0	138.1	2.0	45.0	80.0	162.5	610.0	13
Near road (min)	305	58.8	89.2	1.0	10.0	30.0	60.0	560.0	28
Outdoor-other (min)	512	176.1	179.3	1.0	45.0	120.0	262.5	1290.0	17
In a vehicle (min)	808	73.3	52.5	4.0	30.0	60.0	100.0	240.0	24

a. The number of respondent who spent at least 1 minute in the corresponding microenvironment.

b. Standard deviation; c. minimum values; d. 25th percentile values; e. 75th percentile values; f. Maximum values;

g. The number of outliers according to Tukey 1.5 IQR criteria.

Table S2-2. Summary of benzene concentrations in major microenvironments (Those in bold have been selected; unit: µg m^{-3})

Category	Sduty	Area	Sample size	Concentrations(µg m^{-3})					Note
				Min	Mean	Median	Max	SD	
In-cabin in non-congestion	Batterman et al. (2002)	Detroit, MI	74	-	**4.5**[a]	-	10.8	3.0	Bus commutes
	Chan et al.(1991)	Raleigh, NC	17	-	-	**10.8**	-	6.9	Urban traffic; in morning
			18	-	-	**9.1**	-	6.9	Urban traffic; in evening
	Fedoruk et al. (2003)	Los Angeles, CA	1	-	**2.4**	-	-	-	Moderate heat / static to 90-min driving condition
	Fedoruk et al. (2003)	Foxboro, MA	3	-	**1.9**	-	-	-	Moderate heat / static conditions
	Fedoruk et al. (2003)	Foxboro, MA	3	-	**10.0**	-	14.0	5.8	Extreme heat / static conditions
	Fitz et al. (2003)	Sacramento, CA	20	-	-	-	9.5[c]	-	Bus commutes
	Lawryk et al. (1996)	New Jersey	32	-	16.2[b]	-	-	19.5	Mean speed=72kph
	Riediker et al. (2003)	Raleigh, NC	25	-	**12.8**	-	43.1	10.2	
	Rodes et al. (1998)	Sacramento, CA	29	5.7	**6.5**	-	7.4	-	Freeway non-rush hours
		Los Angles, CA	29	13.8	**14.4**	-	15.1	-	Freeway non-rush hours
In-cabin in congestion	Chan et al.(1991)	Raleigh, NC	18	-	-	**11.6**	-	6.9	Interstate higway traffic; in morning
			16	-	-	**15.9**	-	6.9	Interstate higway traffic; in evening
	Lawryk et al. (1996)	New Jersey	32		26.4	-	-	27.1	Mean speed= 16 kph
	Rodes et al. (1998)	Sacramento, CA	29	7.4	**10.3**	-	13.9		Freeway rush hours
		Los Angles, CA	29	9.8	**14.4**	-	21.9		Freeway rush hours
Near-road	Chan et al.(1991)	Raleigh, NC	6	-	**6.8**	7.1	8.9	1.5	Sidewalk
	Riediker et al. (2003)	Raleigh, NC	25	-	**0.6**	-	2.6	1.0	Near major traffic routes
	Rodes et al. (1998)	Sacramento, CA	20	1.5	**1.9**	-	5.9	-	Downwind distance to road: 3-10m
		Los Angles, CA	20	0.0	**5.4**	-	20.0	-	Downwind distance to road: 3-10m
	Sapkota et al. (2003)	Baltimore, MD	56	-	12.7	-	33.0	8.2	Tunnel roadside
Home	Adgate et al. (2004a)	Minneapolis,MN	282	-	4.6	**3.3**	12.7[d]	0.3	Screening-phase
	Adgate et al. (2004a)	Minneapolis,MN	101	-	3.9	**3.1**	7.5[d]	0.3	Intensive-phase
	Adgate et al. (2004b)	Minneapolis,MN	88	-	-	**2.1**	7.2[e]	-	Spring
	Adgate et al. (2004b)	Minneapolis,MN	93	-	-	**2.2**	6.2[e]	-	Winter
	CARB (1992)	Woodland, CA	104	-	-	**2.2**	8.3[e]	-	
	Jia et al. (2008)	Southeast MI, U.S.	252	-	2.8	**1.2**	47.4	-	
	Mukerjee et al. (1997)	Brownsville, TX	9	-	-	**2.4**	-	-	
	Payne-Sturges et al. (2004)	Baltimore, MD	33	-	**3.7**	-	8.3[e]	-	
	Phillips et al. (2005)	Oklahoma, Tulsa, Ponca and Stillwater, OK	40	-	**0.6**	-	14.0	-	Day
	Phillips et al. (2005)		40	-	**1.2**	-	110.0	-	Night
	Sax et al. (2004)	Los Angles, CA	40	-	**2.5**	-	6.3	1.3	Fall
	Sax et al. (2004)	Los Angles, CA	32	-	**4.9**	-	17.0	2.8	Winter
	Sax et al. (2004)	New York, NY	30	-	**1.7**	-	6.3	1.2	Summer
	Sax et al. (2004)	New York, NY	36	-	**5.3**	-	39.0	6.5	Winter
	Sexton et al. (2004)	Minneapolis/St Paul metro, MN	292	-	5.8	**1.9**	15.3[e]	-	
	Van Winkle et al (2001)	Chicago, IL	48	-	4.1	**2.9**	34.0	4.8	
	Weisel et al. (2005)	Los Angles, CA; Houston, TX and Elizabeth NJ	554	-	3.5	**2.2**	36.4	5.2	
School	Adgate et al. (2004a)	Minneapolis,MN	47	-	-	**0.6**	1.0[e]	-	Spring
	Adgate et al. (2004a)	Minneapolis,MN	39	-	-	**0.6**	1.6[e]	-	Winter
	Godwin et al. (2007)	Southeat MI	65	-	**0.1**	-	1.6	-	
	Whitmore et al. (2003)	CA	73	-	**1.8**	-	4.1[d]	-	
Office	Daisey et al. (1994)	San Francisco, CA	-	-	**1.0**	-	2.7	-	
	Girman et al. (1999)	U.S.	>200	0.6	-	**3.7**	17.0	-	
Ambient	Adgate et al. (2004b)	Minneapolis,MN	10	-	-	**1.1**	1.6[e]	-	Spring
	Adgate et al. (2004b)	Minneapolis,MN	8	-	-	**1.3**	2.2[e]	-	Winter
	CARB (2003)	Barrio Logan, CA	69	-	**3.2**	-	10.0	-	
	CARB (2003)	Boyle Heights, CA	74	-	**3.9**	-	22.0	-	
	CARB (2003)	Crockett, CA	81	-	**0.1**	-	1.9	-	
	CARB (2003)	Fresno, CA	65	-	**1.8**	-	8.2	-	
	CARB (2003)	Fruitvale, CA	83	-	**2.0**	-	7.5	-	
	CARB (2003)	Wilmington, CA	60	-	**2.2**	-	9.5	-	
	EPA (2007b)	U.S.	152	-	**1.5**	-	6.1[c]	-	
	Jia et al. (2008)	Southeast MI	226	-	**1.1**	-	4.4	-	
	Kinney et al. (2002)	New York, NY	35	-	**1.3**	-	-	1.0	Summer
	Kinney et al. (2002)	New York, NY	36	-	2.6	**0.9**	-	1.4	Winter
	Mohamed et al. (2002)	13 sites, LA, TX VT and NJ	30	-	-	-	4.1[c]	-	
	Payne-Sturges et al. (2004)	Baltimore, MD	33	-	**1.8**	-	3.1[e]		
	Riediker et al. (2003)	Raleigh, NC	50	-	0.3	**1.8**	2.0	0.6	
	Rodes et al. (1998)	Sacramento, CA	12	-	-	-	2.9[c]	-	Samples taken during commuting times
	Rodes et al. (1998)	Los Angles, CA	16	-	-	-	6.6[c]	-	Samples taken during commuting times
	Sexton et al. (2004)	Minneapolis/St Paul metro, MN	132	-	**1.6**	-	3.3[e]	-	
	SCAQMD (2000)	South coast, CA	60	-	**3.3**	-	-	-	
	Weisel et al. (2005)	Los Angles, CA; Houston, TX and Elizabeth NJ	555	-	2.2	**1.7**	11.1	2.1	
	Zielinska et al. (1998)	AZ	250	-	-	-	39.0	-	Several urban and rural areas

a. The bold numbers were chosen in calculating wegihted averages; b The unbold numbers indicated the studies were eliminated;
c. Maximum average; d. 95th percentile; e. 90th percentile.

Table S2-3. Summary of $PM_{2.5}$ concentrations in major microenvironments (Those in bold have been selected; unit: μg m^{-3})

Category	Sduty	Area	Sample size	Concentrations(μg m^{-3})					Note
				Min	Mean	Median	Max	SD	
In-cabin in non-congestion	Riediker et al. (2003)	Raleigh, U.S.	25	6.8	**23.0**	-	58.7	10.8	
	Rodes et al. (1999)	Sacramento, U.S.	29	12.2	**14.4**	-	16.6	-	Freeway non-rush hours
		Los Angles, U.S.	29	50.5	**54.7**	-	59.0	-	Freeway non-rush hours
	Adams et al. (2001)	London, UK	26	9.3	-	**26.3**	46.6	-	Summer
			18	5.9	-	**20.1**	80.3	-	Winter
In-cabin in congestion	Rodes et al. (1999)	Sacramento, U.S.	29	3.9	**14.7**	-	21.8	-	Freeway rush hours
		Los Angles, U.S.	29	36.1	**45.4**	-	56.0	-	Freeway rush hours
	Adams et al. (2001)	London, UK	45	14.3	-	**45.6**	97.4	-	Summer
			37	6.6	-	**31.5**	94.4	-	Winter
Near-road	Riediker et al. (2003)	Raleigh, U.S.	25	8.9	**29.9**	-	62.3	12.7	Near major traffic routes
	Rodes et al. (1999)	Sacramento, U.S.	20	0.0	**9.6**	-	19.9	-	
		Los Angles, U.S.	20	35.3	**44.7**	-	76.0	-	
	Levy et al. (2003)	Roxbury, U.S.	307	-	**52.0**	54.0	-	22.0	
	Reponen et al (2003)	Cincinnati, U.S.	24	-	**22**	-	-	14.0	80m from highway
Home	Meng et al (2005)	Los Angles, CA; Houston, TX and Elizabeth NJ	-	-	**17.6**	**14.4**	-	12.6	
Ambient	EPA (2008)	U.S.	-	-	**11.9**	-	-	-	Based on 774 sites

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Chapter 3

Vehicle Emissions in Congestion: Comparison of Work Zone, Rush Hour and Free-flow Conditions

3.1 Abstract

Traffic congestion frequently occurs during rush hour periods and in work zones, and it can account for a significant share of vehicle emissions and air quality impacts. This study estimates vehicle emissions from light-duty vehicles (LDVs) and heavy-duty vehicles (HDVs) in work zone and rush hour congestion, which are compared to emissions under free-flow traffic conditions. Field experiments collected second-by-second vehicle speed and acceleration data on typical weekdays along a freeway segment that experienced both rush hour and work zone congestion. Collected data were smoothed and then simulated using the Comprehensive Modal Emissions Model (CMEM) to generate second-by-second emissions. For LDVs, the transitional period between free-flow and congestion conditions was associated with the highest emission rates when expressed as g mi^{-1} $vehicle^{-1}$ of hydrocarbon (HC), carbon monoxide (CO) and nitrogen oxide (NO_x); the lowest emission rates were associated with low speed work zone congestion. In contrast, work zone congestion consumed the most fuel and produced the most carbon dioxide (CO_2), while rush hour congestion consumed the least fuel and yielded the lowest CO_2 emissions. Results for HDVs differed in that work zone congestion was associated with the highest emissions of HC, CO and CO_2, as well as the highest fuel consumption, while NO_x emission rates were similar under the different traffic conditions. However, considering aggregated or link-based emissions, the emission density estimates expressed as g mi^{-1} s^{-1} show rush hours had the highest rates of HC, CO and CO_2 emissions, as well as fuel consumption. The differences between congestion and free-flow conditions highlight the importance of accounting for

congestion in emission, exposure and health risk evaluations, as well as transportation planning.

3. 2 Keywords

Air quality; CMEM; Congestion; Fuel consumption; Vehicle emissions; Work zone.

3.3 Introduction

Increased traffic in urban transportation networks in recent years has led to widespread traffic congestion, which has now become nearly ubiquitous in many urban areas (Schrank and Lomax, 2007; World Bank, 2006). Since 1980, for example, urban vehicle-miles traveled (VMT) in the U.S. grew 40% faster than urban capacity (BTS, 2006). Such growth in traffic demand and the congestion that results not only affects the mobility of travelers, but also increases vehicle emissions of carbon monoxide (CO), carbon dioxide (CO_2), volatile organic compounds (VOCs) or hydrocarbons (HCs), nitrogen oxides (NO_x), and particulate matter (PM). Emissions increase as vehicles spend more time in congestion, idling or crawling, and undergoing numerous acceleration and deceleration events. While vehicle emission data are available in emission inventories and other datasets that have been compiled for many areas, these data are usually based on models that do not explicitly account for congestion. Information regarding emissions, as well as near-road concentrations, exposures and health risks that pertain to congestion, is very limited.

Vehicles are the dominant source of many air pollutant emissions in urban areas (TRB, 2002), and congestion has the potential to significantly worsen ambient air quality, particularly near major roadways. Impacts due to vehicle emissions have been receiving increasing attention, and many recent epidemiological studies show elevated risks of non-allergic respiratory morbidity, cardiovascular morbidity, cancer, allergic illnesses, adverse pregnancy and birth outcomes, and diminished male fertility for drivers, commuters and individuals living near roadways (WHO, 2005). For a typical working adult, we have previously estimated that a 30 min day^{-1} travel delay accounts for 21 ± 12% of the total daily benzene exposure and 14 ± 8% of $PM_{2.5}$ exposure (Zhang and Batterman, 2009). Means to reduce congestion-related impacts on exposures and health risks are being investigated, including congestion pricing and traffic controls. As examples: in Stockholm, congestion pricing in the center city is estimated to avoid 20-25 deaths annually in the inner city and 25-30 deaths annually in the metropolitan area (Eliasson et al., 2009); and in London, congestion pricing is predicted to gain 183 years of life per 100,000 population in the congestion charging zone, and 1,888 years of life in the greater London area (Tonne et al., 2008).

The aim of this paper is to investigate effects of congestion on vehicle emissions and fuel consumption. We present results of a field study that measured second-by-second speed on a highway segment in which congestion events were caused by both work zone and rush hour activities. After providing some background on traffic congestion and vehicle emissions, we describe field study design, emission models, and data analysis methods. The results and discussion present the measured speed and acceleration data, predicted emission rates from CMEM as well as a standard constant-speed emission model, the application of these models in several case studies, and a sensitivity analysis. The conclusions summarize results and suggest further research needs.

3.4 Background

3.4.1 Traffic congestion and emissions

Traffic congestion occurs when vehicle volume exceeds road capacity, which slows vehicle speeds, sometimes to a crawl or stop. The primary causes of congestion include physical bottlenecks (40% of cases in the U.S.), traffic incidents (25%), work zones (10%), weather (15%), traffic control devices (5%), special events (5%), and fluctuations in normal traffic (CAMSYS and TTI, 2005).

Pollutant emissions in congestion, especially in work zones, have received only a limited amount of attention, although a few experimental studies have been conducted. Sjodin et al. (1998) showed an up to 4-fold increase in CO emissions, a 3-fold increase in HC emissions, and a 2-fold increases of NO_x emissions with congestion (average speed, 13 mph) compared to uncongested conditions (average speed, 38-44 mph). De Vlieger et al. (2000) indicated that CO, HC and NO_x emissions and fuel consumption of passenger cars in rush hour increased 10%, 10%, 20% and 10%, respectively, compared to smooth conditions, and the changes in emissions and fuel consumption varied by vehicle and road type. Frey et al. (2001) used on-board measurements of CO, NO and HC, and found that emissions increased by 50% in congestion. Using dynamometer tests and a driving cycle with more acceleration and a higher average speed than the U.S. EPA's standard Federal Test Procedure (FTP), CO, HC and NO_x emissions exceeded FTP results by factors of 4, 2 and 2, respectively (Department of Transport and Regional Services, 2001). Anderson et al. (1996) found that congestion increased CO, HC and NO_x emissions by 71%, 53% and 4% respectively, compared to free-flow conditions. Bushman et al. (2008) estimated CO, NO_x and HC emissions rates for cars and trucks due to travel delay caused by a work zone. Kendall (2004) and Zhang (2009) used a traffic model (the Kentucky User Cost Program version 1.0, KyUCP) to estimate the average speed in work zones, which then was used to estimate emissions using the Motor Vehicle Emissions Factor Model version 6.2 (MOBILE6.2). However, both the idling emission factors provided by EPA and the MOBILE6.2-derived emission factors used incompletely represented work zone conditions, which included periods of acceleration, deceleration, and idling, as well as some medium speeds. Overall, these studies suggest that congestion elevates vehicle emissions, but that there is considerable uncertainty in quantifying changes due in part to the specific test vehicles tested and differences in traffic conditions.

Emission models based on average speeds do not explicitly account for congestion since they do not incorporate input parameters that describe the presence or nature of congestion (Smit et al., 2008). In contrast, driving pattern-based emission models can account for congestion by specifying instantaneous speed and acceleration/deceleration profiles as model inputs. Such models require extensive input data and are not yet widely used. Details of both modeling approaches are described in the following emission modeling section.

The lack of information regarding congestion-related emissions is an important gap in our understanding of vehicle emissions, especially given the growing frequency and severity of congestion. The relationship between congestion and vehicle emissions is complex (TRB, 2002) and the studies discussed previously show considerable variability. It is clear that improvements in both fuels and vehicle technology, such as low sulfur fuels and 3-way catalytic converters, have substantially reduced emissions on an individual vehicle basis. However, overall emissions may increase due to rapid growth in vehicle miles traveled (VMT) and congestion (Nam et al., 2002; Panis et al., 2006; Smit, 2006). Emission rates depend on vehicle characteristics (e.g., model year, engine, fuel type, and maintenance) and the distributions of speed and acceleration, which in turn depend on road type, traffic flow and other factors (TRB, 2002). In congestion, driving patterns are altered, and the norm in stop-and-go traffic is frequent acceleration and deceleration (Cappiello, 2002; Smit, 2006; TRB, 2002). Acceleration increases the load on engines, and engines operated under load in a fuel-rich and high emission mode can overload catalytic converters (TRB, 1995), which increases CO and HC emissions. NO_x emissions are less likely affected since these are maximized under high temperatures and fuel-lean modes (TRB, 1995). In addition, PM and HC emissions can increase under deceleration due to the presence of unburned fuel (Cappiello, 2002).

3.4.2 Emission modeling

Vehicle emissions are commonly estimated using so-called "macroscopic" emission models, such as MOBILE6.2 that are based on standardized driving cycles intended to represent typical driving patterns along major types of roads (e.g., freeways, arterials, ramps, and local roads; EPA, 2003; Pierce et al., 2008). Pollutant emissions are estimated from measurements on test vehicles subjected to specific driving cycles as simulated on a chassis dynamometer. Emissions associated with specific traffic conditions are then derived by accounting for differences between the desired average traffic speed and other environmental parameters and those associated with the standardized driving cycle. MOBILE6.2 and other macroscopic models are widely used in emission inventory and other regional applications. However, the use of such models to estimate emissions for specific roadways has been criticized. These models do not consider the full range of driving patterns that may be encountered (Joumard et al., 2000). Since emissions are based on an average speed in fixed driving cycles, there is only limited ability to consider alternate driving patterns. While different driving cycles can produce identical average speeds, emissions depend strongly on the specific acceleration and deceleration patterns. Actual emissions can thus be significantly underestimated since acceleration, deceleration and aggressive driving patterns are not fully represented (Joumard et al., 2000). In addition, idling emissions in MOBILE6 are not based on idle testing, but rather on emission rates measured at a speed of 2.5 mph. Overall, macroscopic models may inaccurately estimate emissions associated with congestion for specific road segments and traffic conditions (Smit et al., 2008).

"Microscopic" models provide an alternative and in some ways ideal approach to estimate vehicle emissions in congestion and other driving conditions. Models such as the Comprehensive Modal Emissions Model (CMEM; Scora et al., 2006) and the new EPA Motor Vehicle Emission Simulator (MOVES; EPA, 2009) can estimate emissions for temporal scales ranging from second to hours, and for specific vehicles to vehicle fleets. Microscopic models explicitly account for idling, accelerating, cruising and decelerating engine operating conditions, and then they simulate second-by-second speed and power fluctuations of vehicles on a road network. Temporal and vehicular aggregations are necessary since these models are designed to predict emissions for vehicle categories (Scora et al., 2006). On the downside, microscopic models tend to be data and computationally intensive (Cappiello, 2002).

3.5 Methods

3.5.1 Field study

Instantaneous traffic speed and position data were collected on a 5 mile segment of Interstate 94 in Ann Arbor, Michigan, selected for both convenience and because it had a nearby permanent traffic recorder (PTR) operated by the Michigan Department of Transportation (MDOT; Figure 3-1). The portion of the segment west of US-23 had two lanes in each direction; the segment east of US-23 had three lanes in each direction. The east- and west-bound annual average daily traffic (AADT) and volumes for these segments were 78,300 and 91,300 vehicles day^{-1}, respectively; the commercial average daily traffic (CADT) volumes were 8,000 and 8,900 vehicles day^{-1} (MDOT, 2008). Heavy diesel trucks accounted for nearly 10% of the total traffic. The east-bound traffic volumes measured during the field study averaged 3099, 2153 and 4040 vehicles hr^{-1} (vph) during morning, midday and evening periods, respectively (work zone period excluded). A 70 mph speed limit is posted for passenger cars on the freeway segment, and 60 mph for trucks. On two study days (Sept. 24 and 25, 2008), one east-bound lane was closed from 9 am to 3 pm for road maintenance, leaving two lanes merging to one on the east-bound direction, and three lanes merging to two on the east-bound direction. The resulting work zone congestion lowered average speeds from 70 mph for cars and 63 mph for trucks to 21 mph; east-bound traffic volumes decreased only slightly, from 2153 to 1961 vph.

Data were collected on Tuesdays, Wednesdays and Thursdays to better reflect weekday traffic patterns and to avoid weekend effects on three consecutive weeks in fall 2008: September 16-18, September 23-25, and September 30-October 2. Data were collected during morning (7:00-9:00) and evening rush hour periods (16:00-18:00), and a mid-day comparison period (11:00-13:00). Speed and acceleration data were collected by repeatedly driving a vehicle back and forth on the freeway segment using the floating car technique. This technique, frequently used in traffic studies, is designed to characterize average vehicle speed and acceleration profiles (Dion, 2007). This protocol involves passing as many vehicles as those that passed the test vehicle. Given that behaviors of cars and (large) trucks can differ significantly, separate profiles were obtained for cars and trucks by following them separately. In each 2-hr study period, the test vehicle typically made 5 to 9 runs along the segment and covered 34 to 63 miles, depending on the time of day and the amount of congestion encountered.

Two test cars were used: a 2001 Ford Taurus with 25,000 miles (weeks 1 and 2); and a 2005 Ford Taurus four-door sedan with 40,000 miles (week 3). Both cars were rented from the University of Michigan's fleet and were in good operating condition. Vehicle speed and location were determined every 1 s using a GPS unit (GPS18 USB receiver, Garmin Inc., Olathe, Kansas, US) placed on the car's roof to improve signal quality. The receiver was linked to a laptop via Garmin nRoute software, which stored speed profiles and location information on a second-by-second basis.

3.5.2 CMEM emission modeling and response surface analyses

The microscopic model used in this research, the Comprehensive Modal Emissions Model (CMEM), is a physically-based, power-demand model (Scora et al., 2006). The latest version of the model (version 3.0) predicts fuel consumption and emissions of CO, HC, NO_x and CO_2 in different modes of vehicle operation, e.g., idle, cruise, acceleration and deceleration, and includes two similarly structured sub-models for light-duty vehicles (LDVs) and heavy-duty diesel vehicles (HDVs). Each submodel is composed of six modules: engine power demand, engine speed, air/fuel ratio for LDVs or engine control unit for HDVs, fuel rate, engine-out emissions, and catalyst pass fraction for LDVs or after-treatment pass fraction for HDVs. CMEM has been calibrated using data from the National Cooperative Highway Research Program, which includes both engine-out and tailpipe emissions of CO, HC, NO_x and CO_2 for over 400 vehicles in 35 vehicle/technology categories. The model's inputs include traffic composition, vehicle and operation variables, e.g., speed, acceleration, and road grade, and model-calibrated parameters, e.g., cold start coefficients and engine friction.

To show the sensitivity of CMEM to inputs, CMEM predictions for all possible speed and acceleration combinations were visualized using a response surface analysis (also called emission map). Emissions were predicted over an evenly spaced grid of 80 speed categories (1 to 80 mph, every 1 mph) and 81 deceleration/acceleration classes (-4 to 4 mph s^{-1}, every 0.1 mph s^{-1}). Contour plots of the resulting emission factors were generated using R 2.7.2 (RFSC, 2008) and Matlab 7.8 (R2009a, MathWorks, Inc., Natick, MA).

3.5.3 Emission estimates for the case study

Link-based emissions, defined as emissions per distance traveled, were estimated for cruise, congestion and other traffic flow conditions using the second-by-second field data. This analysis was restricted to the 147 east-bound trips conducted on I-94 because only trips in this direction experienced both work zone and rush hour congestion. Estimating emissions involved the following steps: (1) Vehicle speed and position data collected on the initial and the final 800 m portions of the segment were excluded to avoid ramp effects given that our primary goal was to capture speed/acceleration profiles on the freeway. (2) Speed and position data were checked to identify errors and outliers using criteria proposed by Dion (2007), which defined valid ranges for acceleration or deceleration for various speed intervals, and any errors or outliers detected were replaced by linear interpolations. (3) Observed speeds were smoothed using three second equal-weight moving averages (Dion, 2007), a step taken because GPS data can includes errors, e.g., signal loss and poor electrical contact between the receiver and the laptop. (4) Acceleration/deceleration was calculated as the difference between adjacent speed values in successive one-second intervals. (5) Speed/acceleration profiles for each trip were aggregated for analysis. Initially, profiles were grouped by trip average speed, followed vehicle type (LDV or HDV), and time of day (morning, midday, afternoon), giving 21 categories (shown in Table S3-1). We analyzed emission rates for each speed bin, and then, according to the variations among different speed bins, we further aggregated results by vehicle type and four traffic conditions, primarily indicated by trip average speed: speeds exceeding the speed threshold (65 mph for LDV, 60 mph for HDV) were considered as free-flow conditions; speeds just below the speed threshold (60 to 65 mph for LDVs, 55 to 60 mph for HDVs) were considered as transitional conditions; speeds well below the speed threshold (50 to 60 mph for LDVs, 39 to 55 mph for HDVs) and occurring during peak commuting times were considered as rush hour congestion; and lane closures resulting in low speeds (15 to 25 mph for both LDVs and HDVs) were considered as work zone congestion. (6) Descriptive statistics of speed and acceleration were calculated for each grouping. (7) Emissions for each category were calculated using CMEM simulations of the second-by-second speed and acceleration data.

For further analysis of the speed/acceleration profiles, we calculated and plotted the joint probability distribution of the second-by-second speed and acceleration data using 1 mph speed bins (0 to 80 mph) and 0.1 mph s^{-1} acceleration bins (-4 to 4 mph s^{-1}) in seven groups: LDVs and HDVs in the morning, midday and evening periods, and work zone periods. We also evaluated an alternative and possibly simpler approach to estimate emissions, which also provided insight into the speed/acceleration – emissions relationship. Emissions were estimated using the joint probability matrix representing the speed and acceleration data, which was multiplied by the CMEM response surface matrix representing CMEM outputs, and then divided by total travel miles. This approach is demonstrated for selected scenarios, e.g., 70 - 75 mph speed range for LDVs at midday.

A sensitivity analysis was conducted to examine the effect of averaging time (or smoothing) for the speed/acceleration data. This analysis simulated emissions for LDVs for two speed ranges (20-25 and 70-75 mph, both at midday), and for HDVs using similar speed ranges (20-25 and 60-65 mph, again at midday). Running averages using 1, 2, 3, 5, 10, 50, 100 and 500 second intervals were derived from the cleaned data and imputed data, but without smoothing. Emissions were estimated using CMEM simulations at each averaging time.

The link-based emission density (g mi^{-1} s^{-1}), an indicator of emission intensity relevant to predicting near-road concentrations, was estimated using CMEM estimates for free-flow, rush hour and work zone conditions as the product of the emission factor (g mi^{-1} vehicle^{-1}) and the traffic volume (vehicles s^{-1}). We grouped both transitional and rush hour congestion periods into the rush hour period to obtain values typical of rush hour periods, e.g., 4 to 6 pm. The calculation used estimated emission rates for LDVs and HDVs in this study and the time-specific east-bound traffic composition, namely, 8% HDVs and 92% LDVs at rush hour and 15% HDVs and 85% LDVs at midday, based on PTR counts in October, 2007. (Classification data for the same period in 2008 were unavailable). Traffic volumes used measurements for the segment corresponding to the same periods.

3.5.4 Comparative analyses between CMEM and MOBILE6.2

Emission estimates were calculated for LDVs and HDVs using CMEM and MOBILE6.2 assuming a constant average speed. For MOBILE6.2, annual average emission factors were estimated using the average vehicle speed, the average of summer and winter emission factors, local estimates of vehicle age distributions, fuel sulfur and oxygenate contents (SEMCOG, 2006), and two vehicle categories (light duty gasoline vehicle, LDGV; and heavy duty diesel vehicle, HDDV). CMEM's vehicles categories, which differ from those in MOBILE6.2, use 26 categories for LDVs, broken down by vehicle technology, model year and mileage, weight and fuel (Scora et al., 2006). Total LDV emissions were estimated using eight of these categories and the weights in Table 3-1, which were based on local vehicle age distribution (SEMCOG, 2006) and the Tier 1 and Tier 2 phase-in implementation schedules (1994 – 1997 for Tier 1 and 2004 – 2009 for Tier 2) (EPA, 2000a, 2000b). CMEM did not include HDVs produced after the 2002 model year, and thus we chose the 1998-2002 HDV category, thus both older and newer trucks were not considered. These LDV and HDV categories were assumed to be roughly equivalent to the LDGV and HDDV categories used in MOBILE6.2.

The acceleration noise, defined as the standard deviation of acceleration/deceleration, is a composite indicator of traffic congestion (Smit, 2006). Acceleration noise was calculated for the field study and compared to that derived for the LDV driving patterns in MOBILE6.2 (Smit et al., 2008).

Kruskal-Wallis and Wilcoxon tests were used to investigate differences in trip-based speeds and accelerations, and acceleration noise. Analyses used R 2.7.2 (RFSC, 2008) and Matlab 7.8.

3.6 Results and discussion

3.6.1 Speed and acceleration measurements in congestion and free-flow conditions

Table 3-2 summarizes the speed and acceleration data, showing the mean and standard deviation for each parameter among trips for each traffic condition. (Additional statistics are shown in Table S3-1.) Trip-based speeds and accelerations differed by traffic conditions ($p<0.01$) and vehicle class (LDV vs. HDV) for most conditions, e.g., free-flow conditions ($p<0.01$). Generally, acceleration, deceleration and acceleration noise increased as traffic conditions changed from free-flow, transitional period, and then to congested conditions. As expected, vehicles were driven faster and more smoothly under free-flow conditions than under work zone and rush hours, and trucks were driven more smoothly and more slowly than cars.

The lane closure significantly altered traffic patterns. Work zone speeds were low and acceleration noise was high relative to other periods. (Figure S3-1 shows joint distributions of speed and acceleration/deceleration, stratified by time of a day, vehicle category and traffic conditions.)

3.6.2 CMEM response surface

CO emission and fuel consumption rates response surfaces for LDVs and HDVs are shown in Figure 3-2. Emission rates are shown on a g s^{-1} basis, not the more common g mi^{-1} basis, because this more clearly shows changes in emission rates resulting from short term acceleration and deceleration events. The CO response surface is fairly typical of the other pollutants, which are shown in Supplemental Figure 3-2. Although the mechanisms that generate emissions differ for each pollutant, as noted in the introduction, the general pattern is similar. Under acceleration, emissions (in terms of g s^{-1}) increase with vehicle speed, and there is a sharp boundary or “jump” where emissions rapidly increase. This boundary is more compressed at high speeds for LDVs, a result of engine characteristics, fuel content and catalytic converter performance. Some of the results, especially for HDVs at high speed and high acceleration, may extend via extrapolations to infeasible regions. With deceleration, emissions are constant and speed-invariant, a result of an unloaded, essentially idling, engine.

The CMEM response surfaces represent smoothed outputs because this model's parameters were calibrated using regression or optimization across multiple vehicles and vehicle classes (Scora et al., 2006). The jiggles on the contour lines in Figure 3-2 result from discretization or contour smoothing artifacts. More significantly, the response pattern for an actual vehicle would depend on many factors, e.g., vehicle type, year, condition and maintenance, fuel type, etc.

3.6.3 Emission estimates for congestion and free-flow conditions

Table 3-2 shows emission rates expressed as g mi^{-1} for the two vehicle classes and the four traffic conditions. For LDVs, emissions under transitional and rush hour congestion periods were 1 to 16% higher than under free-flow conditions, with CO showing the greatest difference. The variability among the trips within each congestion condition was large, especially for the transitional condition where fairly large speed and acceleration fluctuations occurred among different trips, and where the higher speeds tended to increase the sensitivity of emission and fuel consumption rates to acceleration. Compared to free flow conditions, work zone congestion decreased emission rates of HC, CO and NO_x by 47, 69 and 38%, respectively, while CO_2 emission and fuel consumption rates increased by 13 and 17%. These trends can be explained by effects of speed, acceleration/deceleration, and travel time. Acceleration can greatly increase emissions of some pollutants, especially at high speeds when the engine and emission control systems are highly loaded, however, since acceleration periods tend to brief, impacts on fuel consumption rates over the segment may not be large. A decelerating vehicle has emission and fuel consumption rates that are largely independent of speed. The slower speeds occurring in work zones considerably increase travel time and fuel consumption, for which CO_2 serves as an indicator, but emissions of other pollutants are well controlled in modern gasoline engines under such light loads.

