Urban Traffic Emission Cost Estimation Using an Integrated Modeling Approach

By

Song Bai

Civil Engineering and Applied Mechanics

McGill University, Montreal

August 6, 2019

A thesis submitted to McGill University

in partial fulfillment of the requirements of the degree of

Master of Engineering

AUTHOR’S DECLARATION

I hereby declare that I am the sole author of this thesis. To the best of my knowledge, this thesis contains no material previously published by any other person except where due acknowledgment has been made. I further authorize McGill University to reproduce this thesis by photocopying or by other means, in total or in part, at the request of other institutions or individuals for scholarly research.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

According to Canadian Environmental Sustainability Indicators (CESI), in 2015, the transport sector was the 4th leading source of $PM_{2.5}$ emissions in Canada. Vehicular emissions contribute significantly to air quality problems and public health issues in urban areas. Nevertheless, previous studies have shown that transport users do not perceive their travel-related emissions as out of pocket costs. In addition, travelers prefer emissions' information in monetary values rather than in their own units (tons or grams of emissions). In this study, I estimate the health-related costs of transport emissions for Montreal residents. In addition, I examine the use of an air dispersion model (AERMOD) in estimating travel-related air pollution concentrations for four intersections in Bucaramanga, Columbia.

In the second chapter, I estimate and quantify emissions generated on the Montreal road network. First, I transform the emissions rates estimated from the MOVES software into air pollution concentrations. Then, I convert the concentrations into health outcomes. Finally, I valuate these health outcomes in monetary terms. My results show that among three key emission types, NO_x has the highest emission cost (up to \$0.38/km), followed by $PM_{2.5}$ (\$0.31/km) and CO (\$0.0074/km), during peak hours. In addition, the downtown and Plateau areas have the highest total emissions costs per km.

In the second part of the thesis, I apply an air dispersion model (AERMOD) to simulate the air pollutant movements at four intersections in Bucaramanga, Colombia. My results show that the higher traffic volume, the higher the emission rates for both $PM_{2.5}$ and Black Carbon, except for when heavy trucks' percentage is high. The La Provenza intersection generates the highest $PM_{2.5}$ rate (90g/h during peak hours and 16g/h during off-peak hours) and Black Carbon (15g/h

during peak hours and 3g/h during off-peak hours). In addition, the air pollution concentrations are highest among the most congested links, in all studied intersections. Moreover, the $PM_{2.5}$ and Black Carbon concentrations drop off substantially when moving away from the intersections' centers, and then gradually decrease after 50 meters. In addition, compared to the real measurements (by the equipment installed in the intersections), the proposed set of models (MOVES+AERMOD) captures most of the general trends in $PM_{2.5}$ and Black Carbon. However, the predicted concentrations are less than the observed measurements. This could be due to the fact that some factors are neglected, and those can affect the results, factors including emissions generated by people's other daily activities (e.g., cooking), the relatively old vehicle fleet in Colombia (different from MOVES's fleet), etc. I conducted a set of sensitivity analyses to understand the performance of the AERMOD dispersion model in estimating $PM_{2.5}$ concentrations, by altering the input data. My results show that AERMOD is highly sensitive to wind conditions. The temperature was observed to have a slightly negative correlation with $PM_{2.5}$ concentrations. My results could be used to raise public awareness regarding the health impacts of traffic-induced air pollution, and eventually could change travel behavior of urban travelers.

Keywords: Urban traffic, health-related emissions cost; Montreal transport users; MOVES; Emission rates; Bucaramanga, Colombia intersections; Air pollution dispersion modeling, and air pollution concentration.

RÉSUMÉ

Selon les Indicateurs canadiens de durabilité de l'environnement (ICDE), en 2015, le secteur de transport est le quatrième secteur d'émissions de $PM_{2.5}$. Les émissions des véhicules contribuent considérablement aux problèmes de qualité de l'air et à la santé publique dans les zones urbaines. Toutefois, des études antérieures ont démontré que les utilisateurs des systèmes de transport ne perçoivent que leurs émissions liées aux déplacements sont des coûts dont ils doivent payer de leurs propres poches. D'ailleurs, ils sont plus intéressés à recevoir les informations sur les émissions sous forme de valeur monétaire au lieu de l'unité brut (tonnes ou grammes d'émission). Par la présente étude, j'estime les coûts liés à la santé engendrés par les émissions de déplacements des utilisateurs de systèmes de transport à Montréal. De plus, j'examine la faisabilité d'un modèle de dispersion de l'air (AERMOD) pour estimer la concentration de pollution atmosphérique connexe aux déplacements de quatre intersections à Bucaramanga, Colombie.

Dans le deuxième chapitre, pour estimer les coûts des émissions pour la santé, je transforme les taux d'émissions estimés à partir de MOVES en concentrations de pollution atmosphérique, par la suite j'ai converti les concentrations aux conséquences sur la santé, et enfin évaluer ces résultats en termes monétaires. Mes résultats indiquent que parmi les trois types d'émissions principaux, NO_x a le coût d'émission le plus élevé (jusqu'à \$0,38/km), suivi de $PM_{2.5}$ (\$0,31/km) et du CO (\$0,0074/km). De plus, les régions du centre-ville et du Plateau ont les coûts d'émissions par km.