For HDVs, rush hour and work zone congestion gave the highest emissions of HC and CO; differences among the transitional period and free-flow conditions were small. Emission and fuel consumption rates under rush hour congestion increased by 5 to 11% compared to free-flow conditions. Fuel consumption rates and HC and CO increased sharply with increasing traffic and decreasing speed, differing from the LDV pattern. The highest emission and fuel consumption rates were associated with work zone congestion emissions when HC, CO, NO_x and CO_2 emission rates increased by 159, 90, 5 and 65% compared to free-flow conditions. Generally, HDVs demonstrated smaller differences between low and high speeds than LDVs.

The predictions for HDVs are largely consistent with the literature, including Sjodin et al. (1998) and De Vlieger et al. (2000). However, the lower emissions found for LDVs at low speeds differ from several reports (e.g., Sjodin et al. 1998; De Vlieger et al. 2000; DoTRS 2001; and Frey et al. 2001). For example, Sjodin et al. (1998) showed emission factors for CO, HC and NO_x for the 19-25 mph speed range that were 200%, 200% and 40% higher, respectively, than at 44 mph (the largest speed evaluated). These differences might be due to several reasons: First, results from tunnel or on-board measurements can differ systematically from the data used in CMEM. Older studies using field experiments may be disproportionately affected by vehicles using non-reformulated gasoline, and by older and high emitting vehicles. In contrast, our modeling study was based on newer vehicles (e.g., ultra low emitting vehicles) and reflected the use of reformulated gasoline and newer emission standards. Second, emission factors in these studies were either fleet-based (e.g., Sjodin et al. 1998) or individual vehicle-based (De Vlieger et al. 2000; DoTRS 2001; and Frey et al. 2001), Fleet-based rates in the tunnel study (Sjodin et al., 1998) might differ from real world due to erroneous dilution assumptions (Jones and Harrison, 2006). The on-board studies used only a few vehicles and might not represent typical conditions. Third, vehicle mix, driving patterns and road type differs among these studies, e.g., the case study reflects relatively young vehicles. Differences in road features and regional driving habits may also contribute to the observed differences.

Often, a small region in the response surface – typically at both high speed and acceleration – accounts for disproportionate fraction of pollutant emissions and fuel consumption. For example, the region defined by speeds between 71 and 75 mph and accelerations between 0.4 to 1.5 mph s^{-1} accounted for 13% of the time in the free-flow condition during midday, it accounts for 20%, 33%, 28%, 19% and 19% of HC, CO, NO_x,

CO_2 emissions and fuel consumption, respectively. Figure S3-3 shows emissions contributed by each speed/acceleration (or deceleration) combination.

We estimated emissions as the product of the response surface and the speed/acceleration probability field. For CO, CO_2, and fuel consumption, these closely matched rates based on CMEM simulations (errors less than 1%). However, errors for HC and NO_x were 10% and 29%, respectively, suggesting that finer bins are needed to avoid discretization errors for these pollutants due to sharp gradients in the emission factor response surfaces.

3.6.4 Comparison of emission rates for instantaneous- and average-speed conditions

Table 3-3 compares three emission factor estimates for each vehicle type and congestion condition: (1) the instantaneous-speed CMEM simulation presented earlier, derived using the observed speed/acceleration profiles; (2) the average-speed CMEM results for a constant average speed; and (3) the MOBILE6.2 results for the same average speed. For LDVs, the average-speed CMEM results show that emissions decrease at lower speeds, and all emission rates are much lower than the instantaneous-speed CMEM rates. The average-speed CMEM emission rates do not account for road-specific driving behaviors. Similarly, MOBILE6.2 results do not account for road-specific behaviors, but these predictions greatly exceed the instantaneous-speed CMEM estimates. The MOBILE6.2 predictions of HC and CO are relatively insensitive to speed (or congestion condition).

The three model applications gave emission factors that were more similar for HDV than those just discussed for LDVs (Table 3-3). In particular, HC and CO emission rates for instantaneous- and average-speed CMEM simulations were similar; NO_x emission rates for the instantaneous-speed mode were considerably higher (59 to 94%) than the average-speed rates. Compared to the CMEM simulation, MOBILE6.2 emission factors for HC were higher by 2-fold, but CO and NO_x emission factors were lower by 2-fold.

CMEM and MOBILE6.2 discussed above have many differences, and many factors can explain the discrepancies seen in Table 3-3. First, as demonstrated below, the CMEM simulation is very sensitive to smoothing of the speed and acceleration data, and differences between CMEM and MOBILE6.2 predictions were significantly using 1 s smoothing (3 s smoothing was used in the Table 3-2). Second, the models used different vehicle classification schemes, and the weights used for vehicle-mapping (Table 3-1) could bias results. Specifically, CMEM used 8 car and 1 truck categories. Moreover, MOBILE6.2 used the local vehicle age distribution, which included vehicles from 1 to 25 years old. MOBILE6.2 is a widely used regulatory emission model for which key auxiliary information, such as vehicle age and vehicle category distributions, have been established nationally and in many cases regionally, thus MOBILE6.2 is a better model to estimate average-speed emission estimates from an application perspective. Third, the models use different approaches for estimating emissions, and calibrations used different databases, e.g., CMEM used a relatively small number of California vehicles (Scora et al., 2006). Finally, MOBILE6.2 does not account for the observed speed/acceleration profiles.

Despite the differences between the emission models, the CMEM simulations suggest that driving behaviors represented by the speed/acceleration profiles can greatly affect emission rates, especially for LDVs. The model-to-model comparisons show the influence of the many assumptions and parameters used in these models, such as driving cycle and the underlying databases, and suggest that the uncertainties are high.

3.6.5 Sensitivity to smoothing and averaging time

Figure 3-3 shows the effect of smoothing the speed/acceleration data on CMEM emission estimates for LDVs and HDVs, free flow and work zone conditions, and the four pollutants. Generally, emission factors decrease with increased averaging time, and changes for LDVs were particularly large, reflecting the sharp boundary shown in the emission response surface (Figure S3-2). The largest changes are seen at short (1 to 10 s) averaging times. At longer averaging times, extreme acceleration and deceleration events are “averaged out,” and at very long times, emission rates will ultimately converge to that predicted using the average speed. The CMEM results shown earlier used a 3 s averaging time, which might be a reasonable compromise between minimizing potential GPS errors and underestimating real emissions rate. However, the use of a 1 or 2 s averaging time significantly increased CMEM predictions, though they still fall below MOBILE6.2’s estimates. Clearly, smoothing is a critical factor for instantaneous emission models such as CMEM and MOVES.

3.6.6 Acceleration noise comparison

Figure 3-4 contrasts acceleration noise in the case study runs with those in the driving patterns used in MOBILE6.2's development. At low speeds, the noise used in MOBILE6.2 exceeded that in the case study, a different pattern of congestion. In the case study, the low speed runs were due to work zone congestion, specifically, traffic narrowing from two to one and then from one to two lanes in the east-bound direction, and the flow was relatively smooth, and not representative of low average speed congestion patterns on freeways. At high speeds, MOBILE6.2's noise was similar to that in the case study. Our results demonstrate considerable variability of acceleration noise, e.g., for speeds above 60 mph, the noise ranged from 0.35 to 1.13 mph s^{-1}, compared to 0.68 (mph s^{-1}) used in MOBILE6.2. The noise under four traffic conditions statistically differed (Kruskal-Wallis, $p<0.01$).

3.6.7 Emission intensity and air quality impacts

Emission density estimates (g mi^{-1} s^{-1}) for the case study freeway segment under the three traffic conditions are shown in Table 3-4. For rush hour congestion, emission densities for HC, CO and CO_2 exceeded those in free-flow periods by 1.5 to 2 times; the NO_x emission density was largely unchanged (4% lower). For work zone conditions, emission densities decreased from free flow conditions, particularly for HC and CO; CO_2 increased as discussed earlier. These changes result from multiple factors: vehicle volume and travel time, which determines the "packing" or spacing between vehicles; changes in vehicle emission factors; and changes in the vehicle mix. For the study segment, this analysis suggests that rush hour concentrations of CO and HC will increase near and on the road, while NO_x concentrations will be similar. Most of this effect is due to higher traffic volumes during rush hour, which increased by 66% compared to free flow, and a smaller fraction of HDVs during rush hour, which account for 83% of the NO_x emissions. Elevated concentrations of HC and CO, and likely other pollutants not modeled by CMEM, e.g., $PM_{2.5}$, would lead to high exposures of commuters who also endure longer travel times during congestion, as well as individuals living or working near major roads.

3.6.8 Evaluation of the approach

Emission estimates are typically derived using macroscopic emission models, such as MOBILE 6.2, in combination with static traffic models, such as TransCAD (a transportation planning software), to predict regional emissions for conformity analyses and other air quality planning purposes. It is clear that models used in such applications may not accurately represent emissions for specific road links and times. Recently, efforts have been made to combine micro-simulation traffic models, such as VISSIM, to instantaneous emission models (like CMEM) and air quality dispersion models (Barth, 1998; Cappiello, 2002; Chevallier, 2005; Fellendorf, 1999; Kim et al., 2006; Malcom et al., 2001; Nam et al., 2002; Niittymaki et al., 2001; Park et al., 2001). By modeling the movements of individual vehicles on a second-by-second basis, or even shorter intervals, micro-simulation models can simulate many of the complex driver behaviors that are observed in real networks. Because driving behavior varies with location, time of day, and day of week, such simulations require data and calibrations for vehicle speed and acceleration/deceleration distributions, as well as parameters related to car-following, lane-changing, and driver aggressiveness. With appropriate input data, micro-simulation models can simulate the wide range of vehicle behaviors found on roads. However, full integration of micro-simulation traffic and instantaneous emission models is extremely computationally intensive, and thus has not yet been attempted for large road networks. Instead, such simulations remain limited to simple road networks (Stevanovic et al., 2009).

The integration of speed-acceleration probabilities and response-surface analyses for instantaneous emission models like CMEM represents a simple and fast way to derive emission factors tailored to local driving behavior, including the stop-and-go transients encountered in congestion. The speed-acceleration data obtained using the car-floating or potentially other technique obviates the need to calibrate and run computationally and parameter-intensive micro-simulation models. The approach is highly amenable to sensitivity and other analyses. However, estimated emission rates might be underestimated because the observed speed profiles tend to represent the fleet average, e.g., aggressive driving behaviors might be underrepresented.

3.6.9 Study limitations

This study has several limitations. First, due to model limitations, we did not estimate emissions of particle matter, ultrafine particles, and black carbon that are emitted primarily by HDVs and that are associated with high health risks (WHO, 2005). Second, as mentioned, the speed/acceleration profiles developed using the car-floating technique tend to represent an average profile among vehicles on the road, and because we followed a limited number of vehicles, results may not necessarily represent the full range of conditions. This would tend to underestimate actual emissions. Third, the mapping between CMEM and MOBILE 6.2 categories was based on the southeast Michigan vehicle age distribution data, not the actual vehicle age distribution on the study segment. Fourth, the vehicle categories in CMEM were calibrated using mainly vehicles before the year 2000. As a result, we could not consider gas-electric hybrid and biofuel-based vehicles. Moreover, we did not consider the newest vehicle emission standards for diesel trucks (EPA's standards for 2004 and 2007 year and later vehicles; EPA, 2002), thus CMEM emissions may be overestimated. Biases may be smaller for LDVs because the super ultra low emission vehicle (SULEV) category used is roughly equivalent to the current EPA Tier 2 emission standards. Fifth, we did not use site-specific monitoring to validate the modeling and the model intercomparison. Sixth, we demonstrated that smoothing of the field study data affect results, but we had no independent test to evaluate the appropriate degree of smoothing. Finally, we examined a single freeway link and further study is needed to be able to generalize findings.

3.7 Conclusions

This study appears to be the first in the literature to examine pollutant emission and fuel consumption rates under free-flow conditions, work zone and rush hour congestion conditions. In the freeway case study, the transitional period was associated with highest emission rates of CO, HC and NO_x compared to free-flow and low speed work zone congestion. A different pattern was seen for HDVs where work zone congestion was associated with the highest emissions of CO, HC, NO_x and CO_2. Considering the combined effect of driving behavior, vehicle volume and mix, and emission factors, on- and near-road concentrations of CO, HC, and NO_x are expected to nearly double during rush hour periods as compared to free-flow periods given similar dispersion. Clearly, link-specific emissions depend on the degree and type of congestion. While only a few congestion conditions were analyzed, the results highlight the importance of congestion, and the findings are relevant to emission, exposure and health risk evaluations, as well as conformity analysis in transportation planning.

Table 3-1. Weights of CMEM vehicle categories for comparison with the MOBILE6.2 categories.

MOBILE6.2 Category	CMEM Category	Weight
LDGV	Ultra low emitting vehicle (ULEV)	0.13
	Super ultra low emitting vehicle (SULEV)	0.13
	Tier 1 < 50k, low ratio	0.10
	Tier 1 < 50k, high ratio	0.10
	Tier 1 > 50k, low ratio	0.12
	Tier 1 > 50k, high ratio	0.12
	3-way catalyst, fuel injected, > 50k miles low	0.15
	3-way catalyst, fuel injected, > 50k miles high	0.15

Table 3-2. Summary of speed/acceleration profiles, emission factors and fuel consumption rates for LDV and HDV grouped by traffic condition.

Category	Traffic conditions	No. of Trips	Speed	Acceleration	Deceleration	Acceleration noise [b]	Emission factors				Fuel consumption
							HC	CO	NO_x	CO_2	
			(mph)	(mph s^{-1})	(mph s^{-1})	(mph s^{-1})	(g mi^{-1})	(g mi^{-1})	(g mi^{-1})	(g mi^{-1})	(g mi^{-1})
LDV	Free flow conditions	51	70 ± 3 [a]	0.22 ± 0.36	-0.20 ± 0.30	0.55 ± 0.12	0.13 ± 0.03	6.81 ± 2.47	0.34 ± 0.05	289 ± 16	95 ± 7
	Transitional period	10	63 ± 8	0.32 ± 0.53	-0.20 ± 0.38	0.75 ± 0.21	0.14 ± 0.06	8.17 ± 4.06	0.35 ± 0.10	293 ± 28	97 ± 15
	Rush hour congestion	10	56 ± 14	0.39 ± 0.56	-0.23 ± 0.45	0.82 ± 0.14	0.13 ± 0.02	6.99 ± 1.64	0.35 ± 0.04	279 ± 26	92 ± 11
	Work zone	11	21 ± 19	0.32 ± 0.51	-0.25 ± 0.50	0.82 ± 0.20	0.07 ± 0.01	2.12 ± 0.63	0.21 ± 0.02	339 ± 15	107 ± 19
HDV	Free flow conditions	41	63 ± 3	0.17 ± 0.28	-0.16 ± 0.25	0.45 ± 0.09	0.10 ± 0.00	3.57 ± 0.28	19.64 ± 1.16	1651 ± 163	516 ± 51
	Transitional period	7	58 ± 6	0.24 ± 0.37	-0.15 ± 0.28	0.54 ± 0.08	0.11 ± 0.00	3.98 ± 0.36	20.74 ± 1.29	1859 ± 202	581 ± 63
	Rush hour congestion	6	48 ± 16	0.31 ± 0.46	-0.17 ± 0.32	0.64 ± 0.12	0.13 ± 0.01	4.61 ± 0.26	18.09 ± 1.19	2122 ± 126	663 ± 39
	Work zone	11	21 ± 19	0.32 ± 0.51	-0.25 ± 0.50	0.82 ± 0.20	0.26 ± 0.02	6.78 ± 0.89	20.56 ± 2.22	2722 ± 449	848 ± 139

a. Standard deviation reflects variations between runs;
b. The acceleration noise is defined as the standard deviation of acceleration/deceleration.

Table 3-3. Vehicle emission factors derived from CMEM and MOBILE6.2 for LDVs and HDVs by traffic condition (unit: g mi^{-1}).

Category	Traffic conditions	HC emission factors			CO emission factors			NO_x emission factors		
		CMEM[a]	CMEM[c]	MOBILE6.2	CMEM[a]	CMEM[c]	MOBILE6.2	CMEM[a]	CMEM[c]	MOBILE6.2
LDV	Free flow conditions	0.13 ± 0.03[b]	0.08	0.66	6.81 ± 2.47	1.84	16.69	0.34 ± 0.05	0.15	0.75
	Transitional period	0.14 ± 0.06	0.06	0.66	8.17 ± 4.06	1.40	16.48	0.35 ± 0.10	0.10	0.74
	Rush hour congestion	0.13 ± 0.02	0.04	0.68	6.99 ± 1.64	1.03	15.89	0.35 ± 0.04	0.07	0.72
	Work zone	0.07 ± 0.01	0.03	0.87	2.12 ± 0.63	0.56	14.00	0.21 ± 0.02	0.02	0.66
HDV	Free flow conditions	0.10 ± 0.00	0.10	0.28	3.57 ± 0.28	3.54	1.81	19.64 ± 1.16	11.11	13.63
	Transitional period	0.11 ± 0.00	0.10	0.28	3.98 ± 0.36	3.41	1.62	20.74 ± 1.29	10.66	11.45
	Rush hour congestion	0.13 ± 0.01	0.12	0.31	4.61 ± 0.26	3.46	1.51	18.09 ± 1.19	10.75	9.05
	Work zone	0.26 ± 0.02	0.25	0.57	6.78 ± 0.89	5.13	2.76	20.56 ± 2.22	12.94	8.54

a. Emission factors estimated using CMEM and observed speed profiles.
b. Standard deviation reflects variability between runs;
c. Emission factors estimated using CMEM and average speeds;

Table 3-4. Estimated emission density and fuel consumption density for traffic on the I-94 segment.

Traffic conditions	Emission density				Fuel consumption density
	HC ($g\ mi^{-1}\ s^{-1}$)	CO ($g\ mi^{-1}\ s^{-1}$)	NO_x ($g\ mi^{-1}\ s^{-1}$)	CO_2 ($g\ mi^{-1}\ s^{-1}$)	($g\ mi^{-1}\ s^{-1}$)
Free flow conditions	0.07 ± 0.02	3.78 ± 1.28	1.93 ± 0.13	295 ± 23	94 ± 8
Rush hours	0.13 ± 0.04	7.25 ± 2.62	1.86 ± 0.16	419 ± 38	135 ± 16
Work zone	0.05 ± 0.01	1.53 ± 0.36	1.78 ± 0.19	379 ± 44	119 ± 20

Table S3-1. Summary of speed (mph), acceleration and deceleration (mph s^{-1}) measured for different traffic conditions and vehicle categories.

Variable	Period	Traffic conditions	Speed bin	No. of Records[a]	No. of Trips	Mean	SD[b]	Min[c]	P25[d]	Median	P75[e]	Max[f]
		Car following	60_65	428	2	64.28	9.91	32.50	59.17	64.90	72.24	77.29
			65_70	2610	13	68.56	3.75	52.50	66.46	68.75	71.04	77.40
	Morning (7-9AM)		70_75	952	5	72.30	3.07	63.13	70.11	72.71	74.38	82.29
		Truck following	60_65	1958	9	63.25	2.75	55.63	61.67	62.97	64.79	75.63
			65_70	416	2	66.23	2.35	57.29	65.21	66.04	67.24	72.71
		Car following	65_70	1413	7	68.16	4.77	42.92	65.63	68.13	71.67	77.29
			70_75	2858	15	71.33	3.01	59.38	69.17	71.25	73.33	80.21
	Midday (11-1PM)	Truck following	60_65	4376	20	62.82	2.68	50.42	61.04	62.92	64.58	71.46
		Work zone	15_20	2154	3	19.09	17.86	0.00	5.83	12.29	26.88	64.79
Speed			20_25	5008	8	22.00	19.07	0.00	7.08	14.79	33.96	64.58
		Car following	50_55	522	2	52.99	20.57	4.79	44.38	60.83	68.96	74.38
			55_60	1958	8	56.47	13.17	14.79	48.13	60.42	65.63	78.54
			60_65	1757	8	62.73	7.77	28.96	59.38	63.96	68.13	75.63
			65_70	1820	9	68.20	3.52	53.54	66.04	68.33	70.42	82.08
	Afternoon (4-6PM)		70_75	390	2	70.75	3.15	61.46	68.96	70.94	73.13	77.50
		Truck following	39_44	666	2	41.53	17.14	11.25	27.71	41.67	56.88	68.54
			50_55	1068	4	51.80	15.04	8.96	40.11	58.54	63.13	67.92
			55_60	1666	7	58.24	6.64	26.67	54.79	59.17	62.71	71.25
			60_65	2231	10	61.76	4.34	40.63	59.79	62.50	64.58	73.13
		Car following	60_65	200	2	0.71	0.56	0.21	0.21	0.63	0.83	3.33
			65_70	1055	13	0.54	0.44	0.10	0.21	0.42	0.63	4.38
	Morning (7-9AM)		70_75	356	5	0.60	0.40	0.21	0.21	0.42	0.83	2.29
		Truck following	60_65	725	9	0.43	0.29	0.10	0.21	0.42	0.63	2.08
			65_70	168	2	0.48	0.34	0.10	0.21	0.42	0.63	1.88
		Car following	65_70	563	7	0.61	0.46	0.10	0.21	0.42	0.83	2.50
			70_75	1135	15	0.48	0.32	0.10	0.21	0.42	0.63	1.88
	Midday (11-1PM)	Truck following	60_65	1646	20	0.41	0.27	0.07	0.21	0.42	0.42	2.29
		Work zone	15_20	938	3	0.79	0.63	0.21	0.21	0.63	1.04	4.17
Acceleration			20_25	2186	8	0.72	0.54	0.10	0.21	0.63	1.04	4.38
		Car following	50_55	273	2	0.84	0.74	0.10	0.21	0.63	1.25	3.33
			55_60	995	8	0.74	0.55	0.10	0.42	0.63	1.04	3.54
			60_65	834	8	0.67	0.62	0.07	0.21	0.42	0.83	7.92
			65_70	753	9	0.56	0.44	0.10	0.21	0.42	0.73	4.38
	Afternoon (4-6PM)		70_75	166	2	0.50	0.38	0.10	0.21	0.42	0.63	2.29
		Truck following	39_44	316	2	0.66	0.52	0.21	0.21	0.42	0.83	2.92
			50_55	533	4	0.61	0.48	0.10	0.21	0.42	0.83	2.71
			55_60	755	7	0.54	0.39	0.10	0.21	0.42	0.83	2.29
			60_65	939	10	0.51	0.39	0.10	0.21	0.42	0.63	2.92
		Car following	60_65	166	2	-0.60	0.65	-4.79	-0.63	-0.42	-0.21	-0.10
			65_70	1118	13	-0.48	0.32	-3.13	-0.63	-0.42	-0.21	-0.10
	Morning (7-9AM)		70_75	423	5	-0.50	0.32	-2.71	-0.63	-0.42	-0.21	-0.10
		Truck following	60_65	821	9	-0.40	0.23	-1.67	-0.42	-0.42	-0.21	-0.10
			65_70	160	2	-0.43	0.27	-1.87	-0.63	-0.42	-0.21	-0.10
		Car following	65_70	639	7	-0.49	0.32	-2.71	-0.63	-0.42	-0.21	-0.10
			70_75	1139	15	-0.42	0.25	-1.88	-0.63	-0.42	-0.21	-0.10
	Midday (11-1PM)	Truck following	60_65	1800	20	-0.37	0.22	-1.88	-0.42	-0.21	-0.21	-0.07
		Work zone	15_20	743	3	-0.82	0.80	-4.38	-1.04	-0.42	-0.21	-0.10
Deceleration			20_25	1794	8	-0.66	0.63	-5.63	-0.83	-0.42	-0.21	-0.10
		Car following	50_55	181	2	-0.78	0.88	-5.21	-0.83	-0.42	-0.21	-0.21
			55_60	710	8	-0.62	0.74	-7.08	-0.63	-0.42	-0.21	-0.10
			60_65	661	8	-0.52	0.52	-7.71	-0.63	-0.42	-0.21	-0.10
			65_70	751	9	-0.52	0.38	-4.38	-0.63	-0.42	-0.21	-0.10
	Afternoon (4-6PM)		70_75	154	2	-0.45	0.29	-1.88	-0.63	-0.42	-0.21	-0.21
		Truck following	39_44	248	2	-0.54	0.42	-2.29	-0.63	-0.42	-0.21	-0.21
			50_55	353	4	-0.45	0.39	-2.92	-0.42	-0.42	-0.21	-0.21
			55_60	576	7	-0.44	0.33	-3.54	-0.63	-0.42	-0.21	-0.10
			60_65	876	10	-0.46	0.36	-3.54	-0.63	-0.42	-0.21	-0.10

a. Number of second-by-second speed records; b. Standard deviation; c. minimum values; d. 25th percentile values; e. 75th percentile values; f. Maximum values.

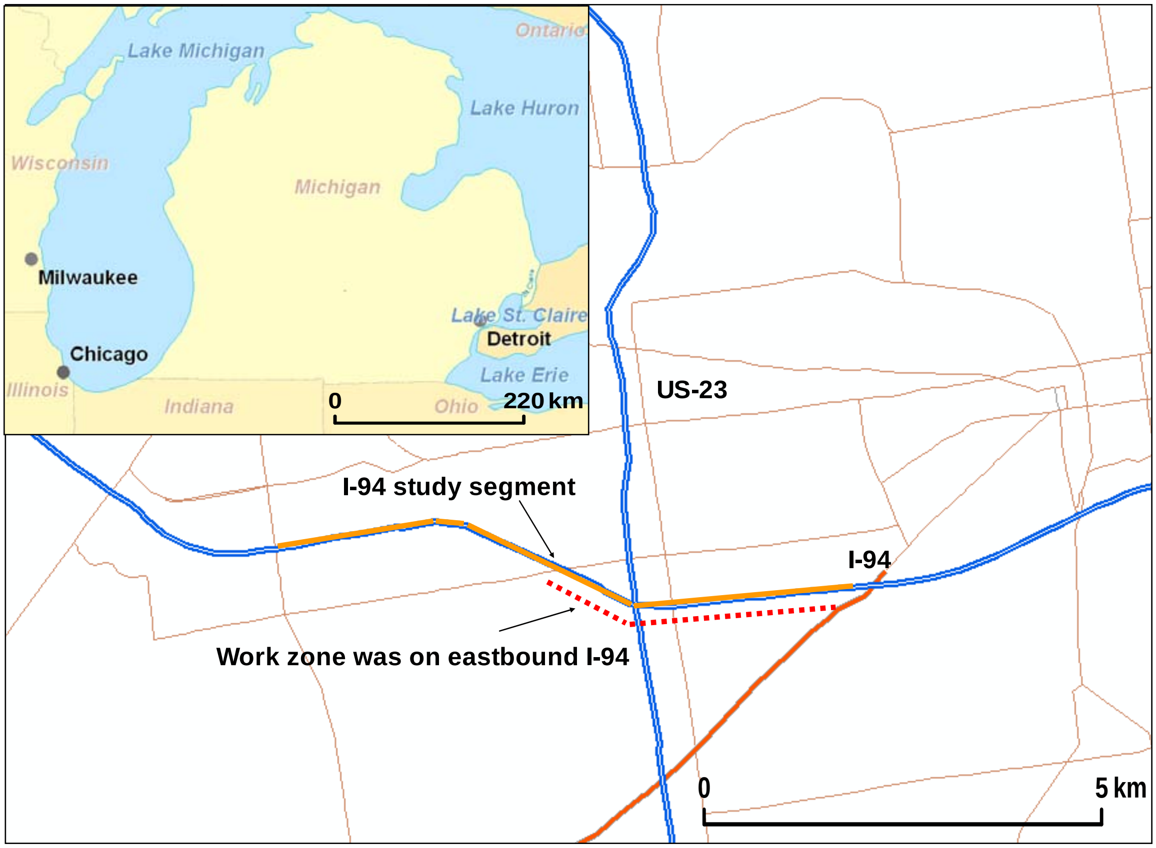

Figure 3-1. Map of study area and study segment for field study, shown in red.

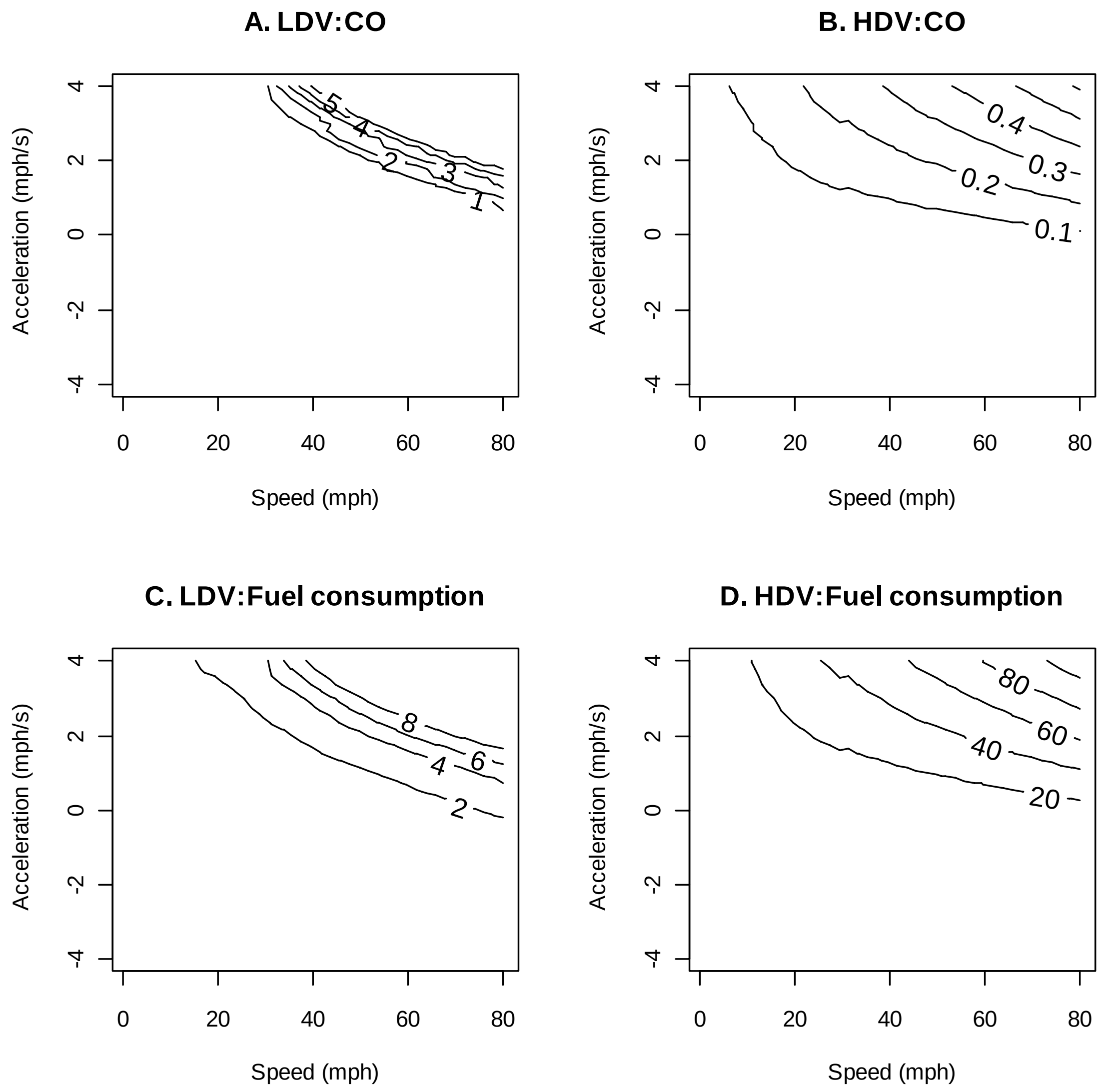

Figure 3-2. Response surface for CO emission rates (g s^{-1}) and fuel consumption rates (g s-1) for LDVs and HDVs.