Dans la deuxième partie, j'ai appliqué un modèle de dispersion (AERMOD) pour simuler le mouvement des polluants atmosphérique aux quatre intersections à Bucaramanga, en

Colombie. Mes résultats démontrent que la quantité de véhicules est directement reliée aux taux d'émission de $PM_{2.5}$ et de carbone noir, à l'exception d'un pourcentage élevé de camions. L'intersection La Provenza a les taux d'émission de $PM_{2.5}$ (90g/h les heures de pointe, 16g/h les heures creuses) et de Carbone Noir (15g/h les heures de pointe, 3g/h les heures creuses) les plus élevés. Parmi les intersections étudiées, les concentrations sont les plus élevées aux liaisons les plus fréquentées. De plus, les concentrations de $PM_{2.5}$ et de carbone noir diminuent à partir du centre de l'intersection, puis diminuent graduellement après 50 mètres. En outre, par rapport aux mesures réelles (à l'aide des équipements installés aux intersections), l'ensemble de modèles proposé (MOVES + AERMOD) capture la plupart des tendances générales concernant les $PM_{2.5}$ et le noir de carbone. Cependant, les concentrations prévues sont inférieures aux observations. Cela pourrait être dû au fait que non seulement les sources mobiles routières et industrielles routières peuvent influer sur la concentration de pollution atmosphérique, notamment les émissions générées par les autres activités de la vie quotidienne (par exemple, la cuisine), le véhicule relativement ancien. Flotte en Colombie (différente de la flotte de MOVES), etc. J'ai entrepris des analyses de sensibilité dans cette étude pour mieux comprendre le comportement du modèle de dispersion AERMOD lors de l'estimation des concentrations de $PM_{2.5}$ en altérant les données d'entrée. Mes résultats indiquent qu'AERMOD est très sensible aux conditions de vent. Mes résultats indiquent que la température avait une corrélation négative avec la concentration en $PM_{2.5}$. Mes résultats pourraient être utilisés pour sensibiliser le public aux conséquences de la pollution de l'air par la circulation, sur la santé, et pourraient éventuellement changer le comportement des voyageurs urbains en matière de voyages.

Mots-clés- Coût des émissions liées à la santé de la circulation urbaine; usagers du transport de Montréal; MOVES; taux d'émission; intersections Bucaramanga, Colombie; modèle de dispersion de la pollution atmosphérique et concentration de la pollution atmosphérique.

ACKNOWLEDGMENTS

I would like to convey my gratitude, first and foremost thanks to my supervisor, Prof. Omid M. Rouhani, for giving me the opportunity to work on this project. I would also like to thank him for his consistent support, guidance, and advice in developing general research contexts, explaining methodologies, and analyzing results.

I would like to thank the Ministère des Transports du Québec (MTQ) for allowing me to use the outputs of the EMME model for the Montreal region. For that, I would like to thank Mr. Pierre Tremblay for allowing me to use their offices and for setting a potential collaboration for future research outputs. In addition, I would like to thank Mr. Tan Minh Phan for his support and guidance when using the software at MTQ.

In addition, I would also like to acknowledge the financial support provided by Natural Sciences and Engineering Research Council of Canada (NSERC) under award number RGPIN-2016-06440.

Lastly, I would like to thank my family and friends for their encouragement and support.

CONTRIBUTION OF CO-AUTHORS

For the third chapter, Yi Han Shao and Zi Sheng Hong (Undergraduate student, McGill University) helped me in data collection, and Ehsan Moradi (PhD candidate, McGill University) helped in data analysis. In addition, Kabisha Velauthapillai (Master candidate, McGill University) provided necessary air pollution concentration data for analysis.

Chapter 1: Introduction

1.1. Background

The economy of any region is tightly linked to the quality and the coverage of regional transportation systems, which can significantly impact passengers' and freights' travel time and distance, especially when developing new transportation infrastructures. However, urban traffic congestion and related air pollution are generated as negative byproducts of travel, so called travel externalities. According to the statistic of Canada, over 34.3 million vehicles are registered on road with a total of 521 billion kilometers traveled in 2017 (Statistic Canada, 2017). Since the transportation sector is the second largest source of CO_2 emissions and also contribute to 44% and 30% of total national nitrogen oxides (NO_x) and carbon monoxide emissions (Environment and Climate Change Canada, 2016) with enormous environmental and public health implications, a better understanding of the overall impact of these emissions and how these emission affect public health and environment based on a social welfare perspective is of significant importance (Rouhani et al., 2016).

The vehicular emissions impact air quality in the form of greenhouse gas emissions (mainly CO_2) and criteria air pollutants including PM, O_3, CO, NO_x, as specified by the United States Environmental Protection Agency (US EPA) as key surface transportation environmental footprints.

With the improvements in vehicle technologies and transportation infrastructure provisions, as well as sustainable policies, such as the Canadian Environmental Protection Act 1999, total emissions generated by vehicles has decreased in Canada over the past years. For instance, total NO_x and CO emissions generated from significantly contributing vehicle categories in

Canada dropped from 0.95 million tons to 0.4 million tons and 10 million tons to 4.5 million tons, respectively, from 1985 to 2010 (Environment Canada, 2012). However, the transportation sector is still identified by the Canadian Environmental Sustainability Indicators (CESI) as the second greatest source of greenhouse gases (GHGs) in Canada, contributing to 24% of the national carbon dioxide (CO_2) emissions (Environment and Climate Change Canada, 2017). In addition, around 4000 tons of $PM_{2.5}$ emissions in 2015 are generated by the transportation sector in Canada, as the 4^{th} leading sector (Environment and Climate Change Canada, 2016).

Many sectors other than transportation contribute to criteria air pollutants. However, transportation-related emissions are of more significant concern, not only because of the high contribution of the sector but also because the emissions affect a large number of residents in urban areas. Especially in large metropolitan areas with relatively high traffic congestion, vehicle emissions are of vital significance as pedestrians are directly exposed to the travel-related air pollutions.

As a result, the quantification of traffic-related pollutants and the associated air concentrations is necessary. Various emissions simulator models have been used to estimate emissions generated by vehicles and their impacts on air pollution concentration considering different emission types. The resulting air pollution has a variety of effects on residents' health, ranging from severe (mortality) to mild effects (morbidity) (Environment and Climate Change Canada, 2015). The typical health effects associated with exposure to CO range from cardiovascular problems to death after exposure to very high concentrations of CO (Satran et al., 2006) while NOx causes severe respiratory problems (Mavroidis & Chaloulakou, 2010). The Air Health

Indicator (AHI) of Canada indicates that about 1% of cardiopulmonary mortalities could be attributable to exposure to fine particulate matters or $PM_{2.5}$ (Sawyer et al., 2007).

A survey conducted in Montreal-Canada finds that urban travelers are interested in receiving their travel-related emission information, mainly monetary metrics (Daher et al., 2018). In order to determine the monetary impacts, the health effects should be translated into welfare money lost by using the value of life (VOL) for mortality cases and people's willingness to pay to accept that specific health problem for morbidity cases (Sawyer et al., 2007).

1.2. Motivation

Transport users cannot perceive their contributions to climate change according to several surveys conducted in the US, Canada, and Mexico (Daher et al., 2018; Lorenzoni & Pidgeon, 2006). In addition, a limited number of research studies have been conducted on quantifying and monetizing transportation-related emissions for Canadian cities. Most of them are based on a regional or provincial scale (Sawyer et al., 2007; Zhang et al., 2004).

Second, the majority of the past researches focus on a single emission type, mainly NOx or CO, as NOx is the most impactful emission type generated by vehicles (Zhang & Batterman, 2013). However, there are several other emission types, such as PM that are generated by the transportation sector and have significant health implications, as discussed in the background section.

Furthermore, numerous studies examined the health outcomes related to air pollution concentration change due to traffic-related emissions. (Shekarrizfard et al., 2017) applied MOVES software to estimate emissions and used Calpuff & Calmet air dispersion model to predict air concentration related to transportation in Montreal. However, air concentration changes were not translated into health outcome or monetary values, and the employed dispersion model is calibrated for California, not Canada. (Chen et al., 2013) studied the relationship between the air concentration of NO_2 and health outcomes using exposure-response relationships These relationships are estimated by linking variance of NO_2 air pollution concentration across all postal-code addresses in Toronto to the database that provides data on all deaths of Canadians that occurred in Canada as well as most of those that occurred in approximately 20 U.S. states between 1982 and 2004. However, these health outcomes were not translated into monetary values to help people understand these emissions impacts.

Hence, my key research goals are (1) to quantify the vehicular emission concentrations for $PM_{2.5}$, NO_x, and CO on a city level (Montreal, Canada) and a project level (Bucaramanga, Colombia) using an integrated modelling framework, and (2) to estimate the welfare monetary impacts of those emissions based on the monetary value of the associated health effects for the city of Montreal.

1.3. Objectives

As mentioned above, the key objectives of this research is to estimate and to monetize the emissions associated with urban transportation in a city or in an area (project level) using and combining a microscopic emission simulator (MOVES), a pollutant dispersion model (AERMOD), an Air Quality Benefits Assessment Tool (AQBAT), and monetary valuations of health outcomes.

The fundamental concept is to monetize emissions on road networks by determining the predicted air pollution concentration level changes as a result of vehicle emissions and then estimating human health problems associated with the changes in air quality using a computer simulation tool, and finally assigning monetary values to specific health outcomes.

The scope of this research includes the following tasks:

1) Estimate emissions rates on all links of the Montreal road network for NOx, CO and $PM_{2.5}$ in October and January 2016, using a vehicle emissions simulator called MOVES.
2) Obtain the air pollution concentration changes due to vehicular emissions estimated from vehicle emissions simulator using an air pollution dispersion model called AERMOD.
3) Estimate and analyze the impacts (risks) of emissions on health outcomes (mortality, morbidity, etc.) based on the changes in air quality.
4) Monetize the health-related air quality impacts caused by transportation emissions (in $/ton) for different Montreal boroughs and various vehicle types.
5) Compare the results of modeling with the measured (real) air pollution concentrations on a project level (four intersections) for a case study in Bucaramanga, Colombia.

1.4. Literature Review

1.4.1. Health and Environmental Impacts of Transport Emissions

With the substantial increase of vehicular emissions in recent years, a large number of epidemiological studies have studied the link between the emissions to various health problems (Brunekreef and Holgate, 2002). The air-pollution-related mortality was examined and estimated in many countries across the world. For instance, (Cohen et al., 2017) found out that the ambient $PM_{2.5}$ was the 5^{th} global mortality contributor in 2015. The exposure to $PM_{2.5}$ emissions caused more than 4 million deaths (around 7.6% of total global deaths) and more than 100 million disability-adjusted life-years (DALYs) (4.2% of global DALYs) in 2015 and the number increased from 3.5 million to 4.2 million from 1990 to 2015 based on the death records. Also, (Cohen et al., 2017) found that exposure to ozone caused additional 254,000 deaths and a loss of 4.1 million DALYs because of chronic obstructive pulmonary diseases in 2015. Based on the above estimates, air pollution, especially $PM_{2.5}$, seems to be the most important environmental footprint of travel, having significant impacts on human health.