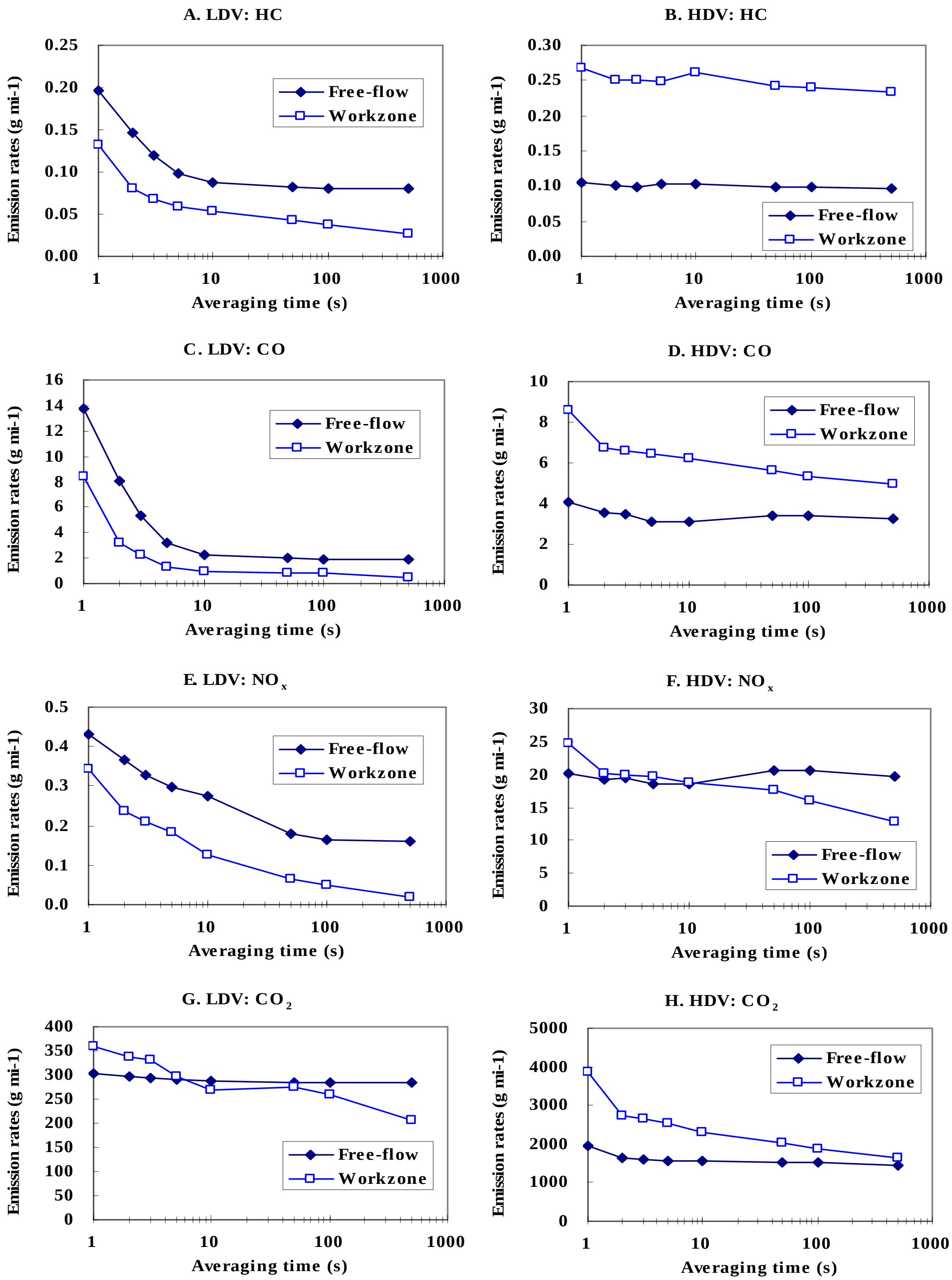

Figure 3-3. Sensitivity analysis for smoothing (averaging time) of speed/acceleration data, showing emission rates for LDVs with two speed ranges (20-25 and 70-75 mph, both at midday) and for HDVs using similar speed ranges (20-25 and 60-65 mph, again at midday).

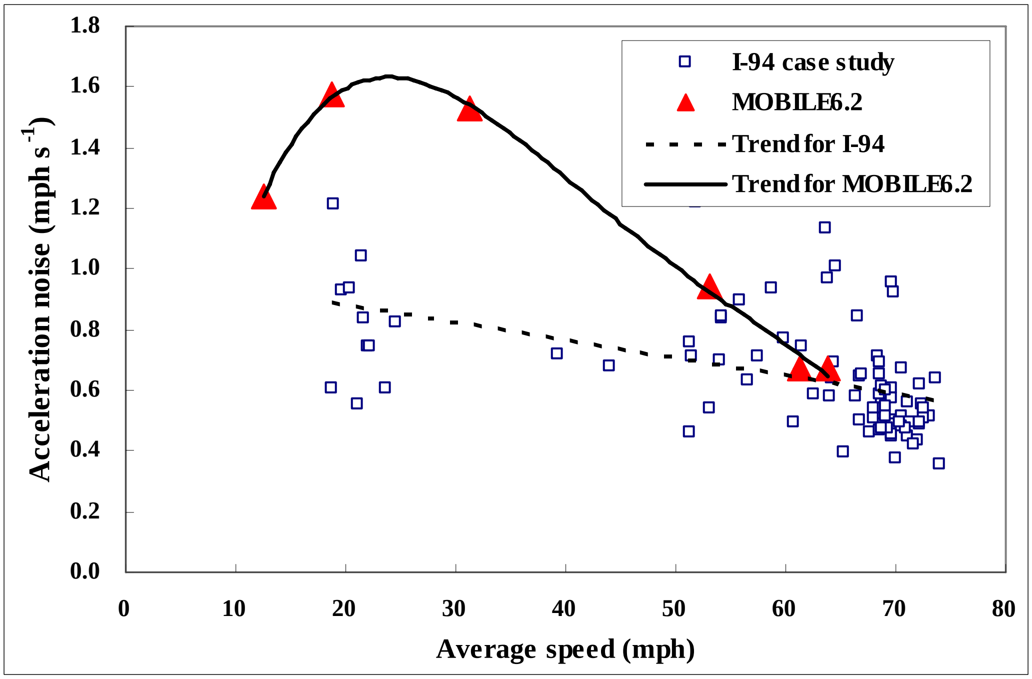

Figure 3-4. Comparison of acceleration noise on using measurements for the I-94 field study and MOBILE6.2 LDV driving patterns.

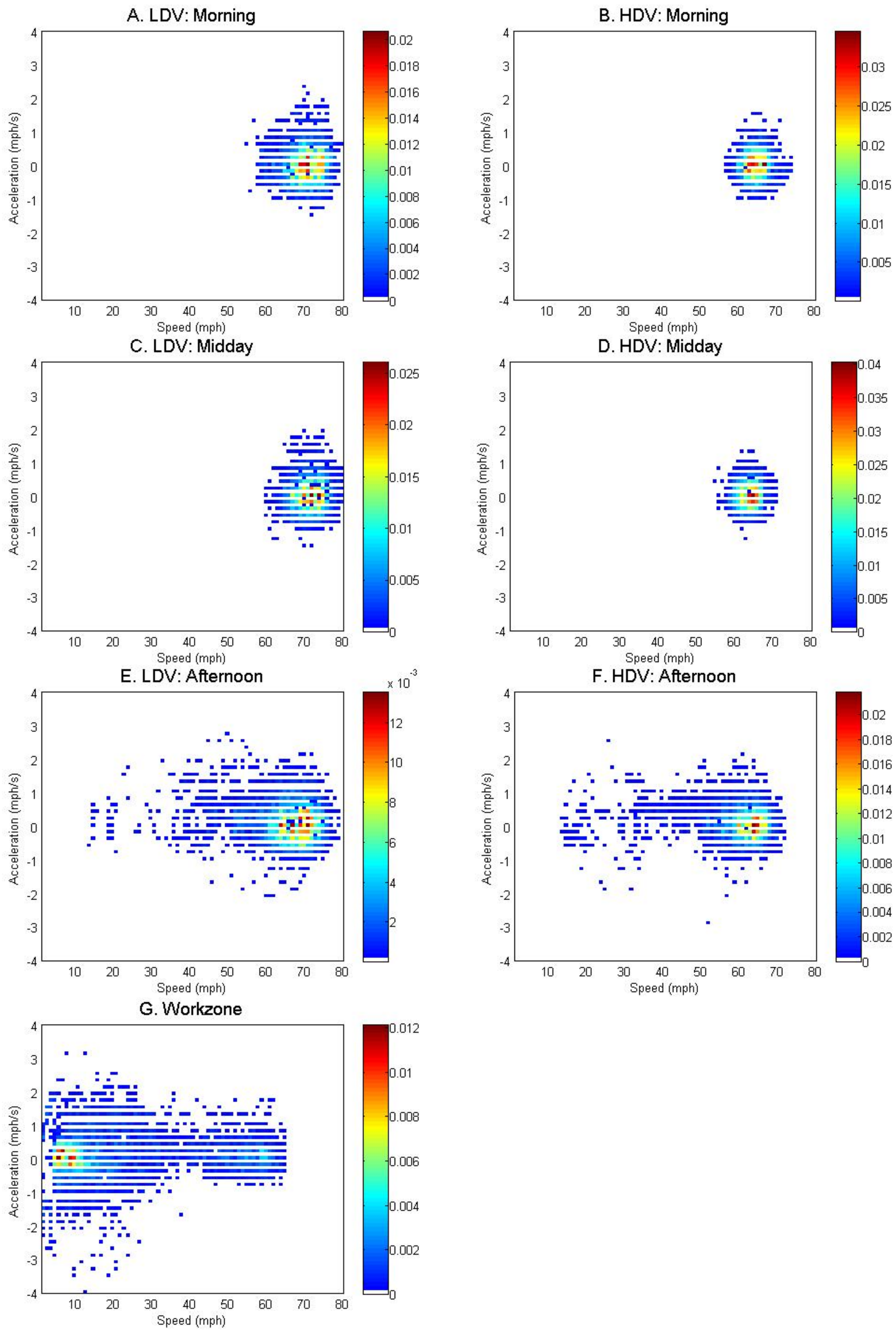

Figure S3-1. Joint distribution of speed and acceleration/deceleration, grouped by time period, vehicle category and traffic conditions.

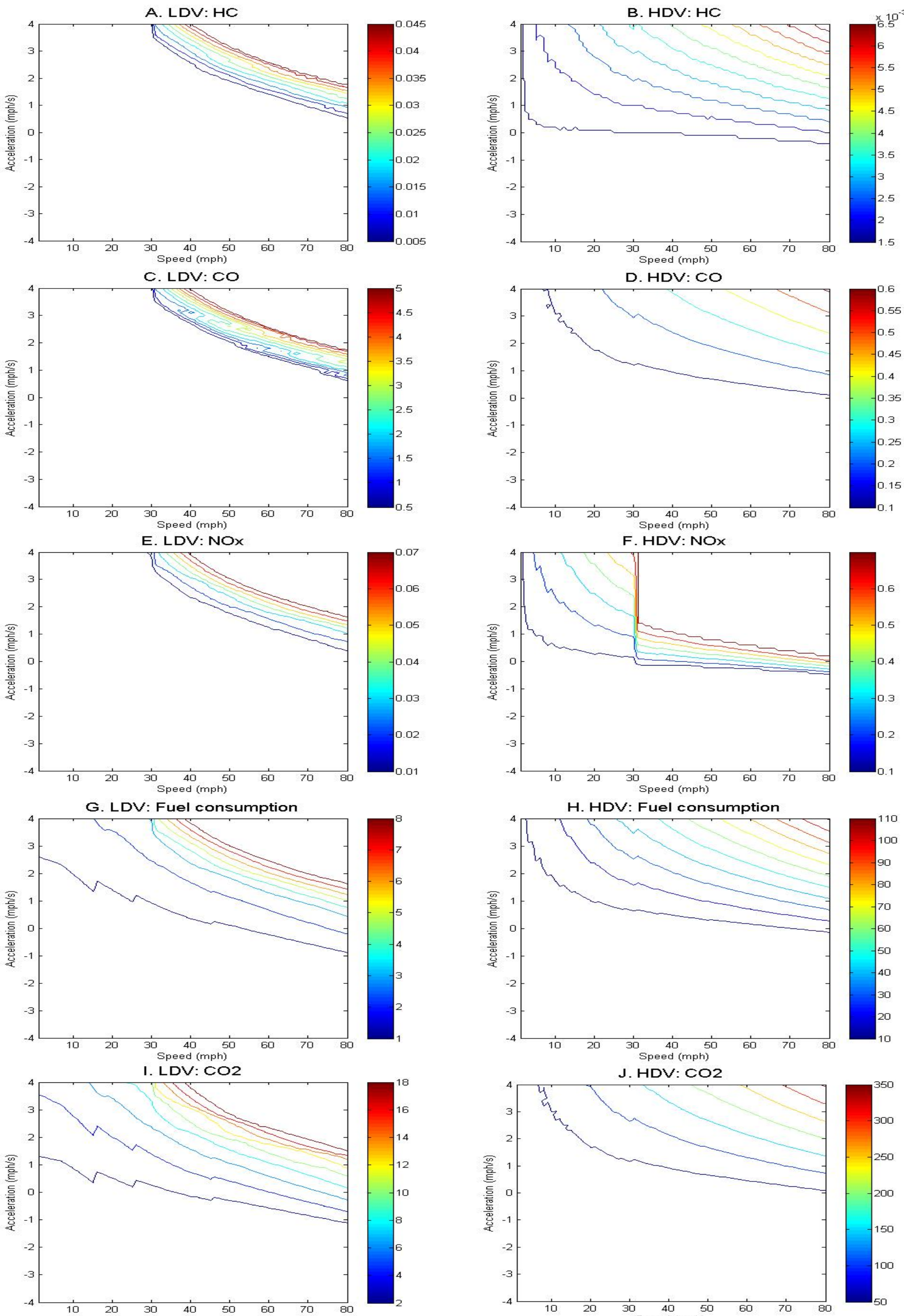

Figure S3-2. Emission response surface for LDVs and HDVs (g s^{-1}).

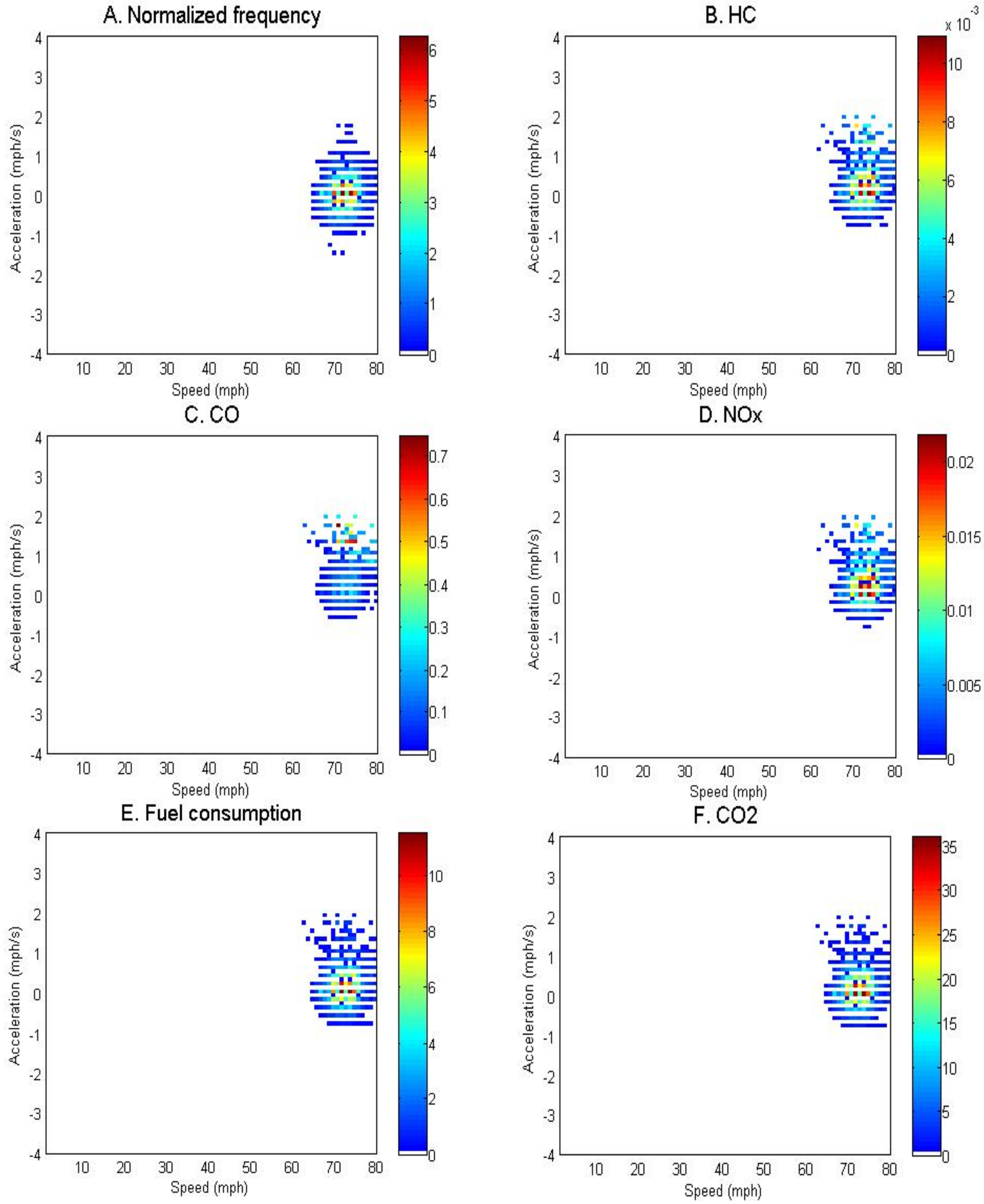

Figure S3-3. Plots of frequency, emissions and fuel consumption for 70 – 75 mph trip average measurements at midday (normalized frequency = frequency / number of trips). Pollutants and fuel consumption rates in g s^{-1}.

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Chapter 4

Near-Road Air Pollutant Concentrations of CO and $PM_{2.5}$: A Comparison of MOBILE6.2/CALINE4 and Generalized Additive Models

4.1 Abstract

The contribution of vehicular traffic to air pollutant concentrations is often difficult to establish. This chapter utilizes both time-series and simulation models to estimate vehicle contributions to pollutant levels near roadways. The time-series model used generalized additive models (GAMs) and fitted pollutant observations to traffic counts and meteorological variables. A one year period (2004) was analyzed on a seasonal basis using hourly measurements of carbon monoxide (CO) and particulate matter less than 2.5 μm in diameter ($PM_{2.5}$) monitored near a major highway in Detroit, Michigan, along with hourly traffic counts and local meteorological data. Traffic counts showed statistically significant and approximately linear relationships with CO concentrations in fall, and piecewise linear relationships in spring, summer and winter. The same period was simulated using emission and dispersion models (Motor Vehicle Emissions Factor Model/MOBILE6.2; California Line Source Dispersion Model/CALINE4). CO emissions derived from the GAM were similar, on average, to those estimated by MOBILE6.2. The same analyses for $PM_{2.5}$ showed that GAM emission estimates were much higher (by 4 to 5 times) than the dispersion model results, and that the traffic-$PM_{2.5}$ relationship varied seasonally. This analysis suggests that the simulation model performed reasonably well for CO, but it significantly underestimated $PM_{2.5}$ concentrations, a likely result of underestimating $PM_{2.5}$ emission factors. Comparisons between statistical and simulation models can help identify model deficiencies and improve estimates of vehicle emissions and near-road air quality.

4. 2Keywords

Traffic counts; CO; $PM_{2.5}$; MOBILE6.2; CALINE4; generalized additive model; dispersion modeling

4.3 Introduction

Attention has been increasing regarding the effects of vehicle traffic on pollutant concentrations and health outcomes. In many cities, air quality problems are caused mainly by vehicle emissions, and recent epidemiological studies have shown excess morbidity and mortality for individuals living near roadways (WHO, 2005). The relationship between air quality, traffic and meteorological conditions is complex and not well understood (WHO, 2005). Air quality impacts from traffic can be estimated using simulation models that represent emission and dispersion of pollutants, geospatial or "land-use regression" models, statistically-based "receptor" models for source apportionment, time series models, and other techniques. All of these approaches have limitations. To date, few studies have integrated or compared simulation and statistical approaches or have developed hybrid approaches that potentially can yield more accurate predictions.

This study compares simulation and statistical models with the goal of improving near-road air pollutant predictions. It focuses on the effect of traffic volume on short-term (hourly) and near-road concentrations. Vehicle emissions and pollutant dispersion are simulated using the Motor Vehicle Emissions Factor Model version 6.2 (MOBILE6.2) and California Line Source Dispersion model version 4 (CALINE4). A time series analysis of historical data is conducted using generalized additive models (GAM) and LOESS (local polynomial regression fitting) smoothers. A synthesis of these independent approaches is used to identify uncertain model parameters, specifically emission factors, and to derive site-specific parameters that improve model predictions.

4.3.1 Emission and dispersion models for traffic pollutants

Many models have been developed to estimate traffic emissions and predict concentrations of carbon monoxide (CO), nitrogen dioxide (NO_2), particulate matter (PM), and other pollutants. Emissions are most commonly estimated using "macroscopic" emission models, such as MOBILE6.2 developed by the U.S.

Environmental Protection Agency, and the Emission Factor Model (EMFAC) developed by the California Air Resources Board. These models are based on laboratory tests of vehicle emissions measured during standardized driving cycles designed to represent typical driving patterns on freeways, arterials, ramps and local roads (Pierce et al., 2008). Outputs from these models are used as inputs to air quality dispersion models, along with information representing traffic volume, the configuration of a road network, and meteorology. CALINE4 is an example of a dispersion model designed for road networks. This model extends the standard Gaussian plume formulation using a line source configuration and mixing zone that accounts for traffic-induced heat flux and mechanical turbulence (Benson, 1989).

While very flexible, simulation models have several limitations. First, macroscopic emission models generally underestimate emission rates since they do not directly account for link-specific conditions, such as acceleration, deceleration, aggressive driving, and high-emitting vehicles (Joumard et al., 2000). Second, these models include only the local (road) sources, and "background" and "regional" pollutant levels must be handled separately, e.g., on the basis of upwind measurements or other modeling. Third, plume-type models typically do not perform well or are inappropriate for representing dispersion in street canyons and under certain meteorological conditions, e.g., low wind speeds (Benson, 1992).

4.3.2 Statistical models for traffic pollutants

Statistical approaches used to predict impacts of traffic on air quality can be classified as (1) "spatial" or "land-use" regression models and (2) "non-spatial" models. Spatial models predict traffic's contribution to long-term or average pollutant concentrations using environmental variables, e.g., land use, traffic intensity, and distance to freeway, and most have used geographic information systems (GIS) to derive and integrate these variables (WHO, 2005). These models are not considered further in this paper given our focus on short-term air quality impacts.

Non-spatial statistical models use a variety of statistical techniques to link roadway pollutants to traffic counts, meteorological conditions, and/or traffic composition. Levy at al. (2003) used linear mixed models to predict concentrations of $PM_{2.5}$ (particulate matter $\leq$2.5 μm in dia), polycyclic aromatic hydrocarbons (PAHs) and ultrafine particles with traffic counts, GIS-based traffic density scores, the percentage of vehicles with diesel engines, wind direction, and distance from the road; these models also accounted for autocorrelation. Abu-Allaban et al. (2003) used multi-linear regression to predict PM_{10} (≤10 μm dia) and $PM_{2.5}$ using traffic volume broken down into vehicle classes, i.e., cars, light-duty trucks, and heavy-duty trucks. deCastro et al. (2008) examined traffic's contribution to black carbon concentrations in Baltimore and accounted for auto-correlated errors using autoregressive models. Aldrin and Haff (2005) used generalized additive models (GAM) to link PM size fractions, NO_2 and nitric oxide (NO) concentrations to traffic counts, temperature, wind speed, wind direction, precipitation, relative humidity and snow cover. Carslaw et al. (2007) modeled traffic-related gaseous pollutants (nitrogen oxide - NO_x, NO_2, CO, benzene and 1,3-butadiene) using GAM and generalized additive mixed models (GAMM).

GAM models have become popular due to their power, flexibility and interpretability, e.g., Schlink et al. (2003) has suggested that GAM (and neural network approaches) yield the best performance because they account for non-linear relationships and differences between sites. GAMs characterize non-linear relationships by estimating non-parametric functions of covariate variables using kernel or spline smoothers (Hastie and Tibshirani, 1990). Their additive structure helps to make results interpretable since each predictor variable enters the model separately (Hastie and Tibshirani, 1990). While GAM and other statistical models can incorporate site-specific information, these models have the disadvantage that results cannot necessarily be generalized to other sites. Comparing simulation and statistical models is challenging because these models utilize independent data sets and different assumptions, but this offers the potential to improve results (Solomon et al., 2008). Differences can help to highlight model deficiencies, and lead to approaches that use models in a complementary or confirmatory manner. As examples, GAM and other "observational" models have the advantages that few assumptions are needed and portray real world behavior, while simulation models are more generalizable and can be used in a predictive manner.

4.4 Methods

We compared simulation and statistical models for hourly CO and $PM_{2.5}$ concentrations monitored near an interstate highway in Detroit, Michigan. Vehicle emissions were estimated using MOBILE6.2, and CALINE4 was used to predict concentrations. GAMs were used to explore and quantify empirical associations between traffic counts and pollutant concentrations in models adjusted for meteorological and temporal factors.

4.4.1 Data sources

The dataset included hourly pollutant (CO, $PM_{2.5}$) and meteorological (wind direction, wind speed, temperature, pressure, relative humidity) measurements for 2004 at the Allen Park monitoring site, which is 150 m SE of Interstate I-75 in flat field largely free of trees (Figure 4-1). CO is monitored using U.S. EPA approved instrumentation (DASIBI 3008 CO analyzer); $PM_{2.5}$ is monitored using a tapered element oscillating microbalance (TEOM; Rupprecht and Patashnick Model 1400A including the Filter Dynamics Measurement System). The dataset also included hourly traffic counts monitored at a permanent traffic recorder (PTR) 3.5 km from the Allen Park site. The estimated annual average daily traffic (AADT) at this site was 101 000 vehicles day^{-1}, and the commercial average daily traffic (CADT) was 13 500 vehicles day^{-1}. To account for the egress of vehicles prior to the Allen Park location, PTR measurements were lowered by 6% (MDOT, 2006).

4.4.2 Data cleaning and exploratory analyses

$PM_{2.5}$ and CO values were confirmed with MDEQ reports (2005). Most meteorological (99.6%) and $PM_{2.5}$ (98.6%) observations were available. Data availability was lower for relative humidity (92.2%), CO (94.7%), and traffic counts (74.3%). A total of 5678 hours had complete meteorological, traffic and $PM_{2.5}$ records; 5477 hours were complete for CO. Pollutant observations with zero values were replaced by one-half of the method detection limit (MDL; 0.5 μg m^{-3} for $PM_{2.5}$; 0.05 ppm for CO). Exploratory analyses included wind and pollution roses; these excluded periods with wind speeds below 1 m s^{-1}.

4.4.3 Simulation modeling

MOBILE6.2 and CALINE4, models recommended by U.S. EPA (1999), were used to predict hourly $PM_{2.5}$ and CO concentrations at the Allen Park site. Emission factors were calculated using the local vehicle age distribution and fleet mix (8% heavy duty diesel truck) for 2004 (SEMCOG, 2006), and typical vehicle speeds (cars and trucks at 65 and 60 mph, respectively). Emission factors across the vehicle fleet averaged 11.4, 16.8 and 22.2 g mi^{-1} for CO, and 0.031, 0.032 and 0.033 g mi^{-1} for $PM_{2.5}$, for summer, spring/fall, and winter, respectively. For modeling purposes, the traffic volume was set to 1000 vehicles hr^{-1} (an arbitrary value since sensitivity analyses showed near-linear relationships between predicted concentrations and traffic volume), and hourly concentrations were predicted by scaling CALINE4 predictions by hourly traffic counts. Because CALINE4 was designed to predict 1 and 8 hr concentrations of CO, PM and NO_x for roadways (Benson, 1989), we modified the modeling approach in order to process hourly data for a full year. Pollutant concentrations were predicted for 16 wind sectors, each subtending 22.5°, and 12 wind speed classes, which spanned the reported range (0.4 to 0.5 m s^{-1}, 0.5 to 1.5 m s^{-1}, 1.5 to 2.5 m s^{-1}, …, 10.5 to 11.1 m s^{-1}). Following sensitivity analyses showing that mixing height and atmospheric stability classes had only minor effects on predicted concentrations, consistent with Benson (1989), mixing height was set to 1000 m, and atmospheric stability was set to neutral stability. Seasonal average concentrations were derived as the sum of predictions weighted by the probability of each wind sector/wind speed class occurring in 2004. Because the highest predictions occurred at low wind speeds, we conducted a limited sensitivity analysis of wind speed by considering three cases: omitting hours with calm winds, which was considered the nominal case; simulating calm winds by setting wind speed to 0.5 m s^{-1}; and omitting hours with wind speed below 1.5 m s^{-1}.

4.4.4 Statistical modeling

GAM was selected due to its ability to describe non-linear relationships and its additive structure. CO and $PM_{2.5}$ were analyzed separately using the following model:

$$P_t = \beta_0 + \beta_1 X_{1,t} + \ldots + \beta_6 X_{6,t} + \beta_7 X_{7,t} + S_1(Z_{1,t}) + \ldots + S_8(Z_{8,t}) \qquad (1)$$

where P_t = pollutant concentration at time t; $X_{1,t} \ldots X_{6,t}$ = indicator variables for days Tuesday to Sunday (Monday is the reference); $X_{7,t}$ = indicator variable for precipitation occurring during last three hours; S is a smoother (a non-linear function); $Z_{1,t}$ = traffic counts (vehicles hr^{-1}); $Z_{2,t}$ =wind direction (degrees); $Z_{3,t}$ = wind speed (m s^{-1}); $Z_{4,t}$ = ambient temperature (degree centigrade); $Z_{5,t}$ = pressure (mm Hg); $Z_{6,t}$ = relative humidity (percent); $Z_{7,t}$ = Julian day (1 to 366); and $Z_{8,t}$ = hour of the day (1 to 24).

These variables were selected based on the literature (Benson, 1989; Dominici et al., 2002; Aldrin and Haff, 2005). Traffic parameters were estimated using both smoothed (nonlinear) and parametric linear forms, that is, replacing the smoothed term $S_1(Z_{1,t})$ by a linear term $Z_{1,t}$, in order to derive emission factors for comparison with simulation model results. LOESS smoothers, which combine the robustness of linear regression and the local fitting of kernel methods (Faraway, 2006), were applied to the continuous variables ($Z_{1,t}$ to $Z_{8,t}$). Smoothing parameters were selected using the automatic and efficient generalized cross-validation (GCV) method (Hastie and Tibshirani, 1990). Partial plots of each smoothed component were constructed to visualize effects of traffic volume and other predictor variables on pollutant levels.

GAM models were fitted for CO and $PM_{2.5}$ using monitored observations. GAM models were also fitted to $PM_{2.5}$ adjusted for "background levels" by subtracting the hourly $PM_{2.5}$ concentration measurements at an "urban background" site located 40 km west in Ypsilanti. In contrast to CO, which is dominated by local sources including traffic, many sources contribute to $PM_{2.5}$ levels, and this adjustment was thought to possibly isolate the contribution from local traffic. We also conducted a sensitivity analysis to investigate effects of calm and low winds, as described earlier.
The fraction of ambient CO and $PM_{2.5}$ concentrations attributable to traffic were estimated by dividing predicted concentration (the product of the linearized traffic count coefficient multiplied by the seasonal average hourly traffic count) by the observed seasonal average concentration.

An exploratory analysis examined interactions among predictor variables, which can degrade GAM predictions (Aldrin and Haff, 2005; Faraway, 2006). These variables showed only moderate correlation, e.g., the maximum Pearson correlation coefficient, r=0.40, was between traffic counts and hour of the day, and did not indicate a serious problem for the analysis. We also stratified analyses by season to reduce interactions and enhance interpretation.

Model fit was evaluated by the fraction of explained deviance, defined as 1 – D_{model}/D_{null}, where D_{model} and D_{null} are deviances for fitted and null models, respectively. Deviance is a measure of fit that is defined as likelihood ratio statistic $2(l_L - l_S)$, where

l_L and l_S denote log-likelihoods for larger and smaller models, respectively (Faraway, 2006). Statistical analyses used SAS (version 9.1, SAS Institute Inc., Cary, NC, USA).

4.5 Results and discussion

4.5.1 CO predictions

Table 4-1 summarizes the pollutant, meteorological and traffic data. CO levels were low, averaging 0.3 ppm and reaching an hourly peak of only 3.6 ppm, far below the national 8-h standard of 9 ppm. Concentrations varied seasonally, averaging 0.29, 0.34, 0.45 and 0.28 ppm for spring, summer, fall and winter, respectively. The annual wind direction rose for the morning rush hour period (6-9 am) shows prevailing winds from the SW and W directions (Figure 4-2A). However, winds varied considerably by season (supplemental Figures 1A-D). Higher CO concentrations sometimes were seen with SW and N winds, suggesting moderate impacts from highway traffic, although the relationship was not strong (Figure 4-2B).

Dispersion model predictions of CO at the Allen Park receptor were small (Table 4-2), as has been observed in other analyses (WHO, 2005). Higher concentrations were predicted under some conditions, e.g., CO levels of 0.3 ppm were attained with low wind speeds (≤ 2 m s^{-1}) and winds parallel to the highway. Like other Gaussian plume models, CALINE4 predicts no contribution from traffic when the receptor site is upwind of the highway. Periods with low wind speeds yielded the highest predictions and contributed most to long term averages, e.g., periods with speeds <3 m s^{-1} accounted for 71, 94, 88 and 70% of the average CO levels in spring, summer, fall and winter, respectively. (The seasonal probabilities of such wind periods were 64%, 89%, 78% and 58%, respectively.)

Despite the low concentrations, the GAM analysis found statistically significant traffic–CO relationships that were approximately linear in fall, and piecewise linear in spring, summer and winter. Figure 4-3 shows the derived relationship (before linearization), including point estimates and the 95% confidence intervals. (Figures S4-2 to S4-5 show all variables on a seasonal basis using centered pollutant levels and the same y scale to facilitate comparisons, as well as the degrees of freedom and p-values.) The piecewise linear traffic–CO relationships, especially in winter (Figure 4-3D) might result from more frequent temperature inversions that increased CO concentrations during relatively low traffic flows. To facilitate comparisons with the CALINE4 predictions, the GAM models were rerun using a linear term for traffic volume, and the resulting coefficients show the covariate-adjusted change in CO concentrations for each 1,000 additional vehicles hr^{-1}. These coefficients range from 0.02 to 0.06 ppm per 1000 vehicles hr^{-1} (Table 4-2), and represent traffic contributions from 24 to 46% of the seasonal CO average. GAM predictions of CO were highest in fall, consistent with observed levels. While traffic explained a large share of observed CO levels, concentrations were low, reflecting the monitor-highway distance and the rapid fall-off in CO levels observed with distance from highways. For example, Zhu et al. (2002) showed CO concentrations in Los Angeles dropped from 2.3 ppm at 17 m distance to 0.4 ppm at 150 m. On a seasonal basis, the GAM models explained 63 to 75% of the null deviance (Table 4-3).