In Canada, the air-pollution-related mortality has been estimated by researchers based on different pollutant types considering their health implications. For instance, (Buckeridge et al., 2002) developed an exposure model and implemented it using a geographic information system (GIS) to estimate the average daily exposure to $PM_{2.5}$ in Southeast Toronto. This study shows that with a $\log_{10}$ increase in exposure of $PM_{2.5}$, admission rates for a subset of respiratory diagnoses (asthma, bronchitis, chronic obstructive pulmonary disease, pneumonia, upper respiratory tract infection) will increase by 24%.

For pollutants other than $PM_{2.5}$, (Burnett et al., 1998) conducted a study on 11 Canadian cities, estimating the urban ambient air pollution impacts of transportation on daily mortality rates for 11 years from 1980 to 1991. The results show that nitrogen dioxide had the most significant impact on mortality rate with a 4.1% increased risk of mortality, followed by ozone at 1.8%, Sulphur dioxide at 1.4%, and carbon monoxide at 0.9% based on a statistical analysis examining multiple pollutant regression models.

(Chen et al., 2013) also conducted a cohort study indicating that individuals living in more polluted urban areas are at higher risks of dying from cardiovascular disease. This research studied the correlation of traffic-related air pollution and cardiovascular mortality among adults who lived in three cities in Ontario, Canada. The results show that the cumulative exposure to NO_2 was associated with a 12% increase in mortality from cardiovascular diseases, for each addition of 5 parts per billion (ppb) of NO_2.

(Parent et al., 2013) examined the correlation between traffic-related air pollution and the prostate cancer risk in Montreal and found out that the risk might increase by 27% with the exposure to ambient every 5 parts per billion (ppb) of $N0_2$ concentrations.

1.4.2. Vehicle Emission Simulator

Vehicular emissions are generally estimated by using a vehicle emissions simulator on links based on the vehicle fleet mixture, the volume, and speed of traffic flow, as well as the metrological data required for the study area, including the temperature and humidity. Early emission simulator models (Noland & Quddus, 2006; Chen & Yu, 2007), also known as aggregate emission factor simulators, only estimate emission rates by relying on the average speed on each link and the specific vehicle type distribution. Emissions for a specific vehicle type, age, time period and weather conditions are generally calculated based on sample driving cycles as pre-tests for the road network under study. Other factors affecting emissions have also been included, such as the air conditioner operation (Okui, 2017). The total emissions for a pollutant type are then estimated by multiplying the emission rate by the vehicle trip characteristics, such as distance and time travelled.

Microscopic emission simulators are the more advanced versions of emission simulators that are calibrated based on high resolution driving cycles and can provide second by second emission rates for a given roadway link based on the observed vehicle driving cycles, including detailed vehicular motion information (idling, acceleration, deceleration, and cruising activity, etc.).

Both macroscopic (aggregate) and microscopic emission simulators provide accurate emission rates for regional scales since detailed driving cycles are not required. However, it is well established in the literature that microscopic emission models could provide more accurate results at project scales than macroscopic models (Moulvi, 2010).

MOBILE (Environmental Protection Agency, 2012) and EMFAC (California Environmental Protection Agency, 2010) are examples of aggregate models that cannot function on a microscale level. Emission models such as the Comprehensive Modal Emission Model (CMEM) (Misra et al., 2013), and Motor Vehicle Simulator (MOVES) (Environmental Protection Agency, 2012) are most-commonly-used microscopic models.

COPERT 4 is another average speed model that estimates vehicular emissions, which has been widely used in Europe (Emisia, 2011). As one example, (Shen et al., 2006) employed the COPERT model to measure vehicular emissions of 195 diesel trucks in six cities in China. As another example, (Wang et al., 2008) applied the International Vehicle Emission (IVE) model to simulate vehicle emissions in order to calculate vehicle-emission factors in Shanghai. The COPERT methodology can be used with a sufficient degree of certainty at high resolution. However, it uses the average speed of a particular link regardless of the type of vehicle, which is the limitation of this traffic model.

MOVES model developed by the US EPA, a new version of the MOBILE6 model, is widely used in North American cities to estimate GHG and criteria pollutant emissions (Abou-Senna & Radwan, 2013). MOVES is commonly used in Canadian cities considering local characteristics, especially for Toronto's (Alam & Hatzopoulou, 2017) and Montreal's (Daher et al., 2018) road networks.

Comparing the performance of two models: MOVES and MOBILE, (Vallamsundar & Lin, 2011) estimated NOx and CO_2 emissions in Cook County, Illinois, 2011. The study found that MOVES can provide more accurate estimations of vehicle emissions, especially at the project scale, or disaggregate levels. Base on my literature review, it seems evident that microscopic emission models, for instance MOVES, should be preferred in order to estimate emission rates on roadway links at the county and project scales along with local data in order to provide accurate estimates.

1.4.3. Emissions to Air Concentration

Emissions from transportation can cause several health problems in some cases even beyond the dispersed location. An air dispersion Model along with the pre-processor information including required weather conditions and land use data can predict the movement of pollutants in the air and then predict the air pollution concentration at the ground level for the study area. In order to estimate the effects, emissions generated from transportation must be translated into the ambient air quality changes by using a dispersion model.

Most commonly-used dispersion models in North America for near field pollutant analyses are (*i*) Steady-State Gaussian Models (AERMOD, CALINE 3, CAL3QHC/CAL3QHCR), (*ii*) non-steady state models (CALPUFF) developed by United States Environmental Protection Agency (EPA) and (*iii*) the Lagrangian particle dispersion model (QUIC) developed by Los Alamos National Laboratory (2010).

(Jungers et al., 2006) and (Indra et al., 2004) reviewed air dispersion models and distinguished the most useful emission dispersion models currently available for analyzing mobile emissions. As far as regulatory applications are concerned, the Gaussian approach seems to perform the best based on their reviews.

As one example, CALINE3 is a steady-state Gaussian dispersion model designed by Caltrans, which determines the air pollution concentrations for relatively uncomplicated terrains. CALINE 3 is incorporated into more refined CAL3QHC and CAL3QHCR models that are based on the CO emission model with some additional features. However, CAL3QHC is not intended for modeling sites with complex geometries.

Other models such as AERMOD and CALPUFF are more common and considered as EPA's main regulatory models. AERMOD is a steady-state Gaussian plume dispersion model that incorporated the air dispersion based on planetary boundary layers and can be employed for both simple and complex terrains (Environmental Protection Agency, 2012). CALPUFF is the EPA's Long Range Transport (LRT) air quality dispersion model. It is a non-steady state model as opposed to AERMOD which is a steady state model. CALPUFF is not recommended for nearby field analysis (Brode & Anderson, 2008). In order to provide a more user-friendly dispersion model, several companies and organizations, for example the Lakes Environment Company, have incorporated a few popular U.S. EPA air dispersion models into one integrated interface both for AERMOD (AERMOD view) and CALPUFF (CALPUFF view), providing all the necessary pre-processors required in the package (Lake environment, 2019).

As another common example, the Quick Urban and Industrial Complex (QUIC) dispersion model is a fast response Lagrangian particle dispersion model, which has been developed by Los

Alamos National Laboratory (2010) in order to compute concentrations of pollutants in a short period of time. QUIC has been used for analyzing the air pollution dispersion effects of roadside barriers on the traffic flow patterns of a high-traffic highway in Raleigh, North Carolina, USA (Bowker, 2007), but the model is not employed on any road network.

Several global studies have used Gaussian models to evaluate traffic emissions. (Hao et al., 2000) used the Industrial Sources Complex Short Term Version 3 (ISCST3), a multi-source pollution dispersion model developed by the US EPA to estimate the air concentration change due to transportation-related emissions on road link levels in Beijing, China. The study verified the data with the results from monitoring stations. The results show that mobile sources contribute 74% to CO concentration and 67% to NO_x concentration, which implies that vehicle emissions are the most important air pollutant source in Beijing. The verification from monitoring stations shows that the ISCST3 method can provide realistic air pollution concentrations in the Beijing urban area. However, additional factors should be taken into consideration, such as the influence of low wind speed and heat island effects. (Alvarez et al., 2018) estimated the concentration of air pollutants generated by road traffic on the main roads of the city of Cartagena, Colombia using AERMOD view. Mobile sources are taken into account as well as other sources using the geographic information obtained from the Geographic Information System (GIS). By implementing the AERMOD software, it is possible to estimate the degree of concentration of pollutants generated by transportation contributes to the total pollution existing in these areas. However, a study that links the concentrations of $PM_{2.5}$ with the different diseases caused by inhalation of this pollutant would be especially required.

In the U.S. context, (Edward et al., 2014) examined the air concentration change due to transportation-related emissions and applied CALPUFF to simulate how pollutants are mixed and dispersed. The results show exceedances of NO_2 and $PM_{2.5}$ concentration of U.S. National Ambient Air Quality Standards (NAAQS) in the study area, with about two-thirds of NO_x emissions and one-quarter of $PM_{2.5}$ emissions from on-road vehicles. However, the CALPUFF modeling system showed an over-prediction bias of 20 to 40% for $PM_{2.5}$ concentration. Using AERMOD, (Rowangould, 2015) estimated the $PM_{2.5}$ concentration of road traffic emissions across Los Angeles County, California. As the software can only estimate point sources, the Los Angeles County road network is divided into a grid composed of 1 km by 1 km cells using the GIS software. Each 1 km cell was assigned meteorological data with some adjustments. The results show that high resolution air dispersion modeling can be performed efficiently for large transportation networks with a few simplifying assumptions.

In the Canadian context, CALLPUFF and AERMOD are also commonly used for estimating air concentrations. (Gibson et al., 2013) estimated the $PM_{2.5}$, NO_X and SO_2 air concentrations for Halifax, Pictou, Sydney, and Port Hawkesbury, Nova Scotia, Canada. The air quality dispersion model AERMOD View was used to estimate the air dispersion of point and major line emissions within four, 50 km x 50 km, domains on annual, monthly and 1–hour averaging concentration period bases. The results show that AERMOD is a suitable model for on-road air pollution concentration estimation in Nova Scotia and annual and monthly SO_2 concentrations estimation in Halifax and Sydney. (Misra et al., 2013) used the CHEM emission estimation model and the AERMOD view dispersion model to estimate NO_x and CO air concentrations for Toronto, Canada in 2011. The results show that AERMOD provides better outcomes for CO concentration than NO_x by comparing modeled air pollution concentration to station air pollution concentration.

For Montreal, (Shekarrizfardet al., 2017) estimated the health impacts of planned public transit projects for 2030 based on the decrease in NO_2 emissions from cars. The emissions are calculated using a modified version of MOVES calibrated for Montreal, while the NO_2 air concentration is simulated by CALPUFF and validated against the measured NO_2 data from the Reseau de Surveillance de la Qualite de l'Air (RSQA). The results show an average 27% decrease in exposure of NO_2 concentration for the 2031 transit scenario compared to the baseline scenario of the year 2018. However, indoor or in-vehicle exposures should be considered for future research.

Based on my literature review of several dispersion models, Gaussian modeling seems to be the most appropriate approach. Therefore, AERMOD view software is utilized in this study. The software benefits from an easy-to-use interface and offers relatively accurate results considering detailed metrological and land use data I used in this study.