The meteorological and time variables in the GAM models were statistically significant ($p<0.05$) and largely consistent with earlier work (Aldrin and Haff, 2005). Wind speed and temperature had a large influence on pollutant concentrations, and impacts varied seasonally. Faster winds have been shown to dilute CO concentrations (Benson, 1989). Temperature's large impact on CO is likely due to poorer control efficiencies that result in higher emissions in winter, as well as poorer dispersion conditions. Other meteorological variables (relative humidity, wind direction, pressure and precipitation) had weaker effects and, in cases, varied by season. Precipitation had only small effects (Table S4-1), not surprisingly since CO is relatively insoluble and inefficiently scavenged. Day-of-week variables (indicator variables X_1 to X_6) were designed to capture changes in traffic volume and vehicle mix (including weekday and weekend effects); their values and significance varied by season (Table S4-1). The Julian day affected CO to a large extent, possibly reflecting vehicle mix, background pollutant levels, and other factors not captured by other variables in eq. (1). The hour-of-day variable, designed to account for the diurnal pattern of traffic volume, vehicle mix and/or dispersion, showed small effects that varied by season, generally lower concentrations around noon and higher concentrations at night.

The overall agreement between CALINE4 and GAM predictions for CO was remarkably close, within 4% based on the ratio between GAM and CALINE4 predictions defined as $C_g/C_c = 0.96$, although differences were slightly larger on a seasonal basis (Table 4-2). Results changed little when calm winds were included ($C_g/C_c = 0.97$), or if wind speeds below 1.5 m s^{-1} were omitted ($C_g/C_c = 1.14$).

Differences between dispersion and statistical models can occur for many reasons. First, MOBILE6.2 does not directly account for local conditions, including acceleration and deceleration (Joumard et al., 2000), which can cause high emissions at both low speeds, e.g., due to frequent acceleration/deceleration in congestion, and at high speeds, e.g., due to rapid acceleration, lane-changing and bypassing behavior (TRB, 2002). Instead, MOBILE6.2 emission rates are based on dynamometer tests and standard driving cycles, and emission rates vary by speed, as shown in Figure 4-4. Second, while we had information regarding the vehicle mix, a large fraction (61%) of the classification data was missing, and segment-specific information regarding fleet speed, vehicle age and high-emitting vehicles was unavailable. Instead, regional data were used. Third, dispersion models are known to perform poorly under low wind speed conditions, which were predicted to cause the highest concentrations at the study site. Still, validation studies have shown that CALINE4 predictions for CO near freeways generally fall within a factor-of-two of measured concentrations (Benson, 1989). The overall agreement between simulation and statistical models in most seasons, however, suggests that errors for CO are small.

4.5.2 $PM_{2.5}$ predictions

$PM_{2.5}$ levels at the Allen Park site averaged 16.8 µg m^{-3}, exceeding the annual National Ambient Air Quality Standard of 15 µg m^{-3} (Table 4-1). The $PM_{2.5}$ pollutant rose for the morning rush hour period (6 to 9 am) suggests that emissions from the local highway are not a significant contributor (Figure 4-2C). While the pollutant rose shows some directionality, the highest levels occurred with S, SW and SE winds, probably due to long range transport of sulfate and other aerosols from the Ohio River valley. CALINE4 predictions of $PM_{2.5}$ at the Allen Park receptor were small, no more than 0.5 µg m^{-3} (Table 4-4), consistent with previous studies (WHO, 2005). The highest $PM_{2.5}$ predictions occurred for low winds that were parallel to the highway, like the CO modeling discussed earlier, since the only difference between the CO and $PM_{2.5}$ simulations were emission factors.

The GAM estimates without the background adjustment showed traffic-$PM_{2.5}$ relationships that differed by season (Figure 4-5). Relationships were piecewise linear in spring and linear in summer, but sigmoidal in fall and decreasing in winter. (Figures S4-6 to S4-9 show estimates for all smoothed variables and each season.) Spring, summer and fall traffic terms were replaced by linear terms, and covariate-adjusted coefficients representing the change in $PM_{2.5}$ levels for each 1 000 vehicles hr^{-1} were estimated. In these three seasons, GAM indicates that traffic accounted for 5 to 8% of observed $PM_{2.5}$ (Table 4-4), and the models accounted for 74 to 89% of the null deviance (Table 4-3). Most strikingly, GAM predictions were considerably higher than dispersion model predictions; the C_g/C_c ratio was 4.2 when calm winds were excluded (Table 4-4). This ratio was similar, 4.0, when calm winds were included, but increased dramatically to 8.5 when the winds speeds below 1.5 m s^{-1} were excluded, mainly a result of changes in CALINE4 predictions. The background adjustment had only a small effect, e.g., linearized spring, summer and fall emission factors were 0.389 ± 0.103, 0.549 ± 0.132 and 0.263 ± 0.082 μg m^{-3} per 1,000 vehicles, and the winter relationship remained negative, similar to results in Table 4-4. Overall, the background adjustment did not enhance performance, possibly because the Ypsilanti site was too far away and influenced by local sources.

The inconsistent results for winter and the variation across seasons can result from many factors, including the lack of counts for diesel-powered vehicles, a significant $PM_{2.5}$ source, the small $PM_{2.5}$ increment from traffic at the monitor site, and poorly controlled meteorological factors. The other study using GAM to examine traffic and $PM_{2.5}$ found a concave relationship between traffic counts and $PM_{2.5}$ levels at a site very near (<10 m) to the road, possibly due to nonlinear effects of vehicle speed, acceleration and deceleration (Aldrin and Haff, 2005). Traffic's contributions to $PM_{2.5}$ may vary seasonally, as shown in Cincinnati where contributions at two sites (including one also near I-75) were the lowest in winter (Hu et al., 2006). Traffic's smaller impact in winter may explain GAM's inconsistent results. In other seasons, GAM and CALINE4 showed similar trends.

The strong effect of wind speed can be explained by several factors. First, the two model types handle wind speed differently, i.e., wind speed is in the denominator of the Gaussian plume equation, but it is an additive term in GAM. Second, we observed some association between wind speed and direction, e.g., some of the lowest wind speeds occurred when the monitoring site was upwind, rather than downwind of the highway. Daily and seasonal changes in vehicle mix, age distribution, and meteorology also affect the traffic–$PM_{2.5}$ association. In particular, truckers tend to avoid rush hour periods and the percentage of heavy duty diesel vehicles (HDDVs), which emit much more $PM_{2.5}$ than cars, increases at night. Based on the I75-9799 PTR 2004 classification (Whiteside, 2006), HDDVs comprised 8 - 10% of the vehicles during the morning rush hour, 11 - 13% from 9:00 to 14:00, 6 - 7% from 16:00 to 19:00 evening rush hour, 10 - 12% from 20:00 to 24:00, and 17 - 23% from 1:00 to 5:00. Based on MOBILE6.2, $PM_{2.5}$ emissions with these HDDV fractions changed significantly (0.032 to 0.078 g mi^{-1} for annual averages) for the range of HDDV fractions at Allen Park (Figure 4-6). The PTR data also show some seasonal variation in the HDDV fraction, which averaged 12, 10, 13 and 11% in spring, summer, fall and winter, respectively. We re-estimated $PM_{2.5}$ levels using the seasonal average HDDV fractions, which reduced the C_g/C_c ratio to about 3; differences approached a factor of two with the maximum HDDV fraction (23%). Ideally, HDDV counts rather than total traffic counts would be used to predict $PM_{2.5}$ emissions. Unfortunately, over half (61%) of the vehicle classification data were missing, thus this analysis was not attempted.

Meteorological variables strongly affected GAM results for $PM_{2.5}$. Higher wind speeds tended to decrease concentrations, consistent with modeling and experimental findings (Benson, 1989; Levy et al., 2003; Aldrin and Haff, 2005). Higher temperatures were associated with higher $PM_{2.5}$ concentrations, especially in spring and summer (Figures S4-6 to S4-9). Higher temperatures can hasten the production of secondary aerosols, but also can evaporate ammonium nitrate and organic aerosols (Dawson et al., 2007). Morishita et al. (2006) reported that coal combustion/secondary sulfate aerosol, including local and regional sources, was the largest source of ambient $PM_{2.5}$ in SE Michigan. Relative humidity was positively correlated with $PM_{2.5}$, possibly due to absorption of water on $PM_{2.5}$ at high humidity (CCPA, 2001). Precipitation tended to drop $PM_{2.5}$ levels by 1 to 3 $\mu g\ m^{-3}$ (Table S4-1). Most of the precipitation fell in summer (15 in), compared to the other seasons (6 – 11 in). Precipitation was included in the model as an indicator variable, which may not have adequately the scavenging processes. Wind direction had only a small effect. Higher barometric pressure was usually associated with higher concentrations, probably because it is associated with stable air conditions, subsidence inversions, and slower wind speeds, all of which decrease pollutant dispersion.

Of the time variables, day-of-week variables had relatively large impacts that depended on season (Table S4-1). Julian day had a large influence on $PM_{2.5}$, possibly due to vehicle mix, regional sources, and other factors not captured in eq. (1).
Many factors can affect the ability to observe traffic-$PM_{2.5}$ relationships, and the differences between statistical and simulation models. As discussed earlier, these include biases in the emission factors in MOBILE6.2, omission of high-emitting vehicles, errors in traffic counts, and the assumed vehicle mix, which is especially important for HDDVs. Recent reports (EPA 2006; 2008) show that actual $PM_{2.5}$ emission factors were 2.3 times higher than MOBILE6.2 predictions for HDDVs (classes 6 through 8), and 1.6 times higher for light duty gasoline vehicles. Since $PM_{2.5}$ arises from many local and regional sources, and not uniquely or predominantly from vehicles, concentration gradients near roads are small. As examples: Roorda-Knape et al. (1998) found that concentrations measured 15 m from a major motorway in the Netherlands were only 10% higher than those at distances from 260 to 305 m; Kingham et al. (2000) demonstrated similar results in the UK. In consequence, the "signal" from traffic can be small and difficult to identify using statistical models. Vehicle emissions depend on changes in vehicle speed, acceleration and deceleration, factors not indicated by the traffic counts and average speed, the key inputs to MOBILE6.2. This model suggests that fleet speed has only minor effects on $PM_{2.5}$ emissions (Figure 4-4). However, relationships between speed, acceleration and $PM_{2.5}$ emissions are complex and incompletely established (TRB, 2002). Finally, MOBILE6.2 does not account for fine particle re-entrainment, although only minor impacts are expected for $PM_{2.5}$.

We also note that CALINE4's capabilities for $PM_{2.5}$ have not been fully evaluated. Yura et al. (2006) used a small dataset (n = 23, three receptors) and found large discrepancies in $PM_{2.5}$ predictions, e.g., only 67% of predictions were within a factor-of-two of measurements at a site 70 m from the road. Chen et al. (2008) noted that

CALINE4 under-predictions increased at higher $PM_{2.5}$ concentrations and with complex terrain. The reasonable agreement between simulation and statistical models found in this paper for CO, however, suggests that a large share of the problem may be inaccurate emission estimates for $PM_{2.5}$, rather than the dispersion model calculations, at least for the simple terrain and other conditions encountered in the case study.

4.5.3 Comparison between source-oriented and statistical models

Simulation and statistical models utilize independent data sets and different assumptions, thus comparisons can represent a form of validation (Solomon et al., 2008). GAM and other "observational" models have the advantage that fewer assumptions are needed, and thus they may better represent real world behavior. In the present application, for example, the GAM model did not require MOBILE6.2's assumptions regarding average speed and fixed vehicle mix. However, simulation models are less data intensive, more generalizable, and useful for predictive purposes.

Our comparisons between the two model types showed generally good agreement for CO. If the dispersion model CALINE4 is unbiased, then this suggests, but does not confirm, that the emission factors predicted by MOBILE6.2 are, on average, accurate. More generally, agreement between empirical and process-based models is a necessary, but not sufficient condition in the performance evaluation of models. For example, emission and dispersion models may have opposite but compensating biases, or both empirical and process-based models may be similarly incorrect. The possibility that the inter-model agreement found for CO is spurious seems small, however, given the extensive evaluation and validation exercises undertaken for MOBILE6.2 and CALINE4, including the use of well-controlled and accurately measured tracer gas releases along roadways, the "gold standard" for such exercises. Our results represent a real-world scenario which supports the usefulness of the both emission and dispersion models for CO, but it does not constitute a validation of these models. In contrast, the divergence in $PM_{2.5}$ results suggests systematic biases. In particular, assuming that the dispersion modeling predictions are reasonable, which is supported by our results for CO and especially by the just mentioned model validation efforts, our results highlight the need for further development of $PM_{2.5}$ emission factors and vehicle mix. Further comparison between simulation and statistical approaches is also suggested, especially to understand traffic's impacts on near-road air quality and when more comprehensive emission models become available.

4.5.4 Study limitations

This study has several limitations. First, a single monitoring site was emphasized, and the site was situated somewhat farther from the highway than desired, thus, traffic's contribution to CO and especially $PM_{2.5}$ was modest. Application of similar methods at sites with high traffic impacts is suggested. While we used a (distant) background site, simultaneous monitoring at locations upwind and downwind of the highway should increase the ability to quantify impacts and account for background concentrations, as would the use of pollutants more specific to traffic. Second, our analysis was performed for a mix of vehicle types, and the $PM_{2.5}$ estimates did not account for fleet speed. Consequently, derived emission factors cannot be attributable to specific vehicle types. Third, only two pollutants were examined. It would be helpful to examine other traffic-related air pollutants, especially those that have greater specificity to vehicle sources and smaller background contributions, e.g., NO, ultrafine particles, and black carbon. (While other parameters were measured at Allen Park, they did not use hourly samples, a requirement for the statistical analysis.) Fourth, only one year of data was analyzed, and traffic counts included a large fraction of missing data. Multiyear datasets and effects of missing data (which are usually not missing at random) should be examined. Fifth, the performance of GAMs relies on the quality, quantity and characteristics of the data. GAM performance might be improved by several factors: incorporating other traffic information, e.g., HDDV proportion and average fleet speed; using different expressions for independent variables, e.g., absolute humidity (an unbounded variable compared to relative humidity); and accounting for the discontinuities in wind direction (from 359 to 0^o) and time (from 24:00 to 1:00). Explicitly modeling autocorrelation in the residuals might also improve results, although only minor changes are expected (Aldrin and Haff, 2005; Carslaw et al. 2007). Sixth, our emission and dispersion modeling was relatively basic, and many techniques and models promised enhanced performance, as reviewed elsewhere (Solomon et al., 2008).

4.6 Conclusions

We contrasted simulation and statistical models to estimate traffic impacts on CO and $PM_{2.5}$ concentrations near highways. Using a GAM approach with adjustments for weather conditions and time trends, CO concentrations were piecewise linearly or linearly related to traffic volume, and the derived emission rates closely matched predictions from MOBILE6.2 and CALINE4 in spring and summer. For $PM_{2.5}$, traffic-related emissions accounted for a small faction (less than 8%) of measured concentrations. Still, we derived GAM-based emission rates for three seasons (except winter), which significantly exceeded MOBILE6.2's predictions, suggesting that MOBILE6.2 significantly underestimates $PM_{2.5}$ emissions. Seasonal analyses decreased potential interactions and increased goodness-of-fit.

Comparisons between simulation and statistical models are helpful for evaluating model performance, identifying potential uncertain model parameters, and improving the prediction of near-road pollutant levels. For example, the use of GAM derived emission factors and CALINE4 for dispersion could improve near-road concentration predictions. This appears to be the first comparison between MOBILE6.2/CALINE4 and GAM to examine the impact of traffic on near-road environments, and our approach and findings are relevant to emission, exposure, health risk evaluations and epidemiological studies.

Table 4-1. Statistics of pollutants, meteorological variables, and traffic variables used in the analysis.

Variable	N	Min	Max	Mean	STD[a]	No of censored data[b]	No of missing data[c]
$PM_{2.5}$ ($\mu g\ m^{-3}$)	8657	0	68.0	16.8	11.6	328	127
CO (ppm)	8316	0	3.6	0.3	0.3	360	468
Wind speed ($m\ s^{-1}$)	8750	0	11.1	2.6	1.6	NA	34
Wind direction (Degrees Compass)	8750	0	359.0	189.6	97.4	NA	34
Temperature (Degrees Centigrade)	8750	-17.4	32.7	10.8	10.7	NA	34
Relative humidity (percent)	8006	23.0	100.0	76.5	17.2	NA	774
Pressure (mm Hg)	8750	725.8	765.7	746.3	5.5	NA	34
Traffic counts (vehicles hr^{-1})	8040	0	9029.0	3221.3	2469.2	NA	2256

a. Standard deviation.
b. Observations with zero values due to less than method detection limit (MDL; 0.5 $\mu g\ m^{-3}$ for $PM_{2.5}$; 0.05 ppm for CO).
c. Observations not available.

Table 4-2. Comparison of GAM and CALINE4 predictions of CO concentrations at 150 m due to vehicles.

Season	CO predictions		Ratio (C_g/C_c [a])	Average CO levels	Average traffic counts	Traffic contribution [b]
	GAM	CALINE4				
	ppm per 1000 vph	ppm per 1000 vph		ppm	vph	%
Spring	0.025 ± 0.001	0.029	0.86	0.29	2836	24
Summer	0.038 ± 0.002	0.034	1.12	0.34	2630	29
Fall	0.055 ± 0.002	0.039	1.41	0.45	3764	46
Winter	0.020 ± 0.002	0.044	0.45	0.28	3465	25
Average	0.035	0.037	0.96	0.34	3221	31

a. C_g = pollutant levels attributed to traffic derived from GAM, C_c = pollutant levels attributed to traffic predicted by CALINE4.
b. Estimated traffic contribution based on GAM results = Traffic coefficient × seasonal average traffic counts /seasonal average levels.

Table 4-3. Performance statistics for GAM.

	CO				$PM_{2.5}$			
	Spring	Summer	Fall	Winter	Spring	Summer	Fall	Winter
Null deviance	41	33	271	43	152751	96865	278057	187100
Deviance for fitted models	15	11	69	13	34230	24847	42446	20730
Explained deviance by fitted models	26	22	203	30	118521	72018	235611	166370
% Explained deviance by fitted models	63	67	75	71	78	74	85	89

Table 4-4. Comparison of GAM and CALINE4 predictions for $PM_{2.5}$ concentrations at 150 m due to vehicles.

Season	$PM_{2.5}$ predictions		Ratio (C_g/C_c[b])	Average $PM_{2.5}$ levels	Average traffic counts	Traffic contribution[c]
	GAM	CALINE4				
	$\mu g\ m^{-3}$ per 1000 vph	$\mu g\ m^{-3}$ per 1000 vph		$\mu g\ m^{-3}$	vph	%
Spring	0.250 ± 0.063	0.063	3.97	15.21	2836	5
Summer	0.510 ± 0.100	0.107	4.77	17.68	2630	8
Fall	0.332 ± 0.055	0.085	3.91	19.87	3764	6
Winter	-[a]	0.074	NA	14.30	3465	NA
Average	0.364	0.082	4.21	16.77	3221	6

a. Smoothing component plot shows traffic effects are negative although it is statistically significant ($p=0.03$).
b. C_g = pollutant levels attributed to traffic derived from GAM, C_c = pollutant levels attributed to traffic predicted by CALINE4.
c. Estimated traffic contribution based on GAM results = Traffic coefficient × seasonal average traffic counts /seasonal average levels.

Table S4-1. GAM coefficient estimates for weekdays, weekends and precipitation in past three hours (unit: CO, ppm; $PM_{2.5}$, μg m^{-3}; bold estimates are statistically significant (0.05 level); Monday is the reference day for weekdays and weekends)

Pollutant	Season	Tuesday	Wendesday	Thursday	Friday	Saturday	Sunday	Precipitation
CO	Spring	0.01	**-0.03**	**-0.02**	**-0.10**	-0.01	**-0.09**	**0.02**
	Summer	**0.09**	**-0.04**	**-0.04**	**-0.05**	**-0.09**	**-0.04**	-0.01
	Fall	**0.09**	**0.21**	**0.12**	**0.15**	**0.13**	0.02	**-0.11**
	Winter	**-0.05**	**-0.09**	**-0.04**	**-0.03**	**-0.10**	-0.02	**-0.10**
$PM_{2.5}$	Spring	**-1.52**	**5.77**	**2.48**	**3.21**	**2.03**	**1.16**	**-1.75**
	Summer	**4.46**	**-2.87**	**-8.14**	**-8.89**	**-9.45**	**-4.25**	**-2.64**
	Fall	**1.72**	**4.99**	**-2.00**	**3.21**	**-2.07**	**-1.70**	**-1.32**
	Winter	**3.82**	**8.57**	**9.93**	**5.23**	**6.13**	**6.34**	**-2.80**

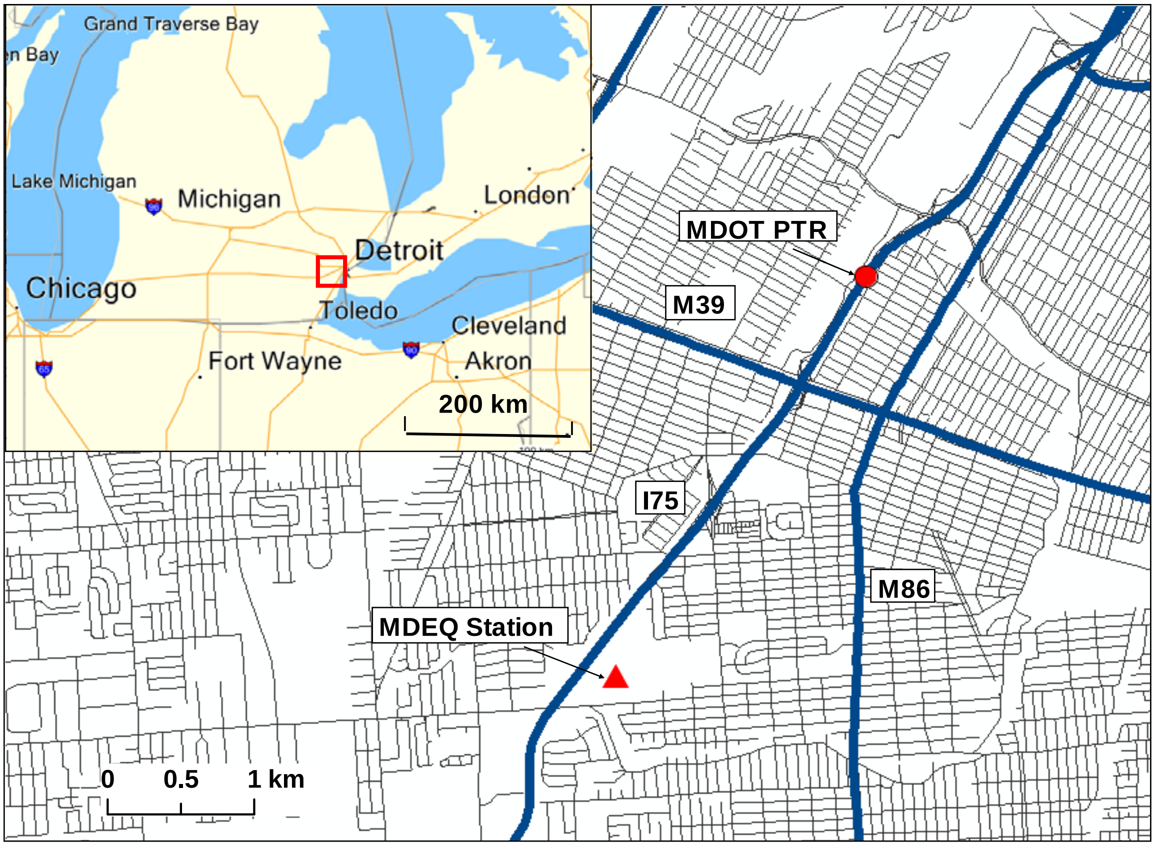

Figure 4-1. I75 Study area in Allen Park, Michigan

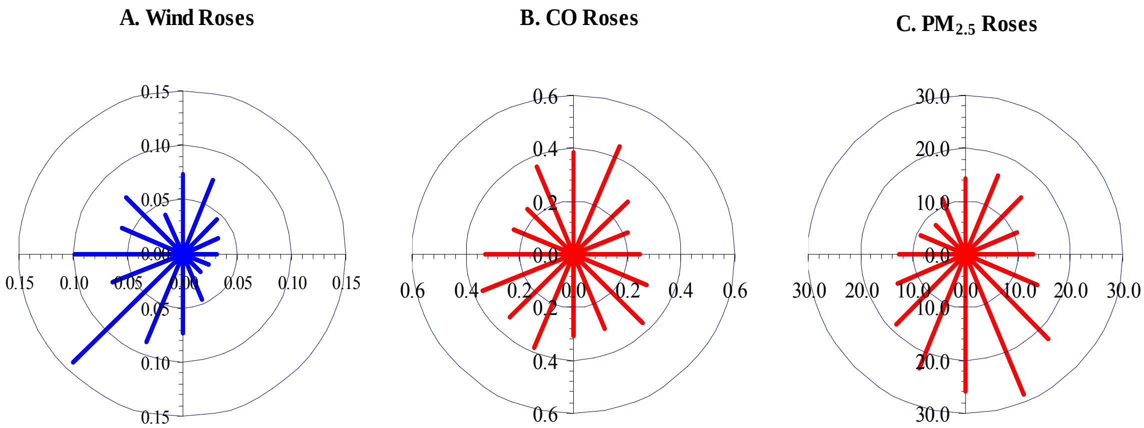

Figure 4-2. Wind and pollutant roses based on measurements at the Allen Park monitoring site and for morning data (6 - 9 am) in 2004. A. Wind direction rose showing sector probability. B. CO pollutant rose showing average concentrations in each (22.5^{o}) wind sector in ppm; C. $PM_{2.5}$ pollutant rose showing concentration in µg m^{-3}.

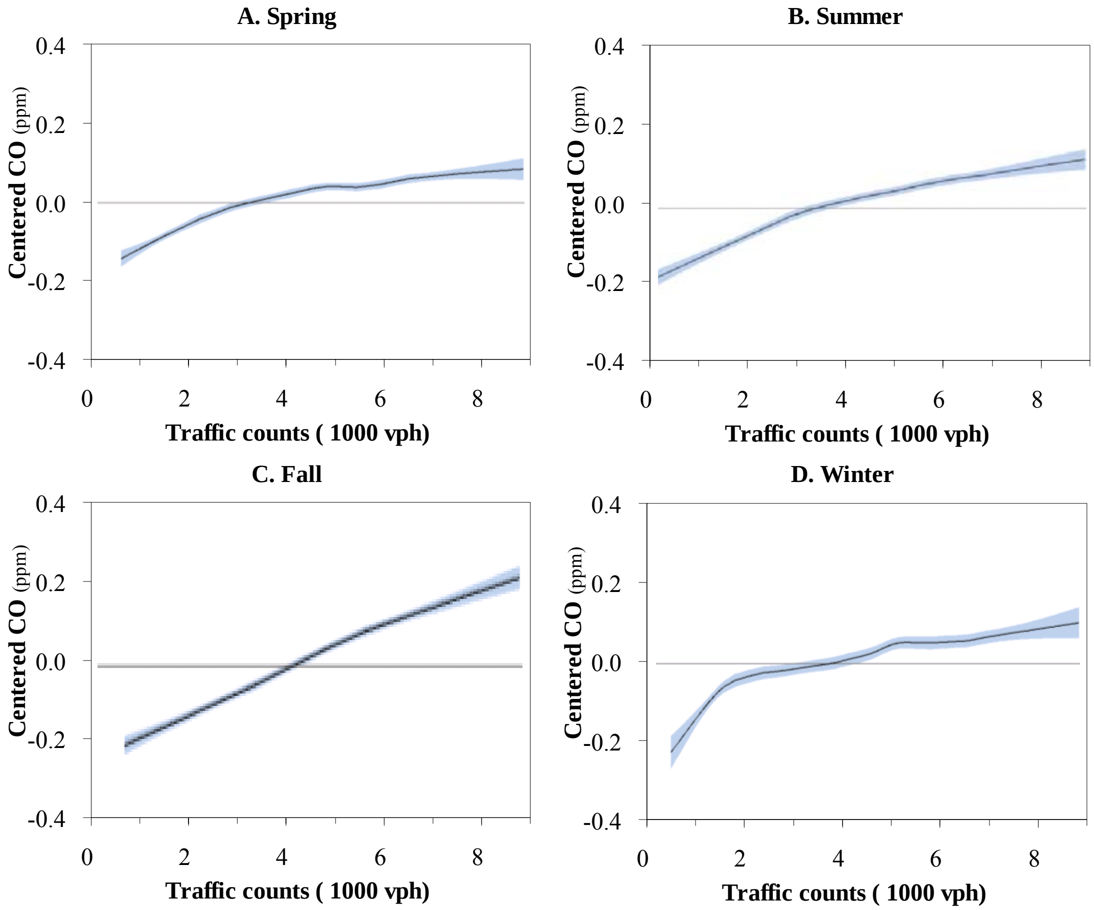

Figure 4-3. Associations between traffic counts and CO levels after adjusting meteorological variables and time trends (x axis: traffic counts, 1 000 vehicle hr^{-1}; y axis: centered CO, ppm)

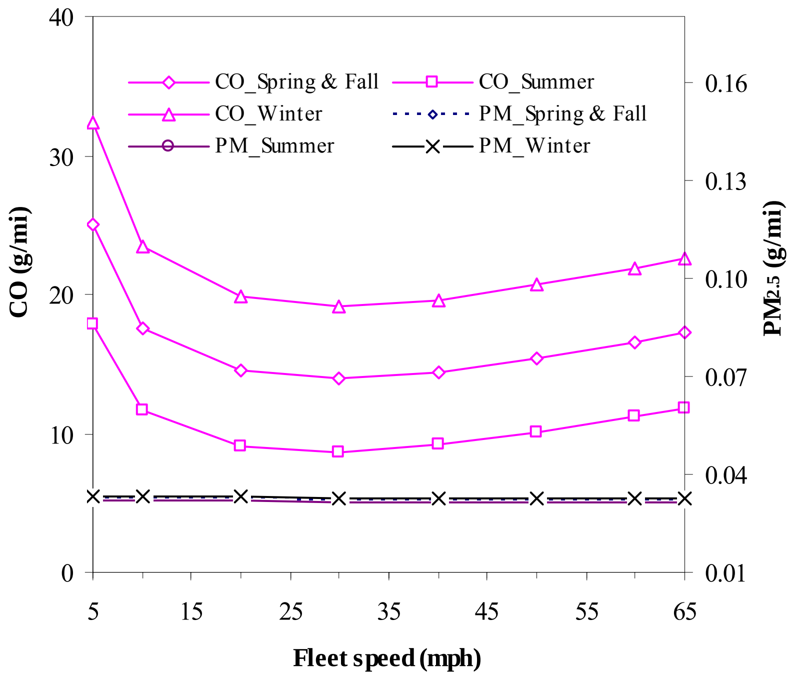

Figure 4-4. CO and $PM_{2.5}$ emission rates for a freeway segment versus average fleet speed. Derived from MOBILE6.2. $PM_{2.5}$ estimates for each season are similar.

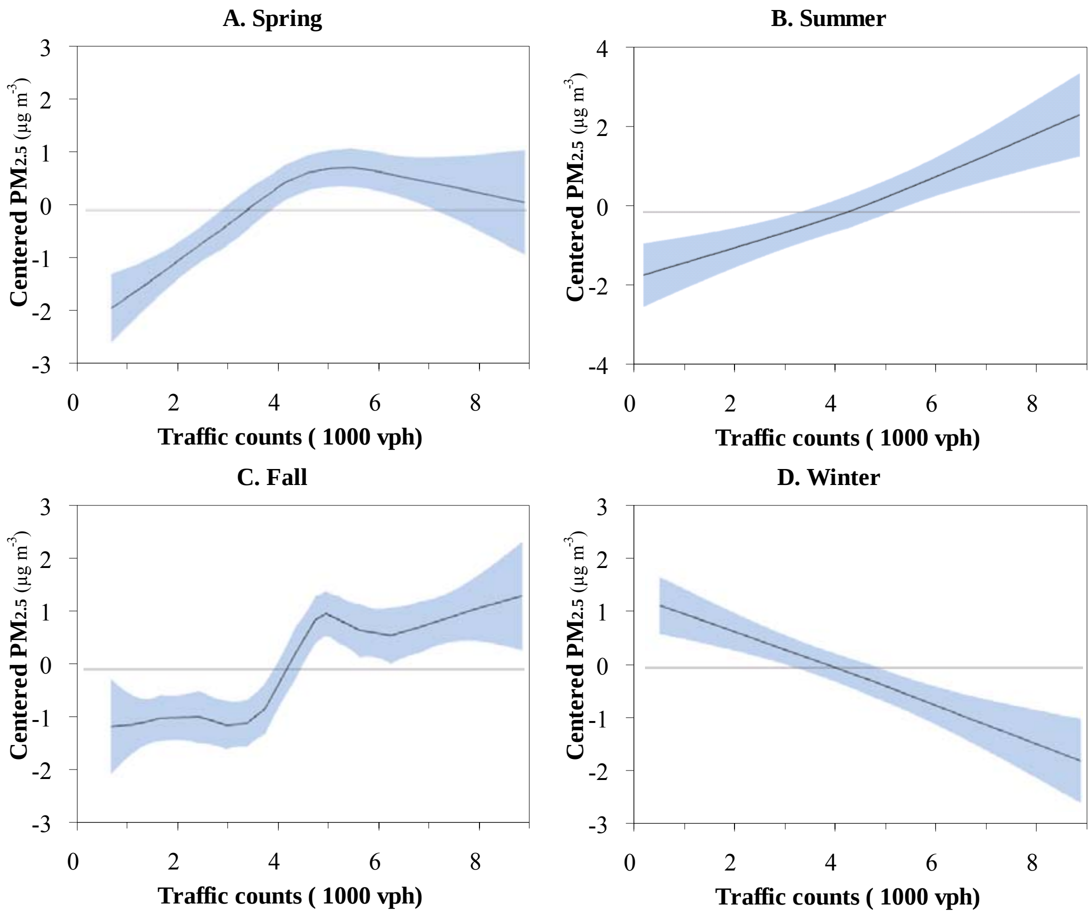

Figure 4-5. Associations between traffic counts and $PM_{2.5}$ levels after adjusting meteorological variables and time trends (x axis: traffic counts, 1 000 vehicle hr^{-1}; y axis: centered $PM_{2.5}$, μg m^{-3})

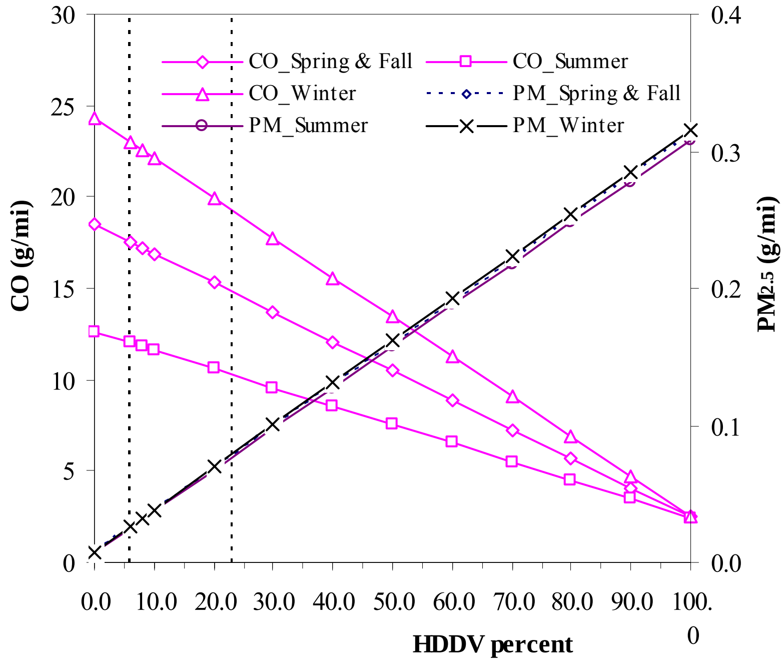

Figure 4-6. CO and $PM_{2.5}$ emission rates for the freeway segment versus the fleet heavy duty diesel truck (HDDV) percentage. Vertical lines show the range of HDDV vehicles in the case study. Derived from MOBILE6.2.