1.4.4. Air Concentration to Health Outcomes

Air pollution has important health implications according to the emission type as discussed in the previous section. All residents are exposed to air pollutions, while the health of vulnerable groups (including children and the elderly) is impacted to a greater extent. Considering both short-term and long-term exposures, one could develop models that can convert air pollution concentrations into health outcomes, which is necessary for policy makers.

Health impact assessment (HIA) analyses describe the health impacts of a proposed or existing project, policy or program on a specific population. These assessments provide information on health implications and take into account socio-economic effects. They serve as valuable tools to measure the air quality impacts of transportation on health. HIAs examine several health outcomes, including health impacts of current air quality in the study area; the impacts of a project that may damage the local environment and people's health; and an evaluation of existing targets on reducing air pollutant exposures. Decision makers can use HIA to determine if changes need to be made to a project, policy or program to minimize the associated health impacts.

In the U.S., the Environmental Benefits Mapping and Analysis Program (BenMAP) is the principal tool being used to quantify the benefits of reducing criteria air pollutants and to determine health impacts anywhere in the world, in order to inform air-quality-related policies (Sacks et al., 2018).

In Spain, BenMAP has been used by (Boldo et al., 2010) to estimate the number of avoidable death incidents associated with reducing $PM_{2.5}$ levels. The results show that around 6 per 100,000 population in all-cause deaths could be prevented annually with an average annual reduction of 0.7 $\mu g/m^3$ in $PM_{2.5}$ levels. It shows the specially adapted BenMAP could be used as a tool for estimating traffic-related health impacts in Spain. However, one significant limitation of this study is that the health impact analyses is the inability to quantify many of the health effects related to fine particulates due to the lack of health data or reliable impact functions. (Voorhees et al., 2014) used BenMAP in Shanghai, China to estimate prevented cases of pollution-related mortality and morbidity taking into account the Chinese air pollution-related epidemiological health functions and Shanghai air quality data. This study evaluated the impact on all-cause mortality of a year with exposure to mean $PM_{2.5}$ concentration ranged from 180 to 3500. By using BenMAP, analysts can run multiple iterative analyses to suitable pollution control and policy options for local, regional or national scale assessment in China. However, Differences in location, times, air concentrations, health functions and population size lead to wide variability in estimated impact and rely on health impact functions from other geographic locations for China might lead to a large number of variables.

In the U.S., BenMAP has been utilized in combination with vehicle microscopic simulation models, emission models, and air pollutant dispersion models in order to quantify social costs of urban freight transportation in the Alameda corridor in Los Angeles (Lee et al., 2012). Results show that during 2008, the total number of mortality cases caused by $PM_{2.5}$ exposure was 43. However, this analysis accounts only for limited health outcomes due to lack of concentration-response functions for mortality, particularly with respect to young adults and children, either because epidemiologic data are not available, or because studies address populations are different from the people who live in the study area (Grabow et al., 2012) simulated the census-tract level changes in hourly pollutant concentrations from reducing automobile round trips in 11 metropolitan areas in the upper mid-western United State regions using the Community Multiscale Air Quality (CMAQ) model and BenMAP to estimate health impacts. This study shows that with a decline of 0.1 $\mu g/m^3$ of $PM_{2.5}$, the mortality rate would decline by approximately 1295 deaths/year across the study region of approximately 31.3 million people. However, this study did not assess health effects from decreases in other pollutants, for example, carbon monoxide and sulfur dioxide that also have impacts on people's health.

Environment Canada and Health Canada jointly developed the Air Quality Valuation Model (AQVM) for monetizing health and environmental outcome changes from air quality programs/policies in Canada (Sawyer et al., 2007). Since its development in 1996, AQVM has been widely used in monetizing emissions' health impacts. Since 2003, Health Canada initiated the development of the Air Quality Benefits Assessment Tool (AQBAT). It is a computer simulation tool designed to estimate the human health and welfare benefits or damages associated with changes in Canada's ambient air quality. The AQBAT model enhances the estimation capabilities of the previous AQVM and provides a more open and transparent modelling environment.

In Canada, (Zhang et al., 2004) estimated the social and environmental costs of transportation using AQVM while (Sawyer et al., 2007) applied AQBAT to model health outcomes for 9 Canadian provinces as well as the whole Canada. Comparing the two commonly-used tools, the AQVM model uses the concentration-response function to calculate changes in the frequency of 9 health endpoints, while AQBAT applied the concentration-response functions of 12 health endpoints (Sawyer et al., 2007). The major contributing pollutants in both tools are NO_X, Ozone, SO_2, and $PM_{2.5}$.

For both AQVM and AQBAT models, DFA and Concentration Response Functions (CRF) are developed and applied by linking databases of transportation-related emission data, concentration changes in ambient air quality data, geographic areas and scenario years to health endpoints.

The CRFs in AQBAT are derived from epidemiological studies and are defined as distributions such as linear or normal. The associated health endpoints in AQBAT includes both short-term exposure (acute) and long-term exposure (chronic), implying that each event reflects either an immediate or cumulative health impact for either mortality or morbidity. Each CRF applies to a specific population age group pre-defined in AQBAT. Tables 1.1 provide detailed health endpoints associated with a variety of pollutants as well as the relevant epidemiological studies. As can be seen in the Table, the considered health endpoints range from sever outcomes like acute exposure mortality to more moderate issues such as restricted activity days.

As AQBAT is the most up-to-date model developed for Canada, I will use it in this research to convert the air pollution concentrations to health endpoints.

Table 1.1 Concentration Response Functions for Various Health Endpoints

Health Endpoint	Pollutant	Distribution Type	Epidemiological Study
Acute exposure Mortality	NO_x	Poisson	Burnett et al. (2004)
Chronic exposure mortality	$PM_{2.5}$	Poisson	Krewski et al. (2000)
Acute respiratory symptom days	$PM_{2.5}$	Linear	Krupnick et al. (1990)
Adult chronic Bronchitis Cases	$PM_{2.5}$	Poisson	Burnett et al. (2004)
Asthma Symptom Days	$PM_{2.5}$	Linear	Ostro et al. (1991); Whittemore & Korn, (1980)
Cardiac Emergency Rooms Visits	$PM_{2.5}$	Linear	Burnett et al. (1995); Stieb et al. (2000)
Child Acute Bronchitis Episodes	$PM_{2.5}$	Poisson	Dockery et al. (1996)
Respiratory Emergency Room Visits	$PM_{2.5}$	Linear	Burnett et al. (1995); Stieb et al. (2000)
Restricted Activity Days	$PM_{2.5}$	Poisson	Ostro (1987)
Cardiac Hospital Admission	CO	Linear	Schwartz & Morris (1995); Burnett et al. (1996)

1.4.5. Health Outcomes to Monetary Values

Emissions from motor vehicles have several effects on human health and the environment. These impacts could be translated into monetary welfare impacts based on either mortality or morbidity outcomes. (Zhang et al., 2004) applied a value of life (VOL) of 7.5 million CAD for 2002 and estimated mortality and people's willingness to pay (WTP) for morbidity changes caused by transportation activities. The valuation of mortality was estimated by multiplying the occurrence of mortality by the value of a statistical life (VSL). The morbidity was estimated by multiplying the occurrence of the health endpoint by people's willingness to pay (WTP) which is estimated by asking people's willingness to pay to avoid different combinations of health or consumption. In another study, (Sawyer et al., 2004) applied the value of life (VOL) & wage risk (range of 3 to 5 million CAD for 2000 on estimating mortality and willingness to pay to avoid a specific morbidity outcome for 9 Canadian provinces. The results show that Quebec represents the second highest costs of all health endpoints among 9 Canadian provinces of 959 to 1630 million CAD for 2002. In the following two sections, I discuss the commonly-employed approaches to determine the monetary implications of transport emissions.

Mortality

An important step to monetize mortality is to estimate the value of life (VOL), or what is also called the value of a statistical life, in the study area. (McCubbin & Delucchi, 1999) have estimated the health costs of motor-vehicle-related air pollution considering different values of mortality, depending on the degree of prematurity as well as the timing of the death in California, with an average value of life of $ 4.0 million (1999US$). They calculated emissions cost for $PM_{2.5}$ ($10,420 - $159,190) $/tons, PM_{10} ($9,750 - $133,780) $/tons, SO_x ($6,900 - $65,520) $/tons, NO_x ($1,020 - $16,560) $/tons, and CO ($10 - $90) $/tons in 1991 USD. The Secretary of Transportation recommends the use of a VOL of $9.6 million (2016US$) which is also used by US Department of Transportation (US Department of Transportation, 2016).

In Canada, (Sawyer et al., 2007) estimate the VOL for Canadian residents in a range from $CAD 3 billion to $CAD 5 billion, with an average value of $C 4 billion in 2000. (Chestnut et al., 2011) reviewed the literature on WTP for changes in the death risk and estimated VOL that could be used in the economic evaluation of environmental issues. They concluded that the VOL for older residents (over 65 years old) at $3.9 million (in 1996 $C), with a range from $7.8 million to $2.3 million. For younger people (under 65 years old), the VOL is estimated at $5.2 million ($3.1-$10.4 million). Taking a weighted average of these estimates and assuming that 85% of air particulate-related deaths are linked to older generations, Environment Canada recommends a central, age-weighted estimate of $4.1 million, with a range from $2.4 million to $8.2 million

For Montreal, (Daher et al., 2017) estimated an average VOL of $CAD 16 million based on a contingent valuation survey conducted in Montreal. The value of life of $CAD 16 million will be utilized in this research as the benchmark value since it is estimated for the same case study (Montreal) and the same study period as for this research.

Morbidity

Morbidity has been valued into monetary values in several ways, including the "observed market" approach with a cost-of-illness (COI) study and the "constructed market" approach with a WTP study. COI studies measure medical costs and lost income associated with exposure to emissions while WTP studies measure people's actual willingness to purchase of other goods and services in return for the improved health (Pervin et al., 2008). COI studies estimate the costs based on the demand and cost functions, market prices, and residents' behavior and choices in the study area (Johnson et al., 1997). However, they do not consider the total welfare impact of an adverse health effect. Therefore, the approach of WTP studies will be employed in this study since it can estimate the appropriate measures of the social value of health based on the traditional economic theory fundamentals.

(Sawyer et al., 2007) and (Zhang et al., 2004) provided a detailed unit cost of 9 health endpoints based on several epidemiological studies conducted in Canada. (Sawyer et al., 2007) estimate all the morbidity values of health endpoints based on the WTP study while (Zhang et al., 2004) applied both COI and WTP studies to monetize morbidity values. The unit morbidity values from (Sawyer et al., 2007) will be utilized in this study and will be modified by considering additional local data (population, age distribution).

1.5. Structure of Thesis

The proposed research framework consists of four key components as follows:

1) A vehicle emission simulator, MOtor Vehicle Emission Simulator (MOVES);

2) A dispersion model, AERMOD, Environmental Protection Agency (EPA) regulatory model for near field dispersion;

3) Air Quality Benefit Assessment Tool (AQBAT) using Concentration Response Functions (CRF); and

4) Valuation of health outcomes: Value of Life (VOL) for mortality and willingness to pay (WTP) for morbidity.