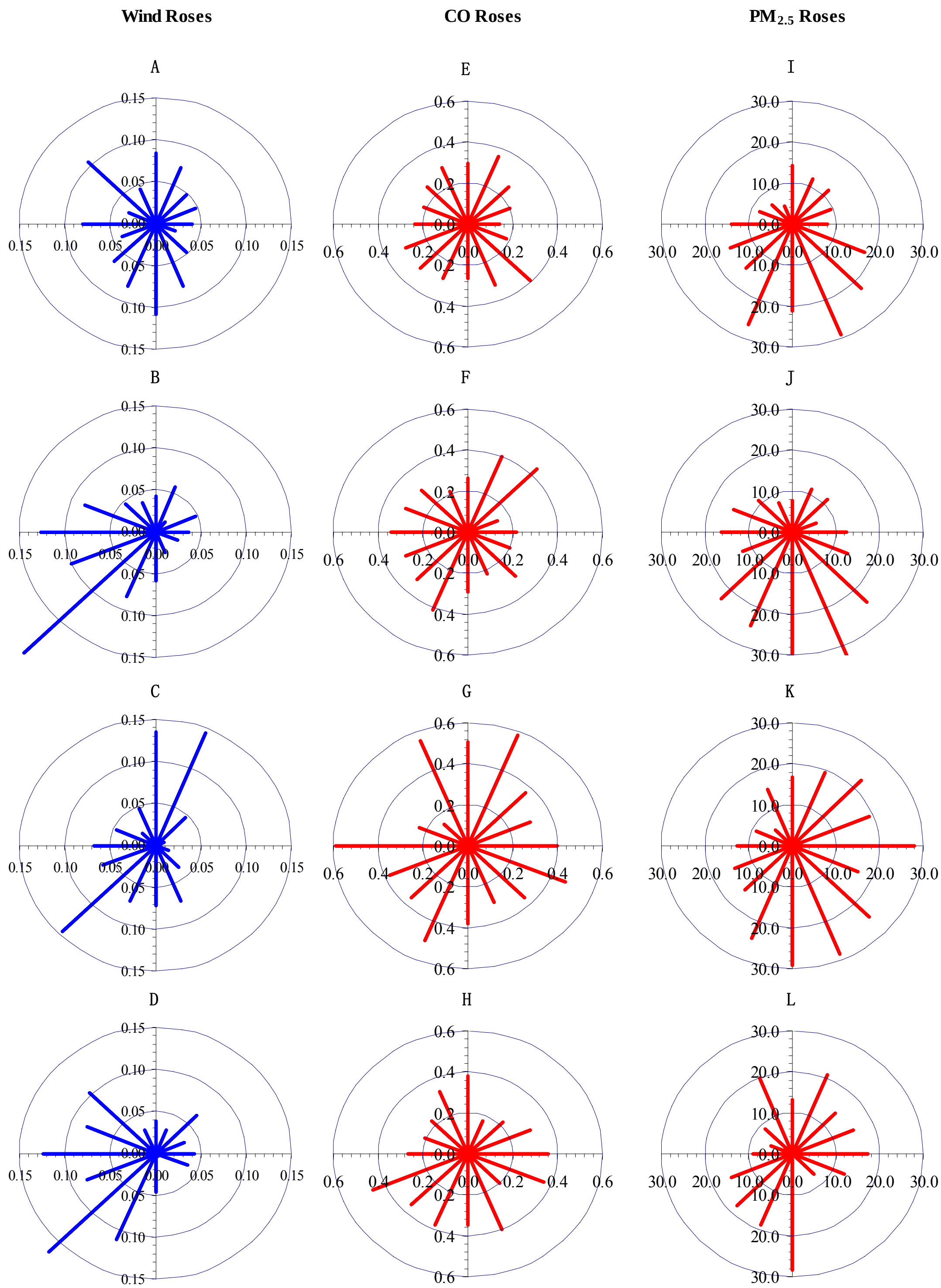

Figure S4-1. Seasonal wind rose in the morning rush hours (6-9am) of 2004 (from left to right: wind direction roses, $PM_{2.5}$ roses and CO roses; from top to bottom: spring, summer, fall and winter; unit:, probability for wind roses, μg m^{-3} for $PM_{2.5}$ and ppm for CO)

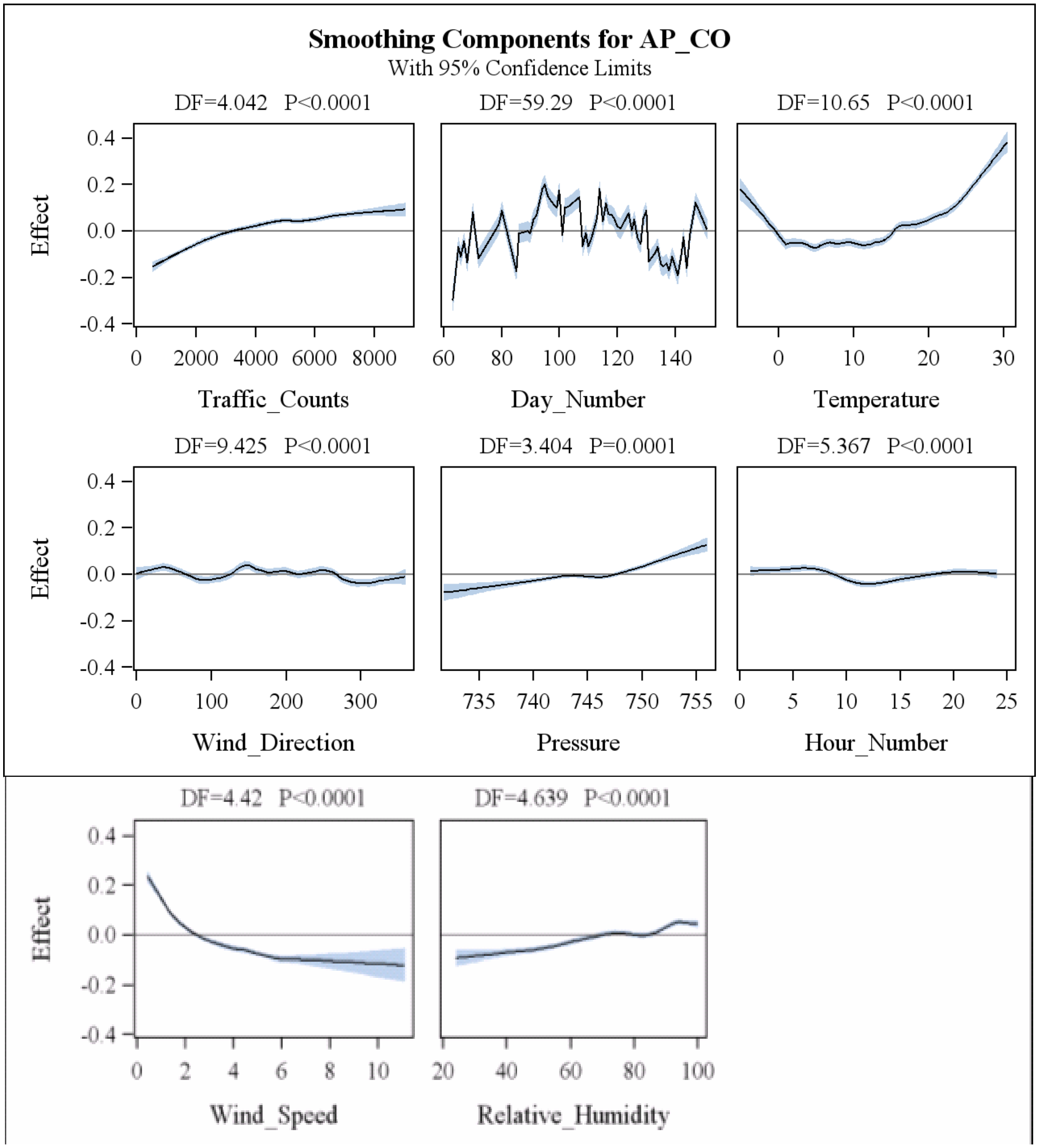

Figure S4-2. Smoothing components for CO in spring, 2004

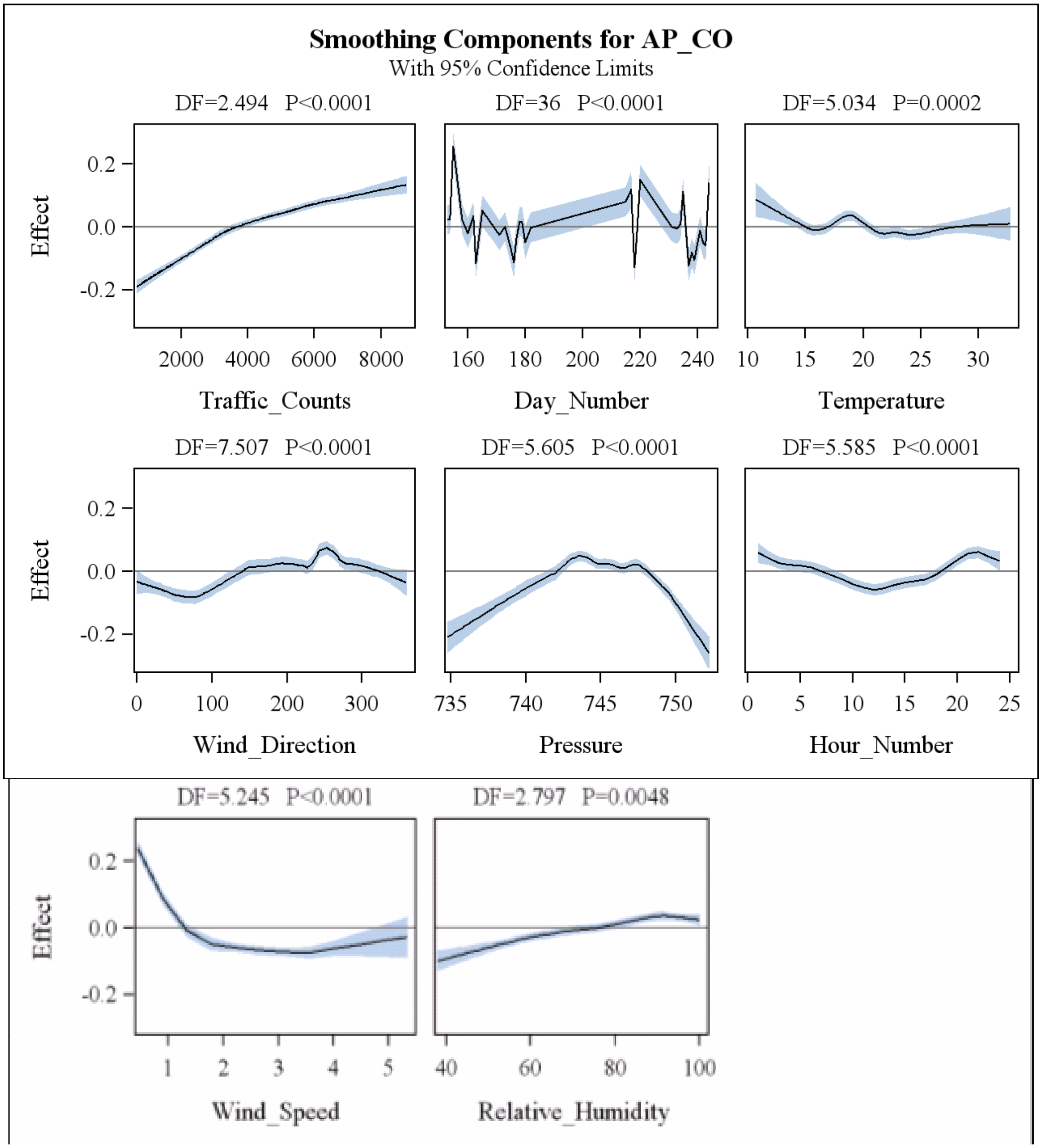

Figure S4-3. Smoothing components for CO in summer, 2004

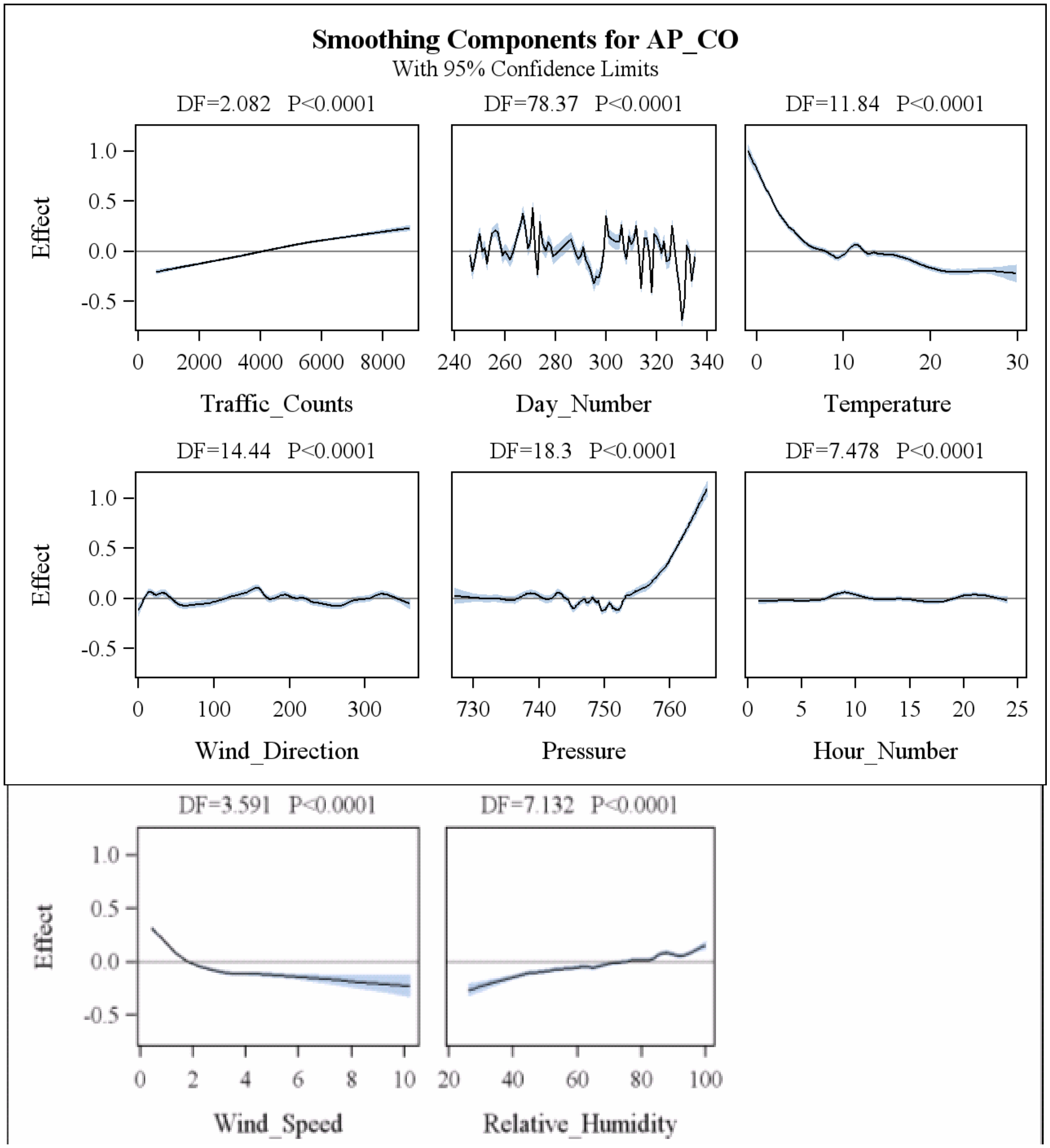

Figure S4-4. Smoothing components for CO in Fall, 2004

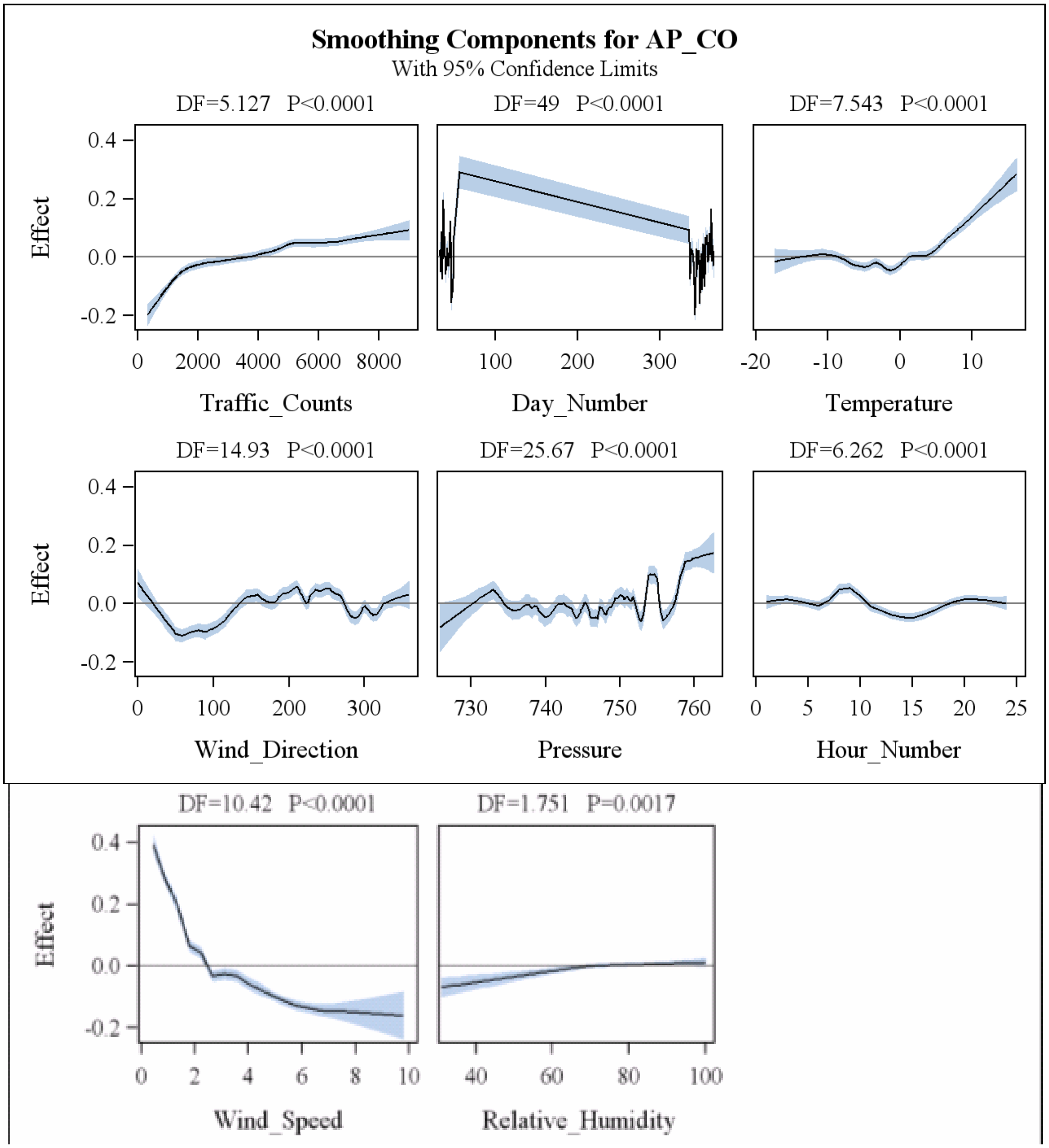

Figure S4-5. Smoothing components for CO in winter, 2004

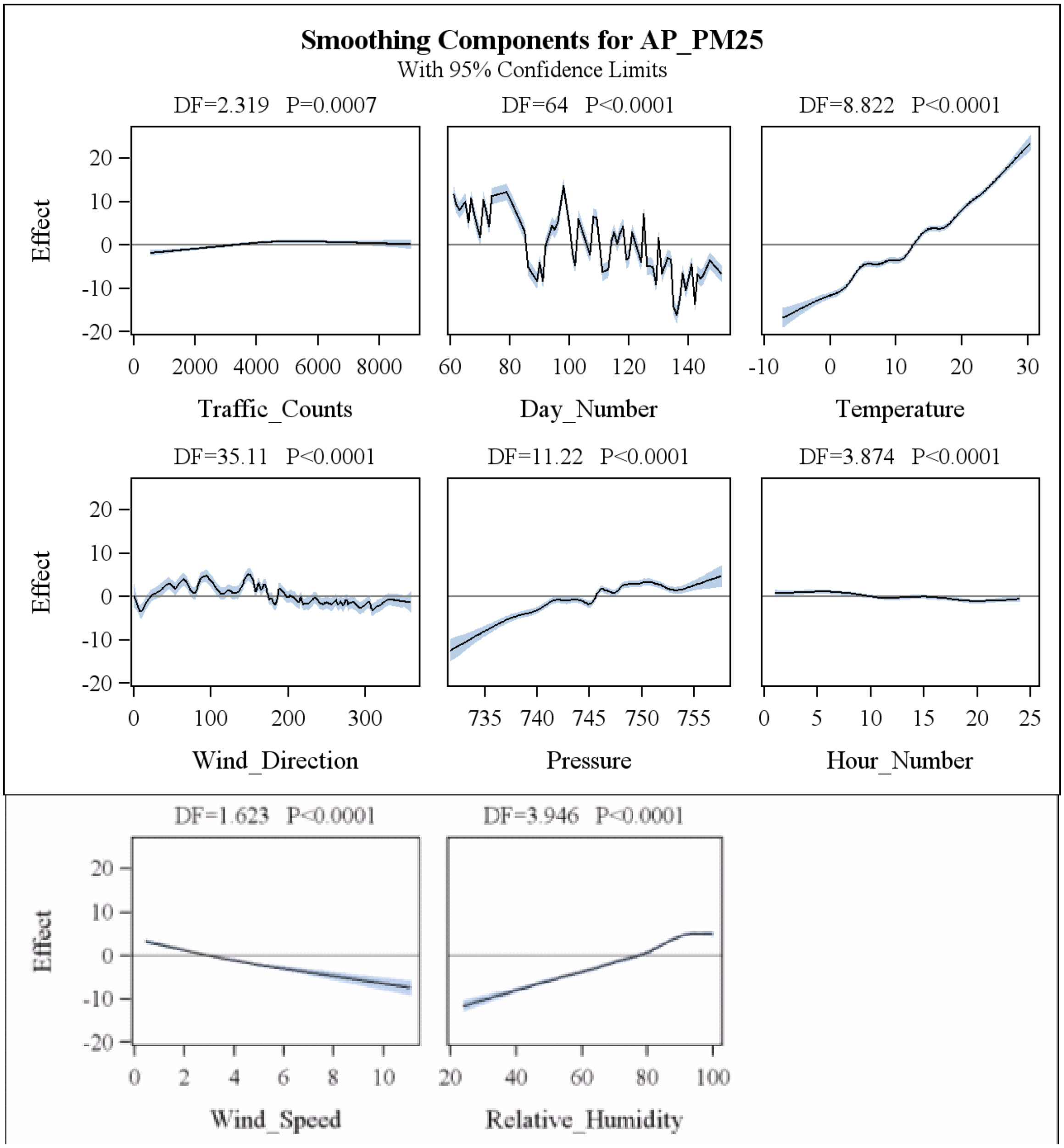

Figure S4-6. Smoothing components for $PM_{2.5}$ in spring, 2004

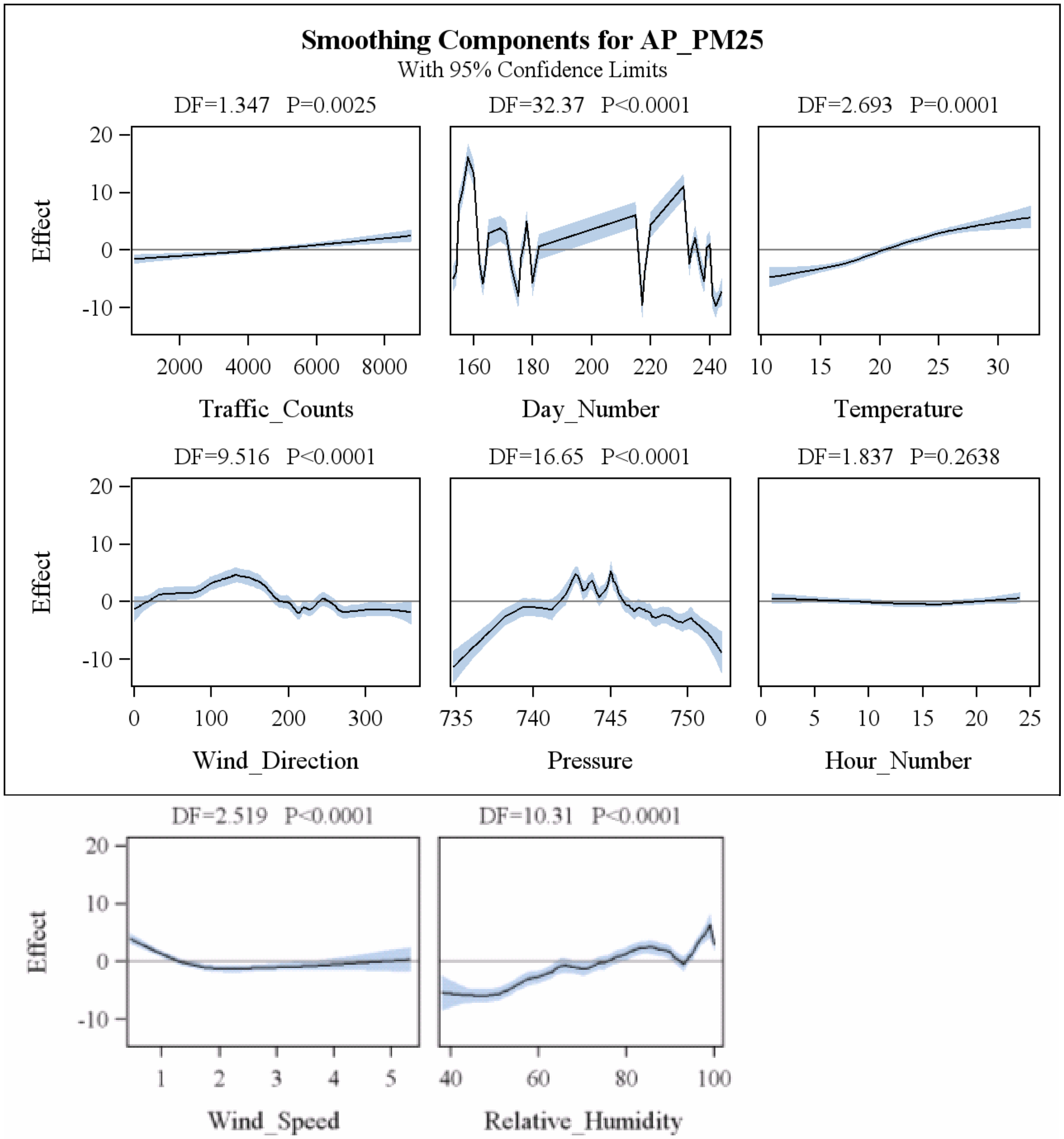

Figure S4-7. Smoothing components for $PM_{2.5}$ in summer, 2004

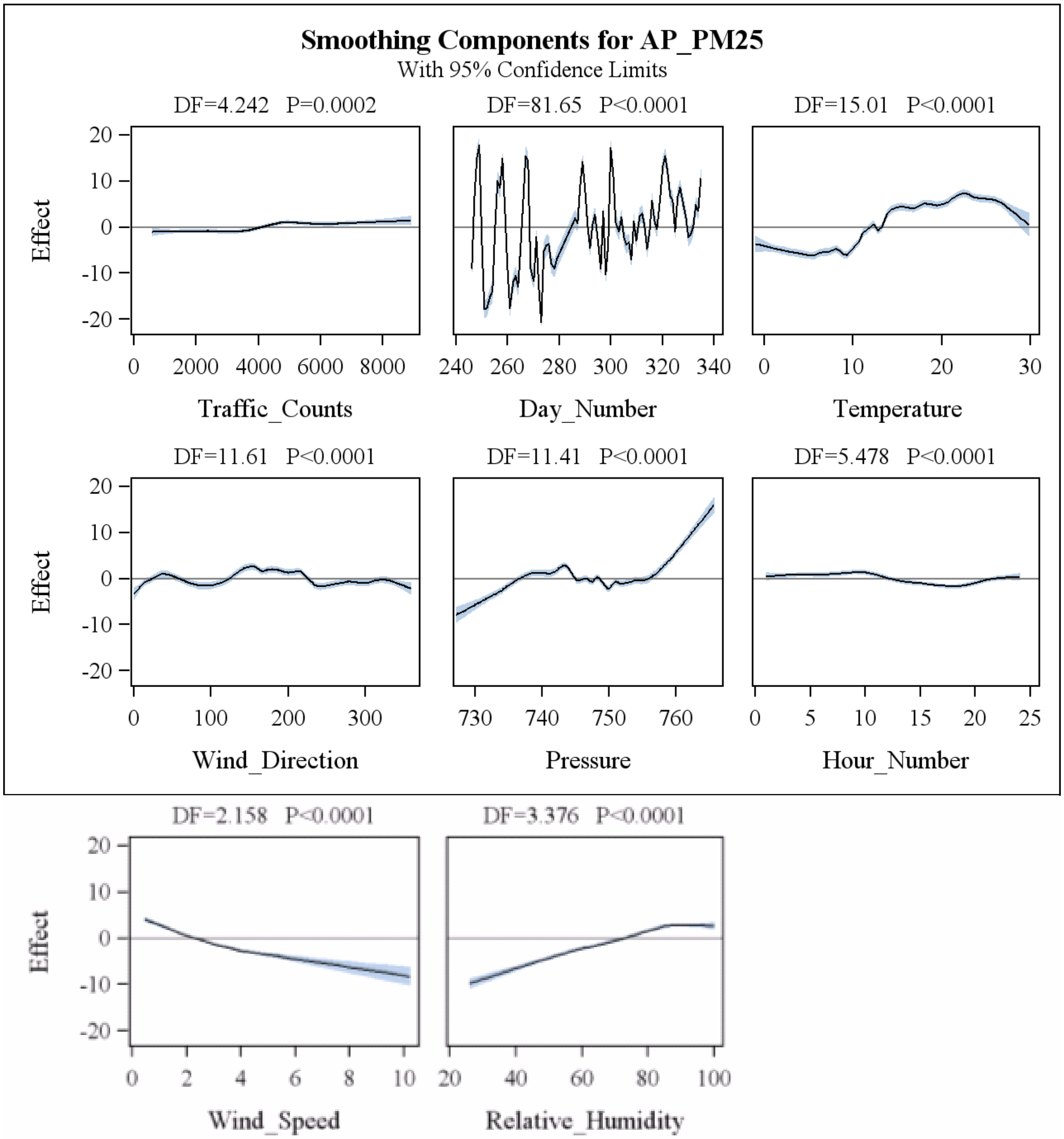

Figure S4-8. Smoothing components for $PM_{2.5}$ dataset in fall, 2004

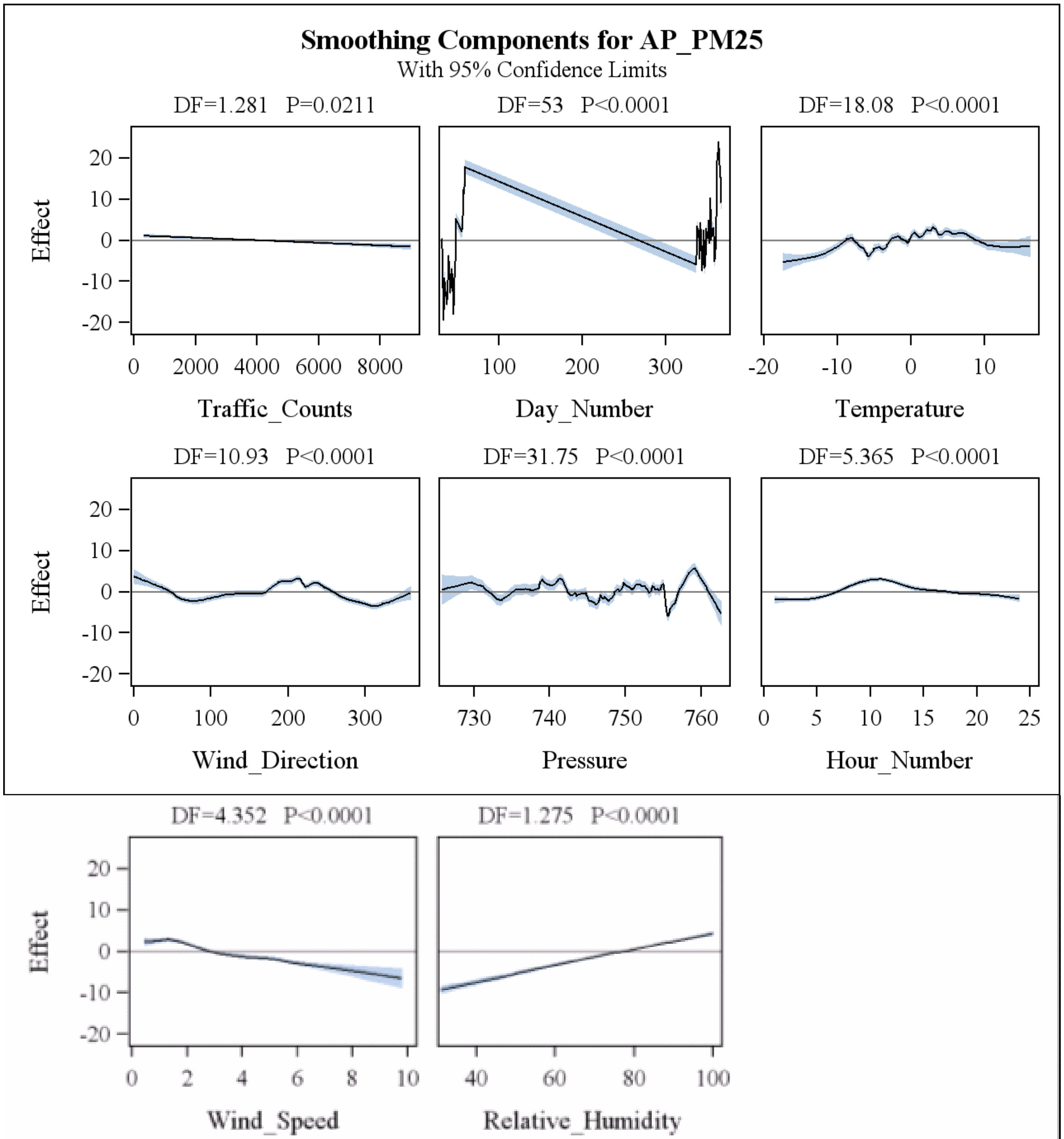

Figure S4-9. Smoothing components for $PM_{2.5}$ dataset in winter, 2004

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Chapter 5
Air pollution and health risks due to traffic and congestion

5.1 Abstract

Traffic congestion increases vehicle emissions and degrades ambient air quality, and recent studies have shown excess morbidity and mortality for drivers, commuters and individuals living near roadways. Presently, our understanding of the air pollution impacts from traffic congestion is very limited. This study demonstrates an approach to characterize risks of traffic congestion for on- and near-road populations for freeway and arterial scenarios. Simulation modeling was used to estimate on- and near-road NO_2 concentrations and health risks attributable to traffic for different traffic volumes during rush hour periods for both scenarios. The modeling used emission factors from two different models (Comprehensive Modal Emissions Model; Motor Vehicle Emissions Factor Model version 6.2), an empirical traffic speed – volume relationship, a conventional dispersion model (California Line Source Dispersion Model), an empirical NO_2/NO_x relationship, estimated travel time changes during congestion, and concentration-response relationships from the literature giving emergency doctor visits, hospital admissions and mortality attributed to NO_2 exposure. An incremental analysis, expressing the change in health risks for small increases in traffic volume, showed non-linear effects. For freeways, on-road exposures, "U" shaped trends of incremental risks were predicted for both on- and near-road populations. For arterial roads, incremental risks increased sharply for both on- and near-road populations as traffic increased. These patterns are due mainly to changes in emission factors, the NO_2/NO_x relationship, travel delay for on-road population and the extended duration of rush hour for near-road population. This study suggests that health risks from congestion are potentially significant, and that the incremental impacts can vary considerably depending on the type of road and many other factors. Further, evaluations of risk associated with congestion

must consider travel time, the duration of rush-hour, congestion-specific emission estimates, and uncertainties.

5. 2Keywords

Air quality; morbidity; mortality; NO_2; risk assessment; traffic congestion.

5.3 Introduction

Traffic on roads has significantly increased in the U.S. and elsewhere over the past 20 years (Schrank and Lomax, 2007), and vehicle emissions have become the dominant source of many air pollutants in urban areas, including carbon monoxide (CO), carbon dioxide (CO_2), volatile organic compounds (VOCs) or hydrocarbons (HCs), nitrogen oxides (NO_x), and particulate matter (PM) (TRB, 2002). The increasing severity and duration of traffic congestion have the potential to greatly increase pollutant emissions and to further degrade air quality, particularly near major roadways. These emissions contribute to risks of morbidity and mortality for drivers, commuters and individuals living near roadways, as shown by numerous epidemiological studies (WHO, 2005; HEI, 2010), evaluations of proposed vehicle emission standards, and environmental impact assessments for specific road projects.

It is useful to separate traffic-associated pollutant impacts and risks into two categories. First, "congestion-free" impacts refer to effects of traffic at volumes below the level that produces significant congestion. In these cases, each additional vehicle added to the road does not substantially alter traffic patterns, e.g., speed or travel time of other vehicles is not affected. Thus, vehicle emission factors are constant, unrelated to traffic volume, and the marginal impact of an additional vehicle is equal to the average impact. The second category, "congestion" impacts, incorporates the effects that can occur with congestion, e.g., when traffic volumes exceed levels mentioned above. In this case, average speeds are lowered, which causes additional travel time and increased exposure on a per vehicle basis, a result of longer emission and exposure periods. For example, the average annual travel delay for a traveler making rush hour trips in the U.S. was 38 h in 2005, based on 437 urban areas (Schrank and Lomax, 2007). A second effect is diminished dispersion of vehicle related pollutants as vehicle-induced turbulence depends on vehicle speed (Benson, 1989). Decreased dispersion during congestion will increase pollutant concentrations. A third effect of congestion is a change of vehicle driving patterns, e.g., increasing the frequency of speedups, slowdowns, stops and starts. These changes can increase emissions compared to "cruise" conditions, especially with high power acceleration. For example, Sjodin et al. (1998) showed up to 4-fold, 3-fold and 2-fold increases in CO, HC and NO_x emissions, respectively, with congestion (average speed, 13 mph) compared to uncongested conditions (average speed, 38-44 mph). It is important to separate congestion-free and congestion impacts because emissions, impacts and risks may differ considerably, and because such analyses might inform the evaluation of congestion management strategies, including mitigation and impact assessments.

There have been a very few evaluations of congestion-related impacts, and the available studies have combined congestion and non-congestion related impacts. Tonne et al. (2008) predicted that the congestion charging zone in London, where drivers must pay fees when their vehicles enter this area, would gain 183 years-of-life per 100,000 population in the congestion charging zone, and a total of 1,888 years-of-life in the greater London area. Eliasson et al. (2009) estimated that the congestion pricing zone in Stockholm will avoid 20-25 deaths annually due to traffic-related air pollution in the inner city and 25-30 deaths annually in the metropolitan area, which contains 1.4 million inhabitants. These studies indicate that congestion pricing is beneficial in reducing traffic-related health impacts, but congestion-free and congestion related impacts were not separated. These European studies focused on congestion charging zones, which are difficult to generalize. Also, the vehicle mix and fleet emission characteristics may differ substantially from those in the U.S. Using a very different approach that used estimated time activity shifts due to travel delays and literature values of exposure concentrations in different microenvironments, we estimated that a 30 min day^{-1} travel delay accounted for $21 \pm 12\%$ of exposures to benzene and $14 \pm 8\%$ of $PM_{2.5}$ exposures for a typical working adult on weekdays (Zhang and Batterman, 2009). These results suggest that congestion poses a substantial share of exposure to drivers/commuters. To our knowledge, no other study has evaluated congestion-related risks, including the effect of rush hour congestion.

The objective of this study is to investigate the magnitude of air pollution impacts and health risks of on- and near-road population that might occur due in recurring congestion, e.g., occurring at rush hour in major urban areas. Recurring congestion is expected to result in repeated and chronic exposures, and an increase in long term health risks. Incident congestion caused by an accident or disabled vehicle is not addressed, although such events may also be important for certain acute health outcomes, e.g., asthma exacerbation. This chapter utilizes predictive risk assessment techniques, simulation models for traffic, emissions, pollutant dispersion and risk, and an incremental analysis that evaluates congestion-free and congestion-related impacts. In the methods section, we describe the modeling approach and two example scenarios. In the results section, air pollution impacts and risks are presented, including a sensitivity analysis of critical assumptions. The discussion elaborates on these and other possible approaches to estimate the impacts of congestion, and discusses study limitations. Conclusions summarize the results.

5.4 Methods

5.4.1 Approach

This study uses risk assessment methods to estimate health risks due to traffic for two scenarios. An overview of the approach used is shown in Figure 5-1. In brief, vehicle emissions are used as an input to a dispersion model to estimate concentrations, which are then multiplied by exposure time and the concentration-response relationship. Exposure time includes delays due to traffic congestion. An incremental analysis is used to estimate the marginal impacts of increases in traffic volume. Such analyses are widely used in economic models to examine effects of small changes of an input on outcomes of interest; they also represent one of the classical "sensitivity analysis" techniques used to identify key variables in modeling systems (Trueman, 2007). One difference here, however, is that a wide range of traffic flows is examined over which relationships are expected to vary considerably.

5.4.2 Scenarios

Two scenarios were developed to examine the associations between traffic volume, exposures and health risks. These two scenarios represented a freeway and an arterial road.

The freeway scenario used the I-94 segment (8 km long, shown in Figure 5-2), selected for that a field study was conducted on this segment to model instantaneous emission rates. This segment had a permanent traffic recorder (PTR) operated by the Michigan Department of Transportation (MDOT). The portion of the segment west of US-23 had two lanes in each direction; the segment east of US-23 had three lanes in each direction. The annual average daily traffic (AADT) volumes for these two segments were 78,300 and 91,300 vehicles day^{-1}, respectively (MDOT, 2008). During a field study described in Chapter 3, traffic volumes were 3099 and 4040 vph in morning rush hour and afternoon rush hour, respectively. Vehicle mix (8% heavy duty trucks and 92% light duty vehicles) in rush hours was obtained based on the records from the PTR on this studied segment in October, 2007. Southeast Michigan vehicle age distribution was assumed to represent the fleet on this studied segment. Traffic volume in the incremental analysis was allowed to vary from 1000 to 10, 000 vph (about 120% of road capacity; designed capacity is 2000 vehicles hr^{-1} lane^{-1} for a freeway; Dowling, 1997). Besides the freeway scenario with an incremental analysis, a scenario using real traffic volumes on I-94 in rush hour was conducted to demonstrate the spatial-temporal patterns of predicted pollutant levels.

The arterial scenario used the Grand River (M-5) segment in Detroit (Figure 5-3). It is an 8.5 km long arterial road, and includes two lanes per direction and a central turning lane. The annual average daily traffic (AADT) for the segment west of M-39 and that east of M-39 were 23,800 and 19,200 vehicles day^{-1}, respectively (MDOT, 2009). Regional vehicle mix in rush hours was used, that is, still 8% heavy duty trucks and 92% light duty vehicles (SEMCOG, 2006). Again, southeast Michigan vehicle age distribution was also used. Traffic volume ranged from 1000 to 4000 vph (about 120% of road capacity; designed capacity is 825 vehicles hr^{-1} lane^{-1} for an arterial road; Dowling, 1997).

Exposures of drivers and commuters were estimated based on several assumptions about their behavior, traffic and in-vehicle concentrations. A driver or commuter was assumed to travel on the segments under a constant traffic volume in both morning and afternoon rush hours every weekday per year. Vehicle mix and age distribution were assumed to be constant with varying traffic volume during rush hours. Their exposed in-vehicle concentrations are assumed to the equal to predicted on-road concentrations.

Exposures of near-road residents were derived using similar assumptions. A uniform population density was assumed on both sides of a road. A resident was assumed to stay at home during rush hour every weekday, which are exactly at a receptor with 100 m to a road. In the real world, this distance varies with a relative large range (e.g., 10- 500 m), rather than a fixed number. For the purposes of demonstration, we used the 100 m distance as an example. Average concentrations at both upwind and downwind receptors with 100 m distance were used since the uniform population density at both road sides was assumed. A few studies indicated that indoor NO_2 concentrations in homes without indoor sources were about 50% of outdoor concentrations (HEI, 2010), and thus the exposed indoor concentrations in this study were assumed to be half of the predicted concentrations at 100 m receptors. Vehicle mix in rush hours was assumed to be constant for each weekday.

5.4.3 Emission modeling

Two emission models were used to estimate emission factors for a vehicle fleet traveling at different speeds. These included the Comprehensive Modal Emissions Model (CMEM) and the Motor Vehicle Emissions Factor Model version 6.2 (MOBILE6.2). In this study, we estimated emissions for NO_x since traffic is its major source, and both models can predict NO_x while adjusting for speed effects. There are other important traffic-related pollutants, e.g., $PM_{2.5}$ is also an important, however, CMEM cannot estimate $PM_{2.5}$, and MOBILE6.2 does not account for speed's effects on $PM_{2.5}$.

CMEM is a physically-based instantaneous model, and can predict fuel consumption and emissions of CO, HC, NO_x and CO_2 on a finer time scale, e.g., second-by-second basis (Scora et al., 2006), as detailed in Chapter 3. CMEM was only used in the freeway scenario because we have only collected driving patterns for this freeway segment. CMEM estimates obtained from the Chapter 3 were only based on the east-bound direction. These estimates are assumed to apply to both directions.

MOBILE6.2 is a widely used regulatory emission model in the US (Pierce et al., 2008). It can estimate emissions of HC, CO, NO_x, PM and air toxics (e.g., benzene), on the basis of chassis dynamometer measurements and driving cycles designed for four road types: freeway, arterial, ramp and local road (EPA, 2003; Pierce et al., 2008).

Emission factors in summer and winter were estimated using MOBILE6.2 based on fleet mix, vehicle age distribution and typical daily temperature under different vehicle speeds. Annual average emission factors were approximated as the average of those in summer and winter.

For both emission models, emission factors are a function of fleet speed, and speed is a function of traffic volume. Speeds corresponding to given traffic volumes were derived using one of the Bureau of Public Road (BPR) formulae (Dowling, 1997):

$$s = s_f / [1 + a(v/c)^b] \quad (1)$$

where s = predicted mean speed; s_f= free-flow speed; v = volume; c = practical capacity, estimated locally as 2000 vehicles hr^{-1} $lane^{-1}$ for freeways and 825 vehicles hr^{-1} $lane^{-1}$ for urban arterials (SEMCOG 2004); a = scalar coefficient ranging from 0.05 to 1; and b = power coefficient ranging from 4 to 11. These two coefficients were obtained from a case study conducted in Detroit, which estimated α = 0.1226 for the freeway, α = 1.00 for the arterial, and β = 4.688 (Batterman et al., 2010)

5.4.4 Dispersion modeling

CALINE4 is a dispersion model developed by California Department of Transportation to estimate roadway pollutant concentrations. It uses a Gaussian-plume type model for a line source of finite length (Benson, 1989). This model employs a mixing zone concept to characterize thermal and mechanical turbulence (e.g., vehicle wake effects), which is defined as the region over the roadway (traffic lanes, not shoulders) plus 3 m on each side (Benson, 1989). Emissions and turbulence in the mixing zone are assumed to be uniformly distributed. Concentrations beyond this zone decay following an empirical Gaussian line source equation (Benson, 1989). Although dispersion parameters are a function of traffic volume, sensitivity analyses show it had minor effects.

CALINE4 was used to estimate NO_x concentrations attributable to traffic. This model requires inputs that include emission factors, traffic flows, meteorological data, and receptor locations. Emissions were modeled for different traffic volumes, as discussed above. Hourly surface meteorological data during morning/afternoon rush hours (7-9 am and 4-6 pm) in 2005 from the Detroit Metropolitan Airport (southwest of Detroit) were used in scenarios. A simplified modeling approach was implemented because CALINE4 was not designed to process hourly data for a full year (Zhang and Batterman, 2010). Pollutant concentrations were predicted for 16 wind sectors (each spanning 22.5^{o}) and some wind speed classes (1 m s^{-1} for each bin, e.g., 0.5 to 1.5, 1.5 to 2.5, …). Annual average concentrations at receptors were estimated as the sum of these predictions weighted by the probability of each wind sector/wind speed category in 2005. Receptors were placed at 0, 25, 50, 75, 100 and 150 m on both sides of a transect perpendicular to the center of the studied road segments.

Predicted NO_x concentrations were converted into NO_2 levels in order to utilize NO_2 based concentration-response relationships. Nitric oxide (NO) emissions usually account for 90–95% of NO_x emissions in traffic (WHO, 2005). Such NO is converted into NO_2 rapidly by reaction with ozone and OH^- radicals. Ambient concentrations of NO and NO_2 vary with distance from traffic and other factors (e.g., background ozone and NO_2 concentrations, sunlight and dispersion conditions) (HEI, 2010). In this study, NO_2 concentrations were derived from CALINE4 predicted NO_x concentrations according to an empirical method recommended by the Department for Environment, Food and Rural Affairs of UK (2003), defined as:

$$NO_{2(road)} = ((-0.068 \times \ln(NO_{x(road)} + NO_{x(background)})) + 0.53) \times NO_{x(road)} \qquad (2)$$

where $NO_{2(road)}$ = the annual mean NO_2 concentration attributable to the road; $NO_{x(road)}$ = the annual mean NO_x concentration attributable to the road; $NO_{x(background)}$ = the annual mean background NO_x concentration. This equation implies NO_2 to NO_x ratios from 0.25 at low NO_x levels to 0.12 at high NO_x concentrations. Although this formula was developed for long-term NO_2/NO_x relationships, it was assumed to hold for short term relationships in this study. Brown et al. (2007) reported an average 28.7 μg m^{-3} background level in 2004 and 2005, based on East 7 Mile monitor (northeast of Detroit). Equation (2) and background level were used in both scenarios of this study.

5.4.5 Exposure assessment

Daily and annual NO_2 exposures of on-road population were calculated as follows

$$E_d = C_{on-road} \times T \times 1/24 \qquad (3)$$

$$E_a = E_d \times 255/365 \qquad (4)$$

where E_d =adjusted daily exposures to NO_2 (μg m^{-3} day^{-1}); E_a =adjusted annual exposures to NO_2 (μg m^{-3} year^{-1}); $C_{on-road}$ = predicted on-road concentrations (μg m^{-3}); T = travel time (hr), calculated by dividing the segment length over vehicle speed; $1/24$ = daily adjusted coefficient (hrs^{-1} day^{-1}), a reciprocal of 24 hrs per day; this coefficient distributes in-vehicle exposures during travel on a daily basis in order to be compatible with daily-average-based concentration-response relationships; 255/365= annual adjusted coefficient; 255 = total weekdays of a year, 365 = total days of a year; this coefficient distributes short-term exposures over a yearly basis to be comparable with annual-average-based concentrations-response relationships.

Exposures for near-road population were derived in a similar way. In eqs. (3) and (4), on-road concentrations were replaced by one half near-road concentrations, and travel time was replaced by rush hour duration, defined in eq. (5):

$$T_{rush-hour} = 2 \times s_f / s \qquad (5)$$

where $T_{rush-hour}$ = actual duration of rush hour; 2 = baseline of rush hour duration (either morning or afternoon rush hour) without congestion; s_f = free-flow speed (mph); s = speed (mph). The duration of rush hour is extended due to increased traffic volume. A resident was assumed to be at home during rush hours every weekday.

5.4.6 Risk characterization

Health risks were calculated by linking the estimated exposures to the relevant concentration-response relationships in the literature. We assumed that the concentration-response relationships between the traffic-related air pollutants caused by congestion and health outcomes are the same with those for "total" (congestion and congestion-free) traffic-related air pollutants. This can be justified if the pollutant mixtures associated with overall traffic and congestion are similar. Health outcomes of interest and available in the literature include short term morbidity and long term mortality. Morbidity estimates represent emergency doctor visits and hospital admissions (EDA). Both short- and long-term endpoints were selected based on the strongest evidence shown by epidemiological and toxicological studies (EPA, 2008).

Health risks were estimated using long term exposures and dose-response relationships in the literature summarized by EPA (2008) and shown in Table 5-1. The intervals in Table 5-1 represent the ranges of the mean estimates from different studies, and not the statistical confidence interval derived from a meta-analysis. EPA states that confidence intervals cannot be established since the underlying studies used different models, e.g., single and multi-pollutant models, different covariates, as well as different cohorts, e.g., some studies only consider one age group, among other differences (EPA, 2008).

The increased incremental risks between nearby traffic volume were derived by dividing the differences of the risks corresponding to nearby traffic volumes by the differences of these traffic volumes. They represented an increased risk for an individual per additional vehicle at different traffic volume. Incremental risks reflected a marginal risk between individuals and traffic volume.

5.4.7 Sensitivity analysis

A limited sensitivity analyses was conducted to examine the impacts of key factors on the predicted incremental risk, including speed, emission factors, and the NO_2/NO_x ratio. This analysis predicted the incremental risks for mortality for the on-road population in morning rush hour in the freeway scenario under different conditions: speed used 50, 55, 60, 65 and 70 mph with the constant emission factor (2.7 g mi^{-1}) and NO_2/NO_x ratio (0.16); emission rates used 1.9, 2.1, 2.3, 2.5 and 2.7 g mi^{-1} given the constant speed (70 mph) and NO_2/NO_x ratio (0.16); the NO_2/NO_x ratio used 0.12, 0.15, 0.18, 0.22 and 0.25 given the constant emission factor (2.7 g mi^{-1}) and the constant speed (70 mph). Emission estimates were derived from MOBILE6.2.

5.5 Results

5.5.1 Spatial-temporal patterns of predicted NO_2 levels

Figure 5-4 shows that the predicted NO_2 levels vary with receptor locations, and that they decrease quickly with distance from I-94, consistent with previous studies (WHO, 2005). Although traffic volume in afternoon rush hour was 30% higher compared to morning rush hour, concentrations in morning rush hour were close to those in afternoon rush hour given the same upwind/downwind directions, depending on receptor locations, mainly due to poor dispersion conditions in morning rush hour, e.g., more frequent low wind speeds.

5.5.2 Air pollution impacts

Figure 5-5 shows the associations between traffic volume, speed and NO_x emission factors for the freeway scenario. Speeds were constant up to volume of approximately 4400 vph, at which point speeds begin to decreases. Emission factors from both CMEM and MOBILE6.2 are also constant at low volumes; at high volumes, CMEM estimates slightly increase while MOBILE6.2 estimates slightly decrease. As noted in Chapter 3, these models have many differences, and specifically the CMEM rates simulated segment-specific driving behaviors using second-by-second speed/acceleration profiles obtained from a field study conducted on the I-94 segment. Additionally, MOBILE6.2 estimates systematically exceed those for CMEM, possibly due to smoothing of speed profiles, the CMEM vehicle category scheme, and other factors discussed in Chapter 3.

For the arterial (Figures 5-6), speed is constant at low traffic volumes, and drops quickly after around 2000 vph. Emission factors are nearly constant at low volumes, and increase after around 2500 vph when vehicle speeds are low.

Figure 5-7 shows NO_2 concentrations predicted for various emission estimates, traffic volume and rush hour periods in the freeway scenario. Concentrations based on CMEM estimates are near-linearly associated with traffic volume (Figures 5-7A and 5-7B), while those based on MOBILE6.2 increase exponentially with traffic volume to about 7000 vph, and then gradually level off (Figures 5-7C and 5-7D). These trends are mainly determined by emission factors and the empirical NO_2/NO_x relationship. MOBILE6.2 has slightly decreased emission factors at high volumes, and thus NO_2 concentrations increase slowly at high volumes. Additionally, given the same traffic volume, predicted concentrations in morning rush hour are 30-50 % higher than those in afternoon rush hour, mainly because of more frequent lower speeds and poor dispersion conditions.

Figure 5-8 shows predicted NO_2 concentrations in the arterial scenario. NO_2 levels increase near linearly to about 3000 vph, and then increase sharply. This can be explained by emission factors that are approximately constant at low volumes, thus, traffic volume dominates the trend of concentrations; at high volumes, increased emission factors make NO_2 levels increase more sharply.

5.5.3 Health risk impacts

Tables 5-2 and 5-3 list predicted short- and long-term health risks for the freeway scenario using CMEM and MOBILE6.2 emission estimates and traffic volumes from 1000 to 10, 000 vph. Traffic during the morning rush hour increases health risks by 20 to 40% compared to afternoon rush hour for the same traffic volume, mainly due to poorer dispersion conditions discussed above. Given the same traffic volume, differences in health risks for an individual between on- and near-road receptors are proportional to the concentrations differences. Differences between Table 5-2 and Table 5-3 are mainly determined by the differences from two emission estimates and the empirical NO_2/NO_x equation.

Table 5-4 shows predicted health risks for the arterial scenario. As shown for the freeway, the arterial scenario also shows higher risks are associated with morning rush hour compared to afternoon rush hour.

5.5.4 Incremental health risk analysis

Figures 5-9 show incremental risks (increased risk for an individual per an additional vehicle) for the upper bound mortality outcomes in the freeway scenario. (Figures S5-1 and S5- 2 show incremental risks for EDA using both CMEM and MOBILE6.2 emission estimates since incremental risks for EDA are proportional to those for mortality.) The incremental risks for the on-road population in the morning rush hour period are about 20 to 45% higher than those in afternoon rush hours. These patterns are mainly driven by travel time (for the on-road population), emission estimates and the empirical NO_2/NO_x relationship. CMEM-based incremental risks were taken as an example to explain how these factors affect general trends: Figures 5-9A and 5-9B show U-shape curves: for 1000 – 4000 vph, the trends were determined by the NO_2/NO_x empirical relationship because speed and emission factors are constant, while the proportion of NO_2 to NO_x slightly decreases from 0.3 to 0.22 with increased volume. Thus, incremental risks decrease slightly; for 5000 – 7000 vph, emission factors are still constant. But speed slows down, and results in longer travel time. Also, the ratio of NO_2 to NO_x slightly decreases from 0.21 to 0.19. These two factors result in slightly increased incremental risks; for volume > 8000 vph, longer travel delay, increased emission factors, and slightly decreased NO_2/NO_x ratio cause increased incremental risks. Similarly, Figures 5-9C and 5-9D show the same "U" shaped trends for the same reasons discussed above. In general, the fluctuations of incremental risks at high volumes for both scenarios suggest incremental risks in real world are variable and complicated because these small changes are easily altered by specific driving patterns.

Incremental risks based on MOBILE6.2 (shown in Figures 5-9) also show U-shape patterns for both on- and near-road populations, but the increases at high volumes after 7000 vph are small. The two emission models produce different patterns: MOBILE6.2-derived emission rates drop when speeds slows from free flow conditions, while CMEM-derived estimates slightly increase with decreased speed in the freeway scenario.

The incremental analysis shows the effect of each additional vehicle. The U-shape trend seen for both on- and near-road populations indicates that congestion-related health impacts could be much higher than congestion-free impacts. The "U" shaped trends of incremental risks are a novel finding of this research.

Figures 5-10 show incremental risks for the arterial scenario. Substantial increased trends of incremental risks are seen for both on- and near-road populations. In this scenario, speeds decrease substantially (from 35 to 10 mph), and emission factors increase markedly at high traffic volume (from 1.7 to 2.3 g mi^{-1}). These findings suggest that congestion could pose risks to commuters on and residents near arterial roads that are greater than the congestion risks associated with freeways, possibly because lower speed might be associated more acceleration/deceleration events than higher speed, and low speed reduces dispersion conditions as discussed in the introduction section.

5.5.5 Sensitivity analysis

Figures 5-11 show the effects of speed, emission factors and the NO_2/NO_x ratio on incremental mortality risks. Generally, incremental risks decrease with increased speed (or decreased traffic volume), but increase with increased emission factors and NO_2/NO_x ratio. The NO_2/NO_x ratio has largest impact on incremental risks compared to speed and emission factors because its relative sensitivity is one order higher than emission factors, and two orders higher than speed's.

5.6 Discussion

This study demonstrates an analysis of health risks for traffic and congestion can be somewhat analyzed using a marginal analysis, specifically on the basis of incremental increases in traffic volume. The two scenarios indicate that the patterns of incremental risks are primarily determined by emission rates, the empirical NO_2/NO_x relationship and travel delay (for the on-road population). In particular, emission rates control the direction of these patterns at high traffic volumes, which are usually associated with congestion. For example, for the near-road population in the freeway scenario, CMEM estimates result in up and down patterns at high traffic volumes, while MOBILE6.2 estimates produce decreasing trends. This suggests that emission estimates, especially those in congestion, play a critical role. Many factors influence results, as described next.

5.6.1 Relevance of the scenario

The scenario analysis is based on two simplified and somewhat hypothetical scenarios. The volumes assumed for the study segments may not be realistic, e.g., the traffic volume was 4040 vph in afternoon rush hour for the freeway scenario, less than half of the highest volume (10,000 vph) simulated. Second, results are expected to vary with roads with different orientation, road topography, as well as some factors discussed above such as meteorological conditions and near-road population density. Third, this analysis only examined NO_2, and it would be helpful to examine other traffic-related pollutants such as $PM_{2.5}$ and black carbon.

5.6.2 Uncertainties in emissions

Smit (2006) suggested that the emission models based on average speeds (e.g., MOBILE6.2) do not explicitly account for congestion since they do not incorporate input parameters representing congestion levels (Smit et al., 2008), although these models might consider congestion levels in a model development process. In contrast, driving pattern-based emission models can predict emission in congestion by specifying instantaneous speed and acceleration/deceleration profiles as model inputs. However, the emission estimates in congestion derived from such models have not yet been fully validated (Smit, 2006). Emissions contributed by traffic congestion can be estimated using MOBILE6.2 to some extent. MOBILE6.2 implicitly accounts for congestion because some urban driving patterns used in the MOBILE6.2 development process are somewhat associated with congestion, but it does not explicitly include any input parameters representing the levels of congestion (Smit et al., 2008). Therefore, we implicitly assumed two scenarios discussed above had the exact congestion levels reflected in the MOBILE6.2 model development.

The emission models have several sources of uncertainty. For CMEM, key uncertainties result from the speed-profiles smoothing and the car-floating technique. It seems likely that the approach used reduces the differences between emissions predicted for congested and free-flow conditions since actual acceleration/deceleration is underestimated. Additional uncertainties result from the mapping between CMEM and traffic vehicle categories. The assumption of CMEM estimates (derived from the east-bound direction) representing two road directions also bring some uncertainties. For MOBILE6.2, a key uncertainty is whether the embedded driving cycles and speed adjustments reflect those in the scenarios. MOBILE6.2 ability to predict congestion-related emissions for specific roads is limited, as discussed above. Other uncertainties include a lack of segment-specific vehicle age distribution, and the performance of the BPR describing the relationships between traffic flow and speed for the studied segments. Moreover, both CMEM and MOBILE6.2 are deterministic models and thus results do not reflect model uncertainty.

There are several alternate ways to estimate emissions. First, the new EPA Motor Vehicle Emission Simulator (MOVES; EPA, 2009) might be used. This model has been calibrated using a larger database than CMEM, and it can account explicitly for congestion by considering user-specified driving patterns (EPA, 2009). It also provides $PM_{2.5}$ estimates, which are omitted in CMEM and which is speed-invariant in MOBILE6.2. A second way to estimate emissions might be to use on-board measurements or near-road emission/concentration measurements. On-board measurements for an individual vehicle are expensive and results can vary dramatically from vehicle to vehicle, although they can directly link transient emissions to transient speed, acceleration and deceleration, and thus can capture emissions that are typical of stop-and-go congestion. Another disadvantage is that emission measurements are difficult to generalize to the whole fleet. Near-road measurements can be difficult to couple to transient driving parameters due to instrumental limitations, changes in meteorological conditions and dispersion delays, among other reasons, although such measurements can reflect congestion's contribution to pollutant levels over a suitably long period.

5.6.3 Dispersion modeling

Concentration estimates involve several uncertainties and limitations, the largest of which might arise from the use of the empirical NO_2 - NO_x relationship. This relationship was derived from a UK study, whereas the traffic composition, vehicle technologies, and emission models were all US-based. The actual NO_2 - NO_x relationship depends on many factors, including background levels of NO, NO_2, and O_3, and the meteorological conditions (Stedman et al., 2001). The empirical relationship was derived for long-term relationships; here it was used for short-term concentrations. The background NO_x levels used might not reflect levels around the studied roads. The meteorological data used were obtained from largely unrestricted airport stations. Conditions near roads might be affected by buildings, trees and other factors (Greco et al., 2007) that might reduce winds and increase turbulence. Because concentrations rapidly decrease at distances over about 150 m from the road, we considered only near-road receptors. This does not account for background concentrations that can be attributed to traffic. The dispersion model estimates also do not include model uncertainty since CALINE4 is a deterministic model. Other limitations of CALINE4, e.g., poor performance at low wind speeds, were discussed in Chapter 4.

5.6.4 Exposure assessment limitations

Assumptions in deriving exposure estimates for two scenarios limit results to generalize to real world. First, commuters usually travel for longer trips than the studied segments: US commuters average 81 min day^{-1} in vehicles in 2001according to US travel surveys (HEI, 2010). Such trips might include both congestion-free and congestion periods, and both freeway and arterial roads. Second, this study only examined exposures in vehicles for the on-road population and in homes for the near-road population, did not examined daily total exposures, taking into consideration dynamic adjustments to time activity patterns due to travel delay, discussed in Chapter 2. Third, concentrations in the vehicle cabin may differ from those on the road, as predicted by

CALINE4. Cabin concentrations are affected opening the car windows, the air intake, the air conditioning system, and other factors. The same applies for indoor concentrations for near-road residents.

5.6.5 Risk characterization

The risk characterization has important qualifications. First, congestion-specific concentration-response relationships are unavailable. The concentration-response relationships in the literature may not represent those needed to understand risks related to congestion. Exposures due to congestion are short (typically less than several hours), however, concentration-response relationships in the literature are based on daily average or annual average concentrations. It is unclear how the aggregation method used in this study affects true risks, i.e., our approach simply calculated long term exposure based on weighting short-term exposures to NO_2 by their exposure time. On the other hand, the available NO_2 concentration-response relationships might be reasonable for use because congestion does not generate new pollutants, but simply changes the magnitude of common traffic-related pollutants.

A second key point is that NO_2 is being used as a surrogate measure of pollutant exposure in that the NO_2 concentration-response relationship represents not only the effects of NO_2, but also that of other traffic related pollutants, e.g., $PM_{2.5}$. This can be justified due to the high correlation between NO_2 and co-pollutants (EPA, 2008; Tonne et al., 2008).

A third limitation is that risk calculations were performed for several receptor locations, which did not account for the population distribution around the road. Considering spatial patterns of traffic-related air pollutant near a road, total health risks due to congestion for an area are driven by the near-road population density. However, considering that the purpose of this work was to develop and demonstrate the methodology to estimate exposures and health risks from rush hour congestion, the real near-road population density were not applied in this study. Additionally, as Tonne et al. (2008) pointed out that there might be a working population near roads, this population has not yet considered in this study due to inadequate information.

5.6.6 Other approaches for estimating congestion-related health risks

It may be possible to estimate the health risks from congestion using epidemiological studies that include indicators for congestion. Such studies might provide tailored dose-response relationships to use in the risk assessment. For example, congestion indicators such as time spent in congestion for commuters, might be linked to health outcomes directly. This would avoid the sequence of model used in the present analysis, e.g., the complicated emission and dispersion modeling and the incremental analysis.

5.7 Conclusions

This study used an incremental analysis tool to estimate pollution impacts and characterize health risks caused by congestion, which appears to be the first such analysis in the literature. Congestion increased risks for individuals driving/commuting on freeway or arterial roads. Increased risks depend on time of a day (morning rush hours vs. afternoon rush hours) and distance to highways. While health risks from congestion can be predicted and are potentially significant for both on-road and nearby residential populations, uncertainties are high. Thus, these results are considered preliminary and additional information is needed, especially related to $PM_{2.5}$, to confirm results. Still, the study suggests that many factors affect risks, that the marginal risks of additional vehicle vary nonlinearly, and that key variables include emission factors in congestion, NO_2/NO_x relationships, travel time changes, and the scenario itself, e.g., road type and receptor location. These factors require further research.

Table 5-1. Concentration-response relationships between NO_2 and health outcomes (Range of NO_2 risk estimates among different studies; EPA, 2008).

Outcome	Air pollutants	Increased risk for 10 μg m^{-3} concentration increase
ED visits and hospital admissions (short term)	NO_2	0.5-5.3%
Total mortality (long term)	NO_2	0 - 14.8%

Table 5-2. Predicted short- and long-term health risks for selected receptors in the freeway scenario for different traffic volume using CMEM emission estimates (EDA , emergency doctor visit or hospital admissions; unit: probability×10^{-6} day^{-1} $person^{-1}$ for EDA and probability×10^{-6} $year^{-1}$ $person^{-1}$ for mortality)

Volume	On-road population				Near-road population[b]			
	Morning rush hours		Afternoon rush hours		Morning rush hours		Afternoon rush hours	
	EDA[a]	Mortality	EDA	Mortality	EDA	Mortality	EDA	Mortality
1000	6-67	0-130	5-50	0-98	20-208	0-406	14-145	0-283
2000	12-123	0-241	9-95	0-184	38-407	0-794	27-286	0-558
3000	16-174	0-339	13-135	0-262	56-598	0-1168	40-423	0-825
4000	21-220	0-429	16-172	0-335	74-785	0-1532	53-557	0-1087
5000	25-264	0-515	20-208	0-405	92-972	0-1896	65-693	0-1352
6000	29-308	0-602	23-244	0-477	110-1167	0-2277	79-836	0-1630
7000	34-357	0-696	27-284	0-554	130-1383	0-2698	94-994	0-1939
8000	41-433	0-844	33-347	0-678	164-1734	0-3382	118-1253	0-2444
9000	47-501	0-977	38-404	0-788	193-2043	0-3986	140-1481	0-2889
10000	57-609	0-1189	47-494	0-965	240-2549	0-4973	175-1855	0-3618

a. Emergency doctor visit or hospital admissions;

b. Near-road population represents individuals living at 100 m to freeways here.

Table 5-3. Predicted short- and long-term health risks for selected receptors in the freeway scenario using MOBILE6.2 emission estimates (unit: probability×10^{-6} day^{-1} $person^{-1}$ for EDA and probability×10^{-6} $year^{-1}$ $person^{-1}$ for mortality)

Volume	On-road population				Near-road population[b]			
	Morning rush hours		Afternoon rush hours		Morning rush hours		Afternoon rush hours	
	EDA[a]	Mortality	EDA	Mortality	EDA	Mortality	EDA	Mortality
1000	9-94	0-183	7-71	0-139	20-208	0-406	14-145	0-283
2000	16-170	0-331	12-131	0-256	38-407	0-794	27-286	0-558
3000	22-235	0-459	17-184	0-360	56-598	0-1168	40-423	0-825
4000	28-294	0-574	22-233	0-455	74-785	0-1532	53-557	0-1087
5000	33-350	0-682	26-279	0-545	92-972	0-1896	65-693	0-1352
6000	38-405	0-790	31-326	0-635	110-1167	0-2277	79-836	0-1630
7000	44-465	0-906	35-376	0-734	130-1383	0-2698	94-994	0-1939
8000	48-513	0-1001	39-416	0-813	164-1734	0-3382	118-1253	0-2444
9000	54-568	0-1108	44-462	0-901	193-2043	0-3986	140-1481	0-2889
10000	62-652	0-1273	50-532	0-1038	240-2549	0-4973	175-1855	0-3618

a. Emergency doctor visit or hospital admissions;

b. Near-road population represents individuals living at 100 m to freeways here.

Table 5-4. Predicted short- and long-term health risks for selected receptors in the arterial scenario using MOBILE6.2 emission estimates (unit: probability×10^{-6} day^{-1} $person^{-1}$ for EDA and probability×10^{-6} $year^{-1}$ $person^{-1}$ for mortality)

Volume	On-road population				Near-road population[b]			
	Morning rush hours		Afternoon rush hours		Morning rush hours		Afternoon rush hours	
	EDA[a]	Mortality	EDA	Mortality	EDA	Mortality	EDA	Mortality
1000	9-96	0-187	7-73	0-142	13-136	0-266	6-67	0-131
1500	13-143	0-278	10-109	0-212	20-207	0-404	10-102	0-200
2000	19-198	0-387	14-152	0-296	28-294	0-573	14-146	0-284
2500	27-284	0-554	21-219	0-427	41-429	0-838	20-214	0-417
3000	43-451	0-880	33-350	0-682	66-698	0-1362	33-349	0-681
3500	74-787	0-1536	58-614	0-1198	118-1251	0-2441	59-629	0-1227
4000	138-1461	0-2851	108-1148	0-2240	226-2397	0-4677	115-1214	0-2368

a. Emergency doctor visit or hospital admissions;

b. Near-road population represents individuals living at 100 m to freeways here.

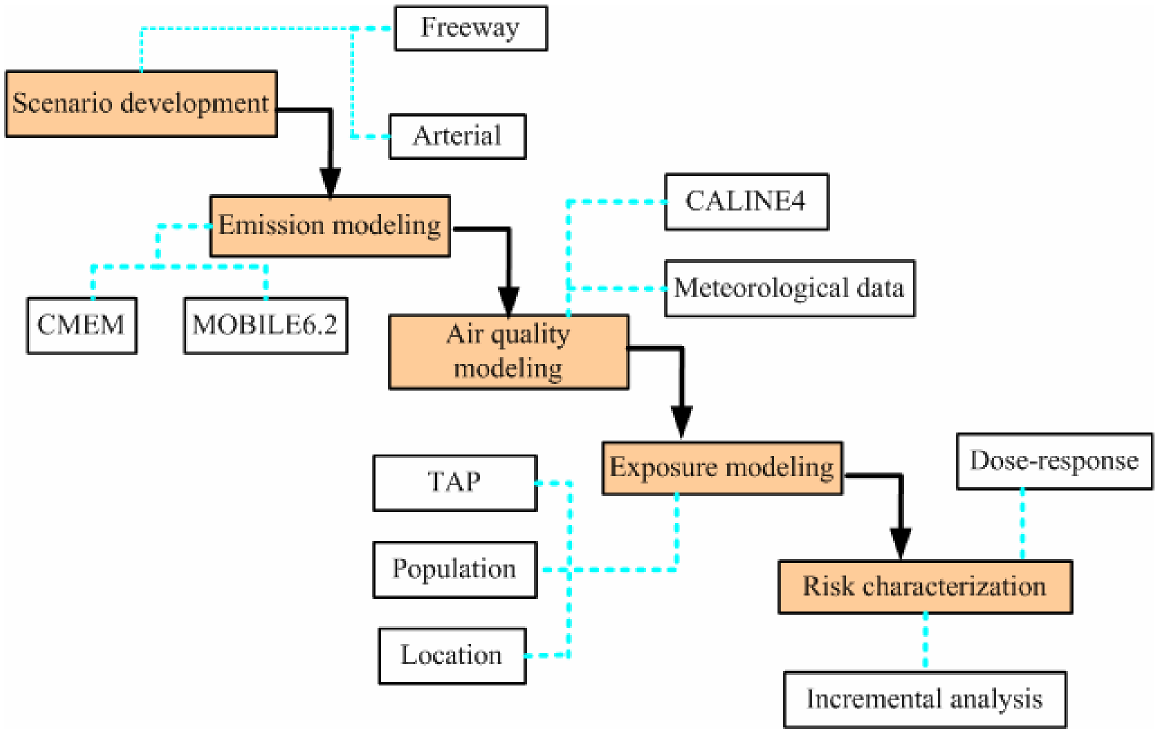

Figure 5-1. Diagram for modeling health risks due to traffic and congestion (CMEM, the Comprehensive Modal Emissions Model; MOBILE6.2, the Motor Vehicle Emissions Factor Model version 6.2; TAP, time activity pattern).

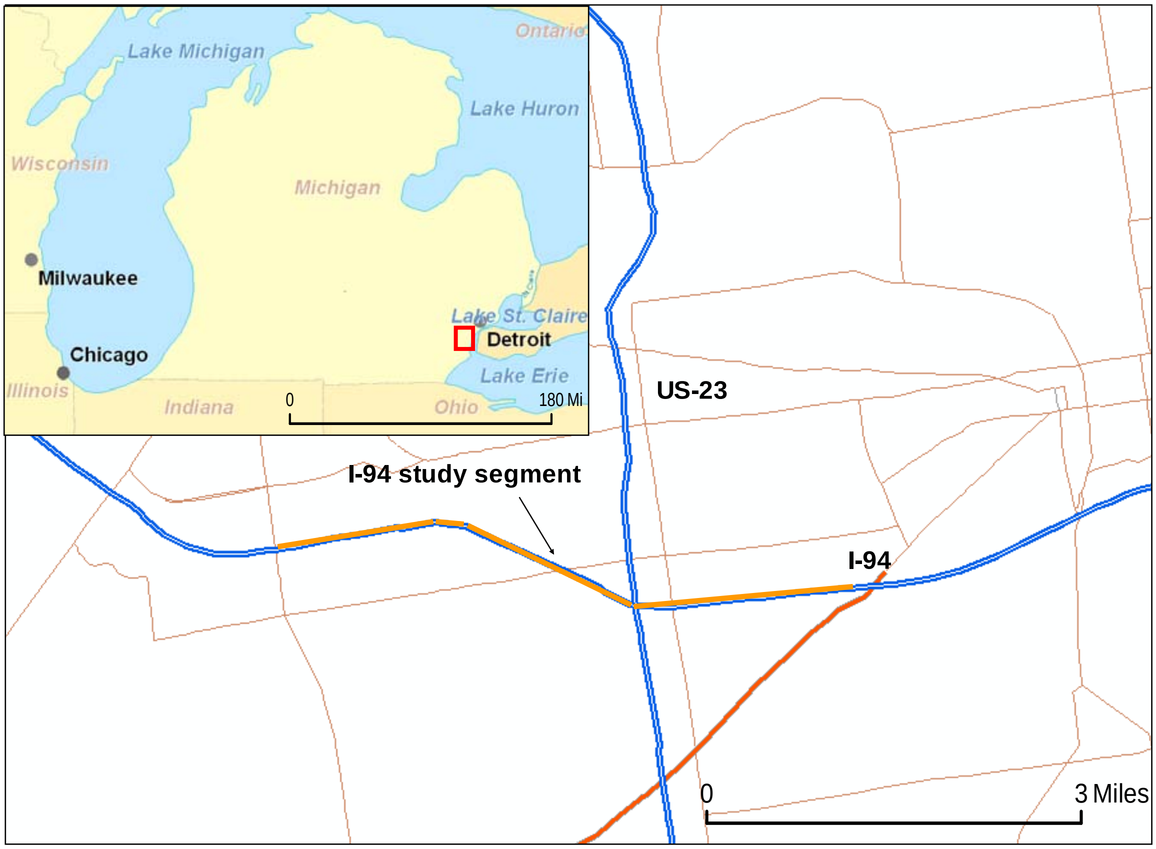

Figure 5-2. Map of study area and study segment for the freeway scenario, shown in orange.

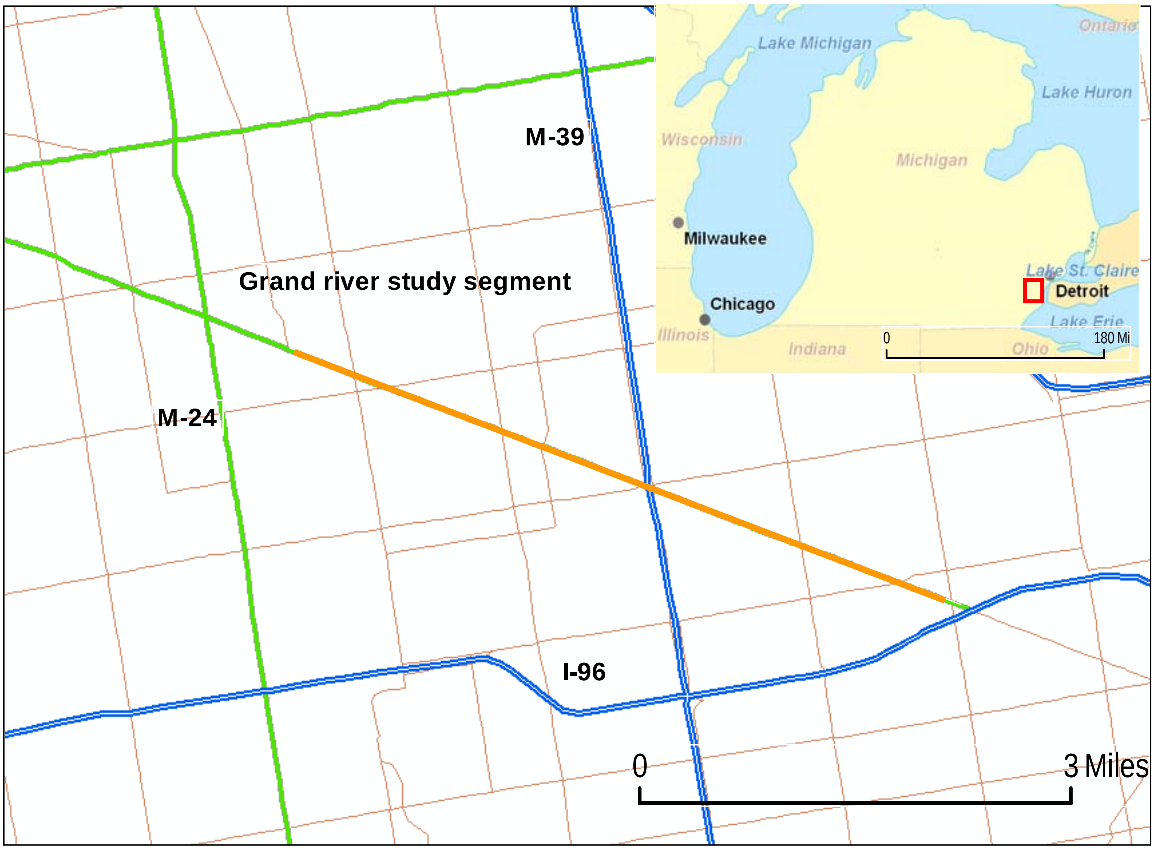

Figure 5-3. Map of study area and study segment for the arterial scenario, shown in orange.

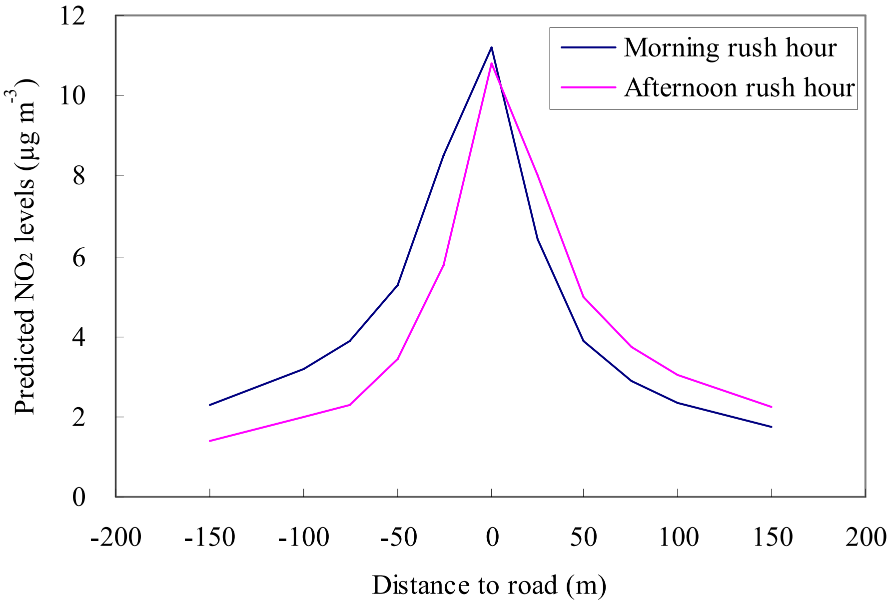

Figure 5-4. Predicted NO_2 concentrations versus distance to the freeway (assuming fixed NO_x background level; traffic volume, 3099 and 4040 vph for morning and afternoon rush hours).

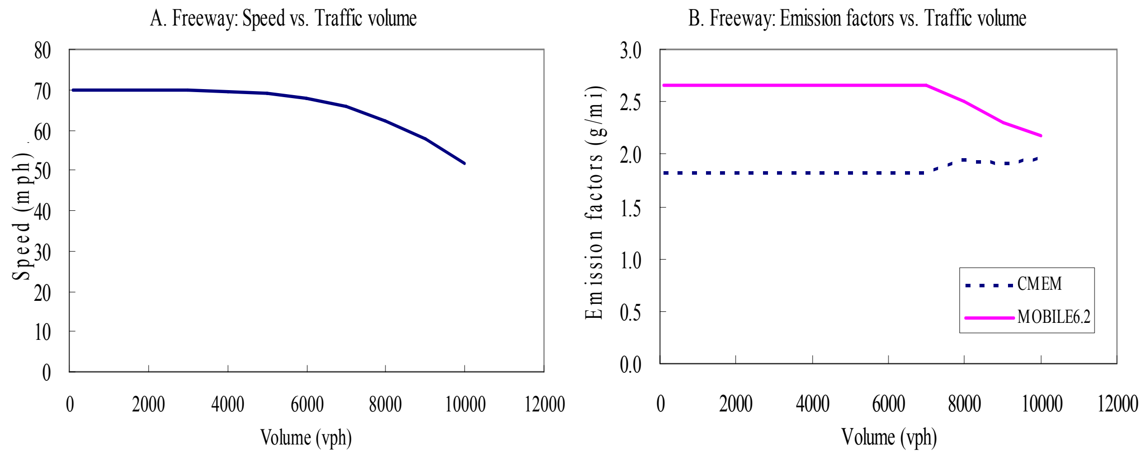

Figure 5-5. Predicted speed and NO_x emission factors for range of traffic volumes in the freeway scenario.

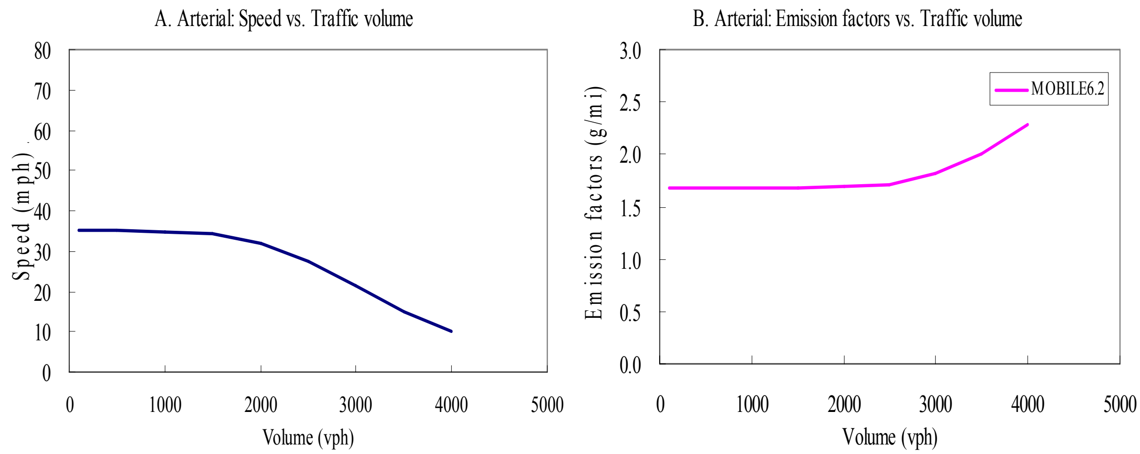

Figure 5-6. Predicted speed and NO_x emission factors for range of traffic volumes in the arterial scenario.

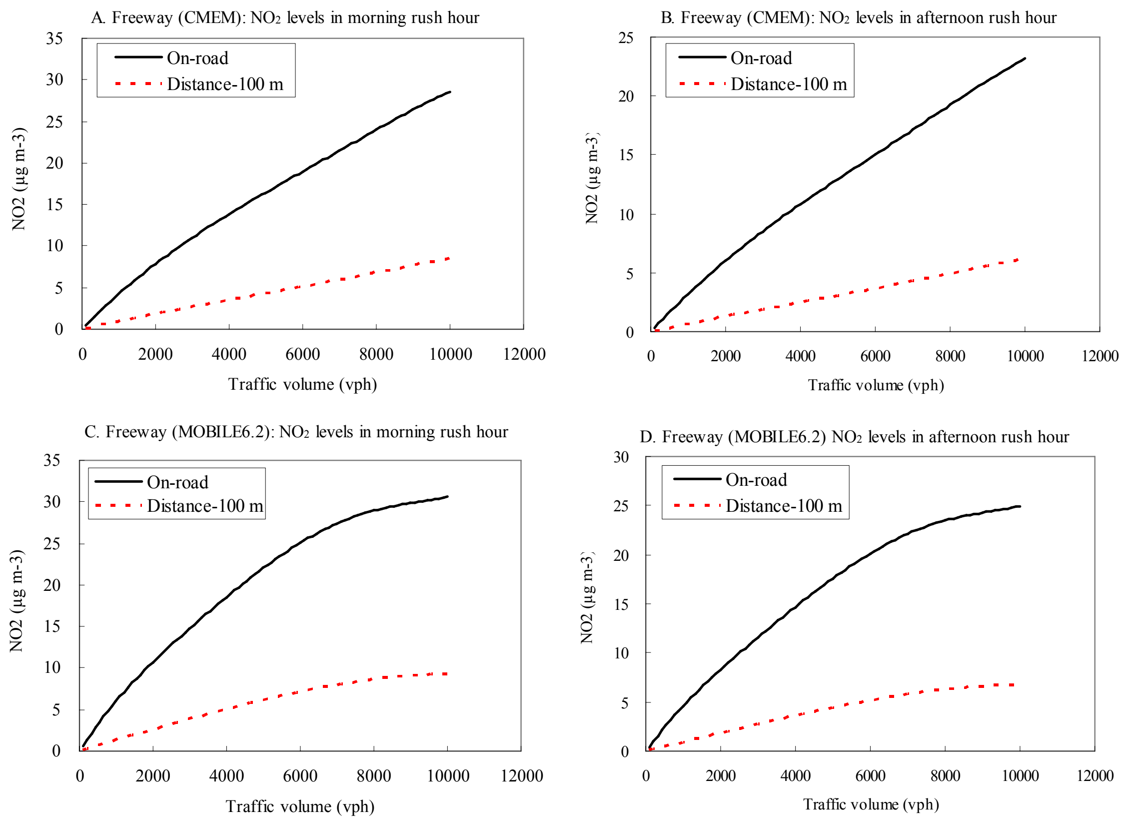

Figure 5-7. Predicted NO_2 concentrations versus traffic volume in the freeway scenario

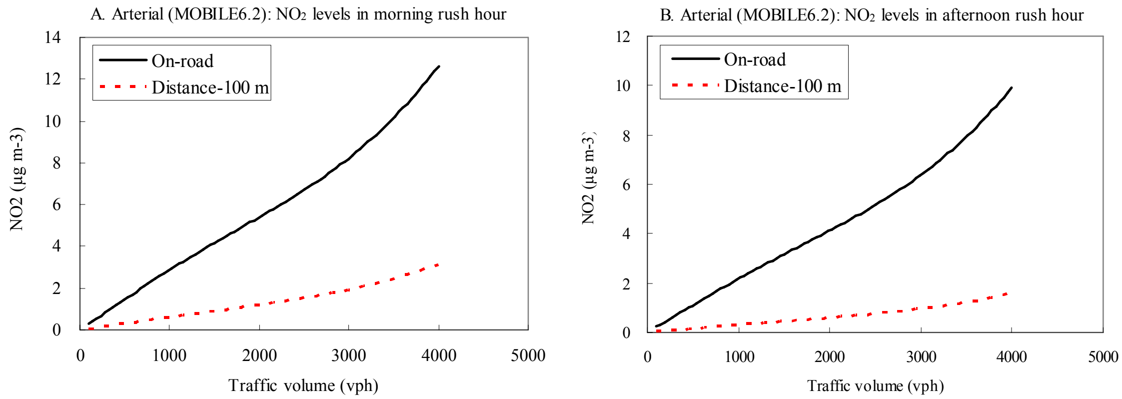

Figure 5-8. Predicted NO_2 concentrations versus traffic volume in the arterial scenario

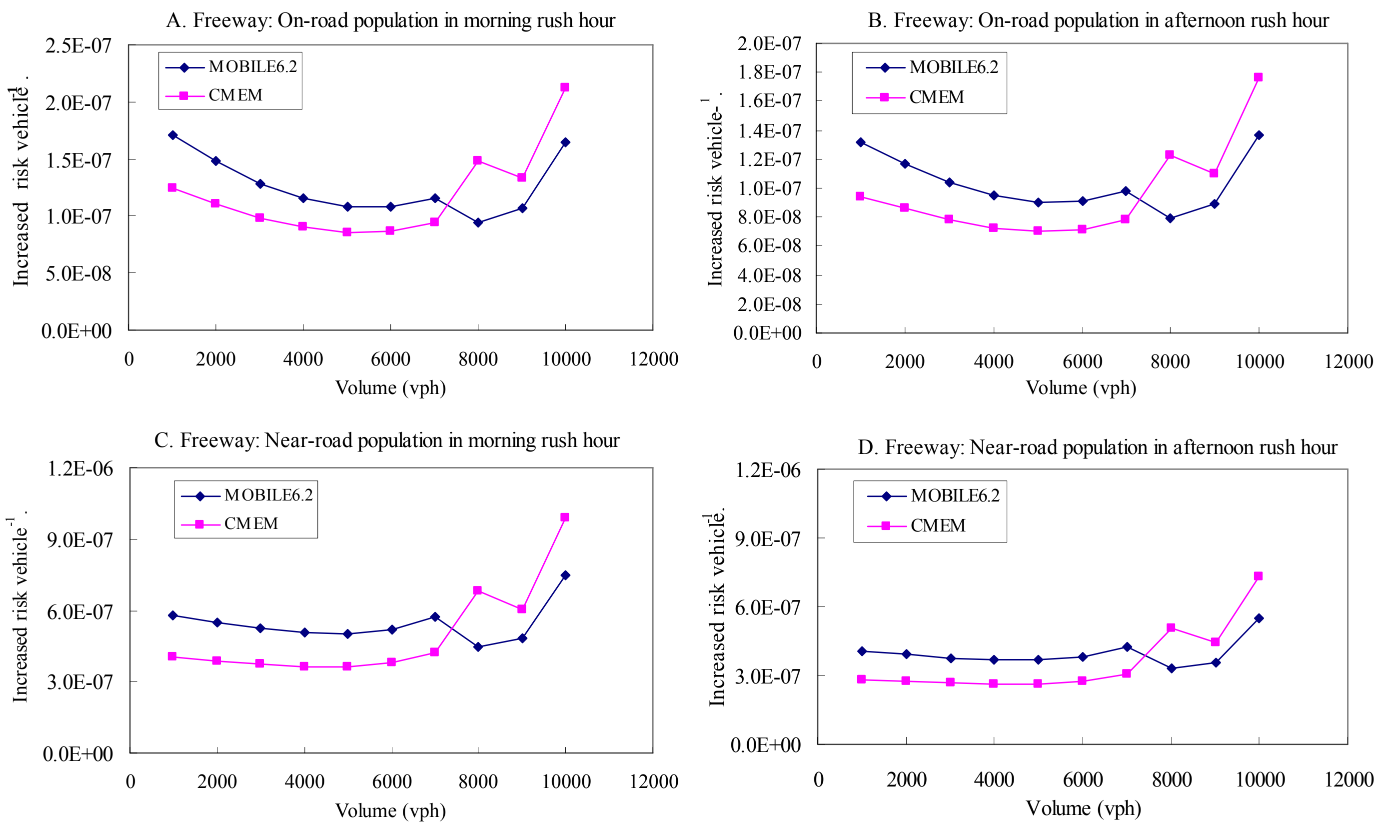

Figure 5-9. Predicted incremental risks per vehicle versus traffic volume for upper bound mortality in the freeway scenario (CMEM, estimated based on CMEM estimates; MOBILE6.2, estimated based on MOBILE6.2 estimates; near-road representing individuals living at 100 m to a highway.)

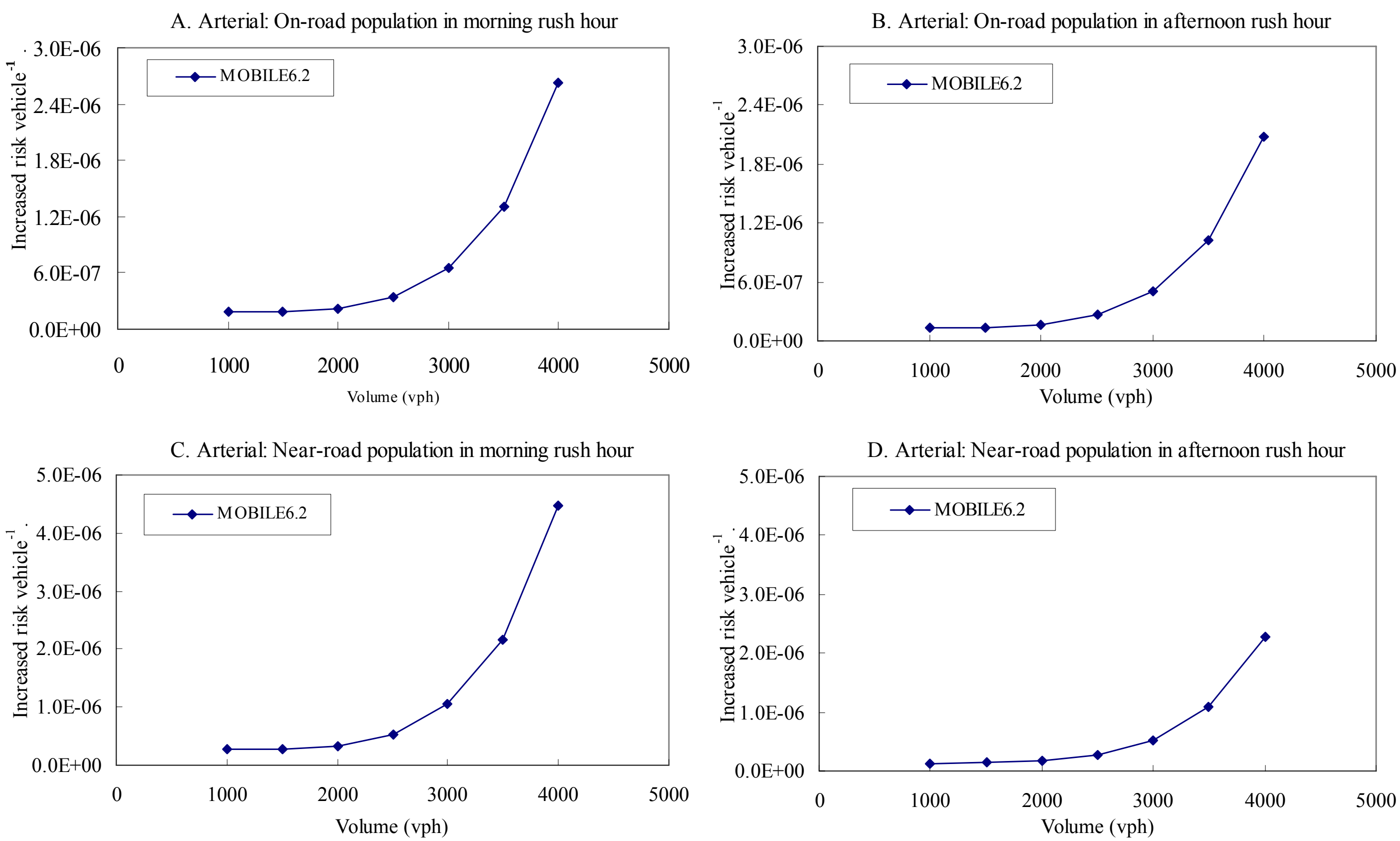

Figure 5-10. Predicted incremental risks per vehicle versus traffic volume for upper bound mortality in the arterial scenario (‘U’, upper bound; ‘V’, traffic volume; near-road representing individuals living at 100 m to a highway.)

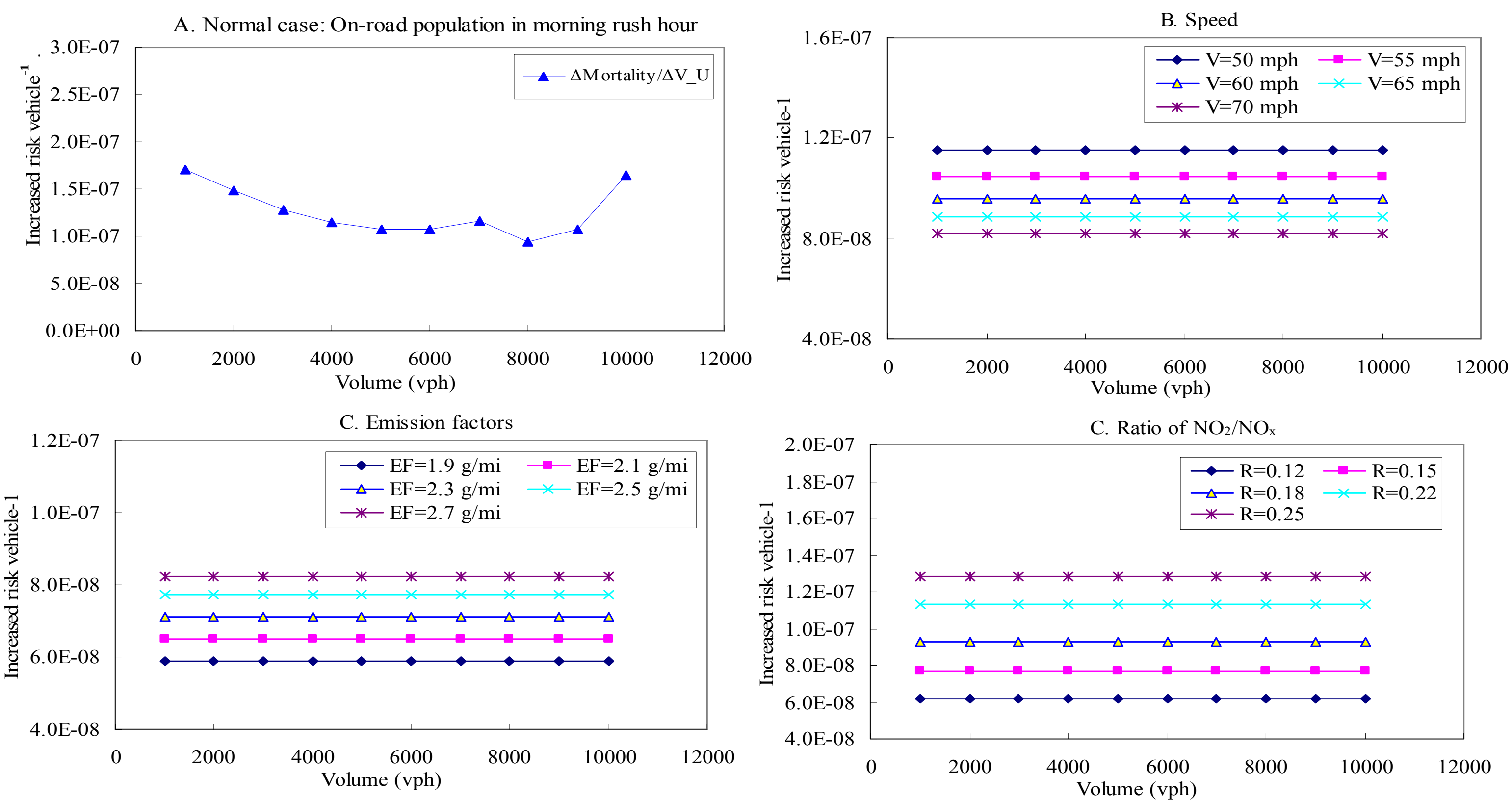

Figure 5-11. Sensitivity analysis for speed, emission factors and NO_2/NO_x ratio (Incremental risks of mortality upper bound for the on-road population as a normal case; 'U', upper bound; V, speed; EF, emission factor; R, ratio)

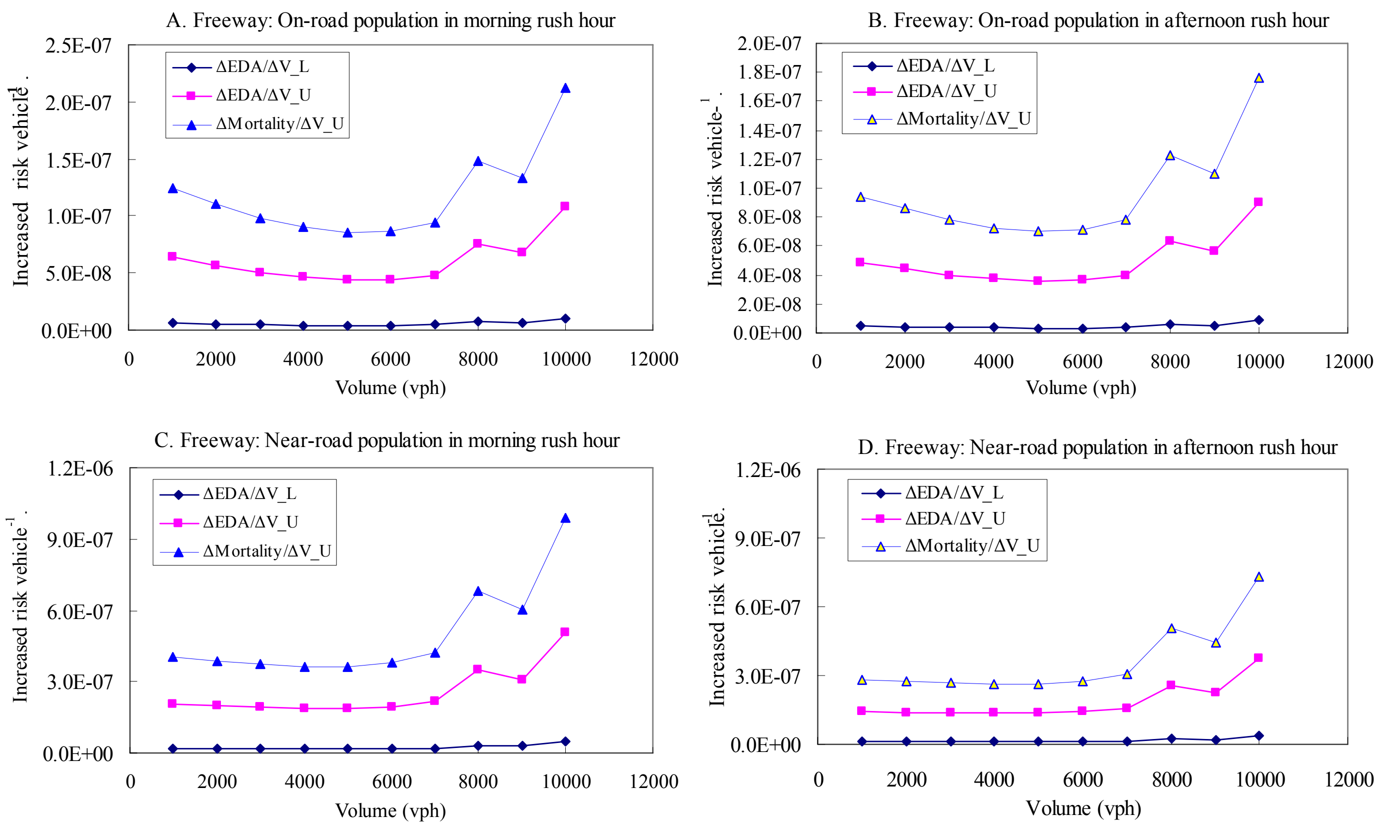

Figure S5-1. Predicted incremental risks per vehicle versus traffic volume for the freeway scenario using CMEM emission estimates ('L', lower bound; 'U', upper bound; lower bound of incremental mortality risk is zero and thus is not shown in the plots; near-road representing individuals living at 100 m to a highway.)

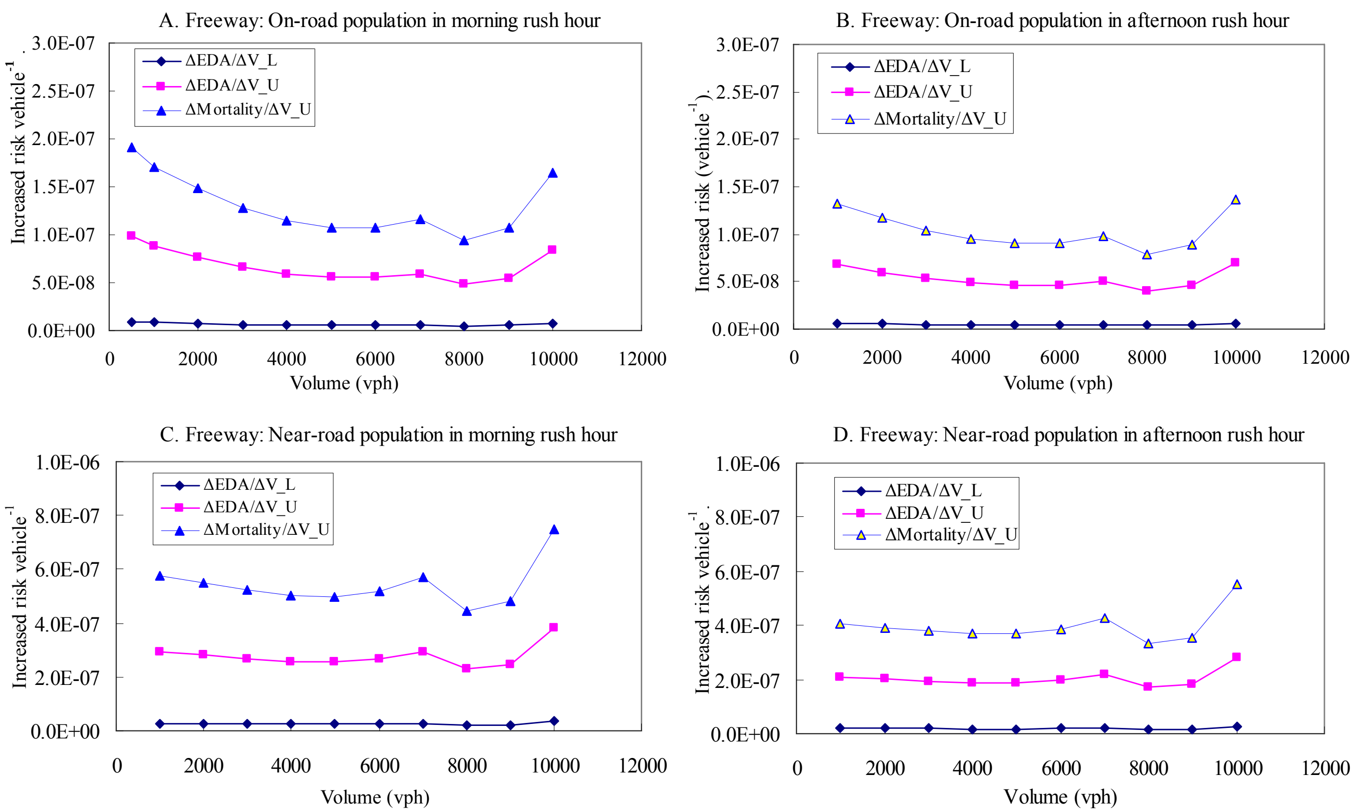

Figure S5-2. Predicted incremental risks per vehicle versus traffic volume for the freeway scenario using MOBILE6.2 emission estimates (‘L’, lower bound; ‘U’, upper bound; lower bound of incremental mortality risk is zero and thus is not shown in the plots; near-road representing individuals living at 100 m to a highway.)

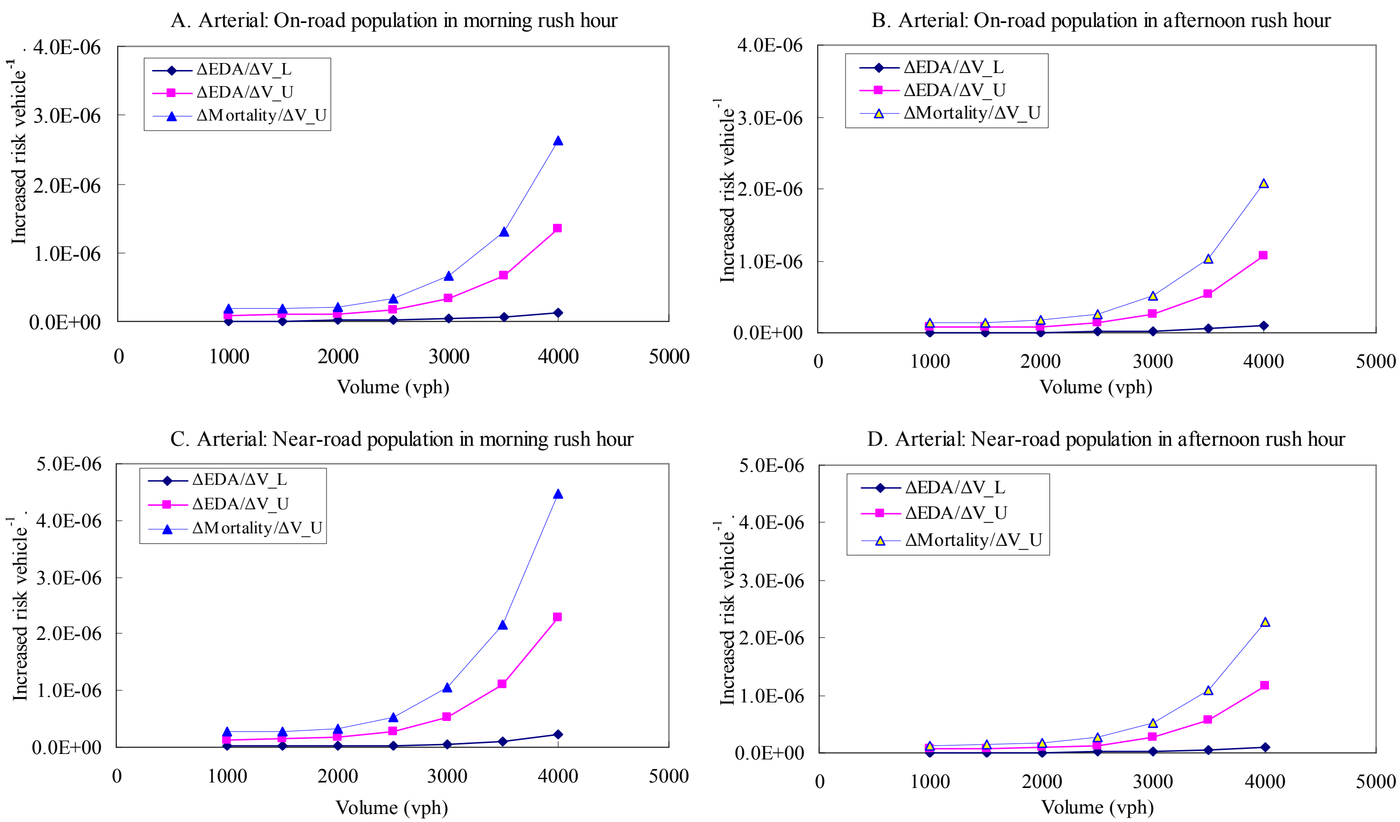

Figure S5-3. Predicted incremental risks per vehicle versus traffic volume for the arterial scenario using MOBILE6.2 emission estimates ('L', lower bound; 'U', upper bound; lower bound of incremental mortality risk is zero and thus is not shown in the plots; near-road representing individuals living at 100 m to a highway.)

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Chapter 6
Conclusion

The goal of this research was to characterize exposures and health risks due to traffic-related air pollutants, including an analysis with and without traffic congestion. Four specific aims were defined: (1) the trade-offs between time spent in vehicles and eight other microenvironments due to traffic congestion were investigated using robust regression and the National Human Activity Pattern Survey (NHAPS) data; (2) vehicle emissions under work zone and rush hour congestion were estimated and compared to emissions under free-flow conditions by conducting a field and modeling study on a local freeway segment and using vehicle emission models; (3) process- and statistically-based models for predicting near-road concentrations were compared with pollutant concentrations monitored near an interstate freeway in Detroit, MI; (4) a methodology to explore air quality and health risks due to congestion was developed and demonstrated using for freeway and arterial roads.

This concluding chapter discusses key findings, implications and significance of this research. The limitations of the study are summarized, and recommendations for further research are suggested.

6.1 Key findings

In this research, a research framework has been proposed that addresses exposures and health risks due to traffic-related air pollutants generated during congestion. The framework uses a systems perspective and highlights the importance of accounting for human behavior, emissions, pollutant concentrations and other factors that affect exposures and health risks. This section summarizes key findings from previous chapters, and formulates overall conclusions.

6.1.1 Time allocation shifts

Chapter 2 investigated how traffic congestion affected time allocations among six indoor and two outdoor microenvironments, and investigated changes in exposures of individuals to benzene and $PM_{2.5}$, two traffic-related air pollutants. Data obtained from the National Human Activity Pattern Survey (NHAPS) were stratified by age, employment status and day type (weekday vs. weekend). Robust regressions were conducted to deal with outliers and influential points. Results showed that for children and the elderly, congestion primarily reduced the time spent at home and, for older children and working adults, congestion affected the time spent at home as well as time in schools, public buildings, and other indoor environments. The estimated time shifts were used to estimate changes in benzene and $PM_{2.5}$ exposures for scenarios representing 9 and 30 min day^{-1} travel delays. A Monte Carlo simulation was used to represent variability, and exposures among the major microenvironments were apportioned. Concentrations in typical microenvironments were obtained from a review of the recent literature. This analysis showed that congestion represented a significant contribution of the total benzene and $PM_{2.5}$ exposures, and changes in exposures depend on the duration of the congestion and the pollutant.

This chapter makes two primary contributions in exposure science. It represents the first exposure assessment study to investigate dynamic trade-offs in time allocations among different microenvironments, and specifically those caused by traffic congestion. The research methodology and findings are important for understanding time budgets, behavioral changes, and pollutant exposures. Second, it appears to be the first study to separate traffic-related exposures into free flow and congestion modes, and it examines the effect of congestion on the total exposure. Its findings are helpful in understanding the significance of traffic and congestion to an individual's total exposure.

The two scenarios discussed in Chapter 2 showed that exposures were mainly driven by the concentrations occurring in several of the microenvironments affected by congestion, namely, in-vehicle and near-road. Chapters 3 and 4 address some of the factors affecting these concentration in an examination of roadway emissions and near-road concentrations.

6.1.2 Emissions under congestion

Chapter 3 estimated vehicle emissions for light-duty vehicles (LDVs) and heavy-duty vehicles (HDVs) under work zones, rush hours and free-flow traffic conditions. Field experiments collected second-by-second vehicle speed profiles on typical weekdays for three weeks along a segment of an interstate freeway in Ann Arbor, Michigan. The collected data were smoothed and then entered into the Comprehensive Modal Emissions Model (CMEM) to generate vehicle emissions, expressed as g mi^{-1}. For LDVs, the transitional period between free-flow and congestion conditions and rush hour congestions was associated with highest emission rates of CO, HC and NO_x, and the lowest emission rates were associated with low-speed work zone congestion. A different trend was seen for fuel consumption and CO_2: work zone congestion consumed the most fuel and produced the most CO_2. For HDVs, work zone congestion was associated with the highest emission rates of HC, CO and CO_2, as well as the highest fuel consumption; NO_x emission rates were similar under the different traffic conditions. These results show that emission rates depend on vehicle type, and the degree and type of congestion. A sensitivity analysis conducted for the averaging time for smoothing speed profiles suggests smoothing has large impacts in predicted emissions. Instantaneous-speed based CMEM emission rates were shown to be significantly greater than average-speed based CMEM rates for LDVs, but similar for HDVs. However, instantaneous-speed based CMEM emission rates were systematically lower than those predicted by the Motor Vehicle Emissions Factor Model version 6.2 (MOBILE6.2), possibly due to smoothing, different model mechanisms, and different calibrations of the models.

This study appears to be the first to examine pollutant emissions and fuel consumptions under free-flow, work zone and rush hour congestion conditions. Its results fill a gap in the literature and have important implications for congestion, especially work zone congestion, which accounts for 10% of total traffic congestion (CAMSYS and TTI, 2005). The degree of smoothing applied to the vehicle speed and acceleration data appears to be a critical factor for instantaneous emission models, such as CMEM and MOVES (EPA, 2009), and there are substantial uncertainties in model predictions, as discussed later. Still, the results in this chapter highlight the importance of congestion, and are relevant to emission, exposure and health risk evaluations, as well as transportation planning.

6.1.3 Comparison of process- and statistically-based models

Chapter 4 used simulation and statistical models to estimate traffic's contributions to near-road concentrations of carbon monoxide (CO) and $PM_{2.5}$ (particulate matter less than 2.5 μm in dia), and to compare these two types of models. The analysis used hourly measurements of CO and $PM_{2.5}$ monitored near a major freeway in Detroit, Michigan for a one year period, along with local meteorological data and hourly traffic counts obtained from the Michigan Department of Environmental Quality (MDEQ) and the Michigan Department of Transportation (MDOT). The data were stratified by season to account for seasonal effects. The simulation model was implemented by linking MOBILE6.2 to the California Line Source Dispersion Model version 4 (CALINE4). The statistical model used generalized additive models (GAMs) with LOESS smoothers to fit pollutant observations to traffic counts, meteorological variables and time trend variables. Traffic counts showed statistically significant and approximately linear relationships with CO concentrations in fall, and piecewise linear relationships in spring, summer and winter. The average CO emissions derived from the GAM were similar to those estimated by MOBILE6.2/CALINE4. The same analyses for $PM_{2.5}$ showed that GAM emission estimates were much higher (by 4 to 5 times) than the dispersion model results, and that the traffic-$PM_{2.5}$ relationship varied seasonally. Overall, these comparisons indicated that the CO emission factors derived from MOBILE6.2 were unbiased, but $PM_{2.5}$ emission factors were significantly underestimated, a likely result of underestimating $PM_{2.5}$ emission factors. This is supported by recent reports indicating that the actual $PM_{2.5}$ emission factors are two to three times higher than those predicted using MOBILE6.2 (EPA 2006; 2008). The discrepancy in $PM_{2.5}$ emissions could be reduced using the seasonal average heavy truck fraction as measured at a nearby traffic monitor, but large differences remained.

This analysis demonstrates that comparisons between simulation models like MOBILE6.2/CALINE4 and statistical models like GAM have a role in evaluating the performance of models used to predict air quality impacts. Because these models are based on different mechanisms and assumptions, such comparisons can help to improve predictions. Agreement between the models suggests that their assumptions and parameters are reasonable; discrepancies show areas that require improvements. Overall, the statistical models require fewer assumptions, and thus may be more realistic, but these models may not be generalizable to other locations. One approach is to combine empirical emission factors, e.g., as derived by GAM, using process-based dispersion model, e.g., CALINE4, to improve model predictions. This approach may be more generalizable and accurate than the use of either type of model alone.

6.1.4 Health risks due to congestion

Chapter 5 used a predictive risk assessment in an incremental analysis mode to explore the health risks associated with traffic and congestion. This chapter used the emission and dispersion models and some of the results discussed in Chapters 3 and 4. Simulation modeling was used to estimate on- and near-road NO_2 concentrations attributable to traffic for two scenarios representing on- and near-road exposures on a freeway and an arterial segment. The modeling including emission factors predicted using MOBILE6.2; dispersion modeling to predict pollutant concentrations using CALINE4 and local meteorological conditions; traffic density predictions using the Bureau of Public Road (BPR) formula; estimates of emergency department visits, hospital admissions, and mortality based on concentration-response relationships in the literature. In the incremental analyses, health risks were expressed on the basis of marginal increases in traffic volume. The incremental analysis showed very different patterns for the two types of roads. Key results are the "U" shaped trends for incremental risks for freeways, indicating higher incremental risks at both high and low levels of congestion, and the sharply increasing incremental risks with congestion on arterial roads. These patterns are due mainly to changes in emission factors, the NO_2/NO_x relationship, and travel time/duration of rush hour.

This analysis shows that health risks from congestion can be predicted by combining the relevant models, and that risk are potentially significant for the on- and near-road residential population. While uncertainties are high, especially for the emission estimates and the dose-response characterization, the analysis suggests the importance of accounting for congestion in emissions, exposure and health risk evaluations, as well as transportation planning.

6.1.5 Overall conclusions

This research suggests that periods of congestion can have significant impacts on exposures to traffic-related air pollutants, which increase the associated health risks for the on-road population. This novel finding has been demonstrated by investigating the dynamic adjustments of time activity patterns as well as the separation between normal traffic and congestion periods. Additionally, the dependence of exposures on shifts in time allocations caused by congestions highlights the importance of a dynamic perspective in exposure assessment. This finding, which has not been previously reported, is a novel contribution to exposure science methodology.

This research improves the understanding of congestion, emissions and air quality and demonstrates analyses that use both mechanistic and empirical methodologies. As noted in Chapter 1, the relationships between congestion, emissions and air quality are complicated. This research appears to the first one to indicate that the type of congestion has important impacts on emissions, at least for the congestion occurring in work zones and rush hour. Moreover, the GAM discussed in Chapter 4 has the potential to identify what levels of near-road concentrations are due to traffic and congestion. Unfortunately, the type of traffic congestion was not available for the analysis in Chapter 4, which was one of the original motivations for this work.

This research identifies a number of challenges in estimating exposures and health risks due to traffic congestion using models that link emissions, dispersion, and concentration-response relationships. As shown in Chapter 5, the models are complex; they involve many assumptions and uncertainties; and it is difficult to assess the reliability of results. Additionally, congestion is affected by many local factors, such as segment-specific driving patterns and road type, and this can makes it difficult to generalize the impact of congestion across large urban areas. The dynamic behavior of the on- and near-road populations add yet more complexity, due to time shifts, travel patterns that cross several types of road segments, including those with congestion, and other reasons. Finally, it is not clear where and how near-road residents spend time during rush hour.

6.2 Study limitations

The trade-off analysis of time allocations in Chapter 2 is recognized to have a number of limitations. First, time shifts due to congestion were derived using travel time and time allocation in typical microenvironments indirectly, and were not estimated based on time specifically spent in congestion. This appears to be reasonable for short congestion, which corresponds to a small increase in travel time. Second, time shifts were estimated based on a cross-sectional analysis, not a longitudinal or panel survey. Therefore, results represented shifts at a population level, not at an individual level. Third, limited information was available regarding pollutant concentrations in vehicles and other microenvironments, and the scenario analysis was driven by the selected typical concentrations in different microenvironments. Thus, these factors may limit the generalizability of the results.

The study on examining emissions during congestion in Chapter 3 includes several limitations. First, this study did not examine air pollutants such as fine particles, ultrafine particles, and black carbon which have large impacts on human health (WHO, 2005; HEI, 2010). Second, the car-floating technique used tended to represent the average of the speed profiles of on-road individual vehicles, and a limited number of vehicle-following trips did not necessarily represent the full range of traffic conditions. This would likely underestimate actual emissions. Third, large uncertainties existed in the mapping between CMEM and MOBILE 6.2 categories because they categorized vehicles differently. Fourth, smoothing of the speed profiles had a large impact on emission results, but an independent dataset to evaluate the appropriate degree of smoothing was lacking. Finally, predicted emissions were not validated using field measurements.

The comparison study between process- and statistically-based models in Chapter 4 has several limitations. First, the data was taken from a single monitoring site situated somewhat farther from the freeway, and thus traffic's contribution to CO and especially $PM_{2.5}$ was modest. Second, this analysis used total traffic counts, not vehicle-type specific counts and did not take speed into account. This information has the potential to improve GAM's performance on discovering traffic's influence on near-road pollutant concentrations. Third, this study did not examine other traffic-related air pollutants (e.g.,

NO_2, ultrafine particles, and black carbon) that have significant increased health risks (WHO, 2005; HEI, 2010). These pollutants are primarily emitted from vehicles, especially heavy trucks, and can improve model fitting.

The analysis of health risks due to congestion in Chapter 5 was designed as a preliminary investigation to demonstrate a methodology, and results have considerable uncertainty and many limitations. As discussed previously in this dissertation, the MOBILE6.2 emission model does not explicitly simulate traffic and vehicle driving cycles during congestion. The coefficients in the BPR method used to predict average speed require calibration for specific study road segments. Large uncertainties might be caused by the relationship assumed between NO_2 and NO_x concentrations. No concentration-response relationship is available for congestion and health outcomes, and the analysis considered only NO_2, which was used as surrogate for other pollutants. It would be helpful to examine other traffic-related pollutants, e.g., $PM_{2.5}$ and black carbon. All of the models used are deterministic, and they do not reflect variability and uncertainty. This analysis is based on two simple scenarios with many assumptions, and the results can be affected by many factors, e.g., road orientation, number of lanes, road topography, meteorological conditions, and the near-road population density. These factors were not explored.

Perhaps the most important limitations of this research are that the data used in each chapter were obtained from difference sources, rather than from one integrated and comprehensive study, and that direct measures of traffic-related emissions, exposures and risks are not available, thus it is difficult to both link all of the elements of this work together, and to directly evaluate the accuracy and reliability of the models. In particular, the data in Chapter 4 did not include potential congestion information, which makes it impossible to investigate the relationships between congestion and near-road pollutant concentrations. However, GAM is expected to characterize the congestion-concentration relationships if information that indicates congestion, e.g., traffic density and speed at fine time scales, is available. While emission models such as MOBILE6.2 and CMEM have some ability to characterize emissions in congestion, these models were not designed for these applications and their predictions did not agree. As examples, MOBILE6.2 cannot incorporate segment-specific acceleration/deceleration, thus limiting its use in congestion applications, while CMEM vehicle category scheme differs from that used in MOBILE6.2, and it has been calibrated using a modestly-sized vehicle database. At this point, this research cannot recommend one of these models over the other, but can only suggest that the large magnitudes of uncertainties when modeling impacts of congestion. Comparisons to the new MOVES model would be warranted, as discussed below in recommendations for further study.

The empirical and process-based approaches have different strengths and limitations. GAM might be more useful to improve understanding of congestion-emission-concentration relationships. Congestion is a short-term event, and is location-specific. GAM is a data-driven approach, and it requires fewer assumptions compared to the process-based approach. Thus, GAM may better identify and characterize congestion-emission-concentration relationships. Knowledge of these relationships, empirically determined, might guide the application of simulation models for the emission and dispersion processes, which tend to be more generalizable and less data-intensive than statistical models. Additionally, the use of simulation models might be more helpful in regulatory actions and other policy applications, e.g., congestion-mitigation evaluations, since results are predictive in nature and uniform in many respects, and these models do not require the collection of much additional data. However, better emission models are needed to characterize emissions during congestion periods.

6.3 Recommendations for further study

Further research is needed to improve the trade-off analysis of time allocations. First, studies specifically investigating congestion would help to improve the estimation of time-shifts and validate our results. Second, longitudinal surveys and other analyses are needed to extend the travel trade-offs derived here at a population level to be useful at an individual level. Emerging technologies such as global positioning systems (GPS) and cellular phones with GPS functions would be useful for tracking the location and travel behavior of a large number of individuals. Third, the time trade-off and exposure models should be validated by collecting and analyzing simultaneous personal exposure and time activity data in order to monitor and quantify the impacts of both congestion and non-congestion periods. Improved results would be helpful to decision makers. Finally, in terms of examining exposures and apportioning the contribution of traffic and congestion, it would be worthwhile to examine other pollutants, including ultrafine particles and black carbon, both of which are toxic and strongly associated with traffic.

Research is clearly needed to improve and validate predictions of vehicle emissions in traffic. New instantaneous emission models are needed because the vehicle categories used in CMEM are old and different from those used in the Federal Highway Administration (FHWA) and MOBILE6.2 classifications. Field studies are needed to improve and validate emission models. Models should be extended to predict instantaneous emissions of additional pollutants, including $PM_{2.5}$, black carbon and ultrafine particles, pollutants that are traffic-related and potentially very significant in terms of their health effects. Simultaneous upwind and downwind measurements would be helpful to validate the models.

Research to improve model comparison can take several forms. First, simultaneous monitoring at locations both upwind and downwind of the highway could be used to diminish the impact of "background" or regional concentrations. Second, local measurements of vehicle speed, category types, and traffic density at finer time scale (e.g., 5 min) would be useful for quantifying congestion's impacts on near-road air quality and for better understanding temporal variation. Third, considering both multiple years and multiple pollutants might help improve model performance. It might also help to identify the relationships between traffic and pollutants such as ultrafine particles and black carbon.

Further research is needed to improve the risk evaluation of exposures and health risks attributable to traffic congestion and to reduce uncertainties. First, concentration-response relationships between direct congestion indicators, such as time spent in congestion or congestion levels, and health outcomes are needed since the previous epidemiological studies have used aggregated traffic indicators, e.g., daily traffic volume or traffic density within a buffer zone. Such indicators do not represent congestion levels. Second, emission models that directly account for congestion are needed. The application of EPA's new Motor Vehicle Emission Simulator model (MOVES) might be useful in this context; this will also require the development of representative congestion-oriented driving patterns. Third, it is important to understand the population density for individuals living near roads at fine distance scale since air pollutant concentrations produced by traffic decrease quickly with distance.

6.4 References

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