Chapter 2 provides an analysis of emissions from road links in Montreal based on the county scale using MOVES software. I will discuss the vehicle emission simulator (MOVES) used in this study as well as its framework in Section 2.2.2 and followed by the discussion of the required data for running MOVES in Section 2.2.3. Starting from Section 2.3, I will examine the detailed emission estimation rates from MOVES. Emissions generated from transportation will be then translated into air pollution concentration changes for Montreal based on the relationships found in the literature, and it will be discussed in Sections 2.4 to 2.5 offering detailed information on the transformation of air concentration changes into health endpoints and finally convert health outcomes into monetary values using VOL and WTP measures. Limitations and future research will be discussed in section 2.6.

In Chapter 3, AERMOD will be used to simulate the dispersion of emissions in the atmosphere by assuming roadway links as emissions' sources for four intersections in Bucaramanga, Colombia. Section 3.5 will discuss the software, pre-processors, the required local data as well as air pollution concentration distribution from AERMOD. Section 3.6 will provide discussions regarding the air pollution concentrations estimated from AERMOD with the observed concentrations measured by equipment in order to evaluate the performance of the model. Section 3.7 will provide the correlation of predicted PM2.5 air pollution concentration with temperature and wind speed from AERMOD. Figure 1.1 provides a 'Basic Emission Valuation Framework' considering each four component of the framework.

In Chapter 4, I will summarize the findings of previous chapters, and I will discuss some of the limitations of this research and provide recommendations for future research studies in the last section. Figure 1.2 illustrates the research outline for chapters 2 and 3.

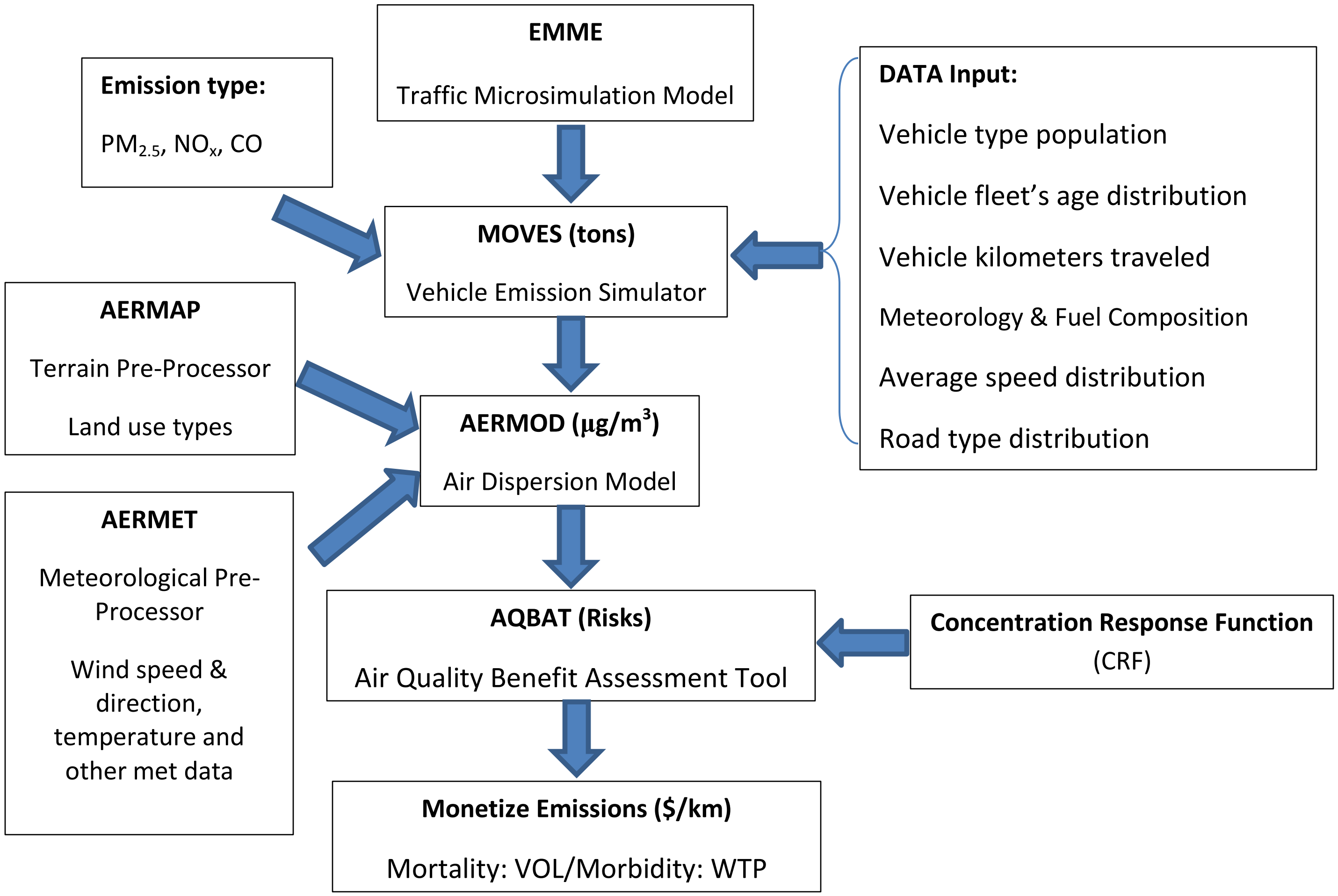


Figure 1.1 An Overview of Basic Emission Valuation Framework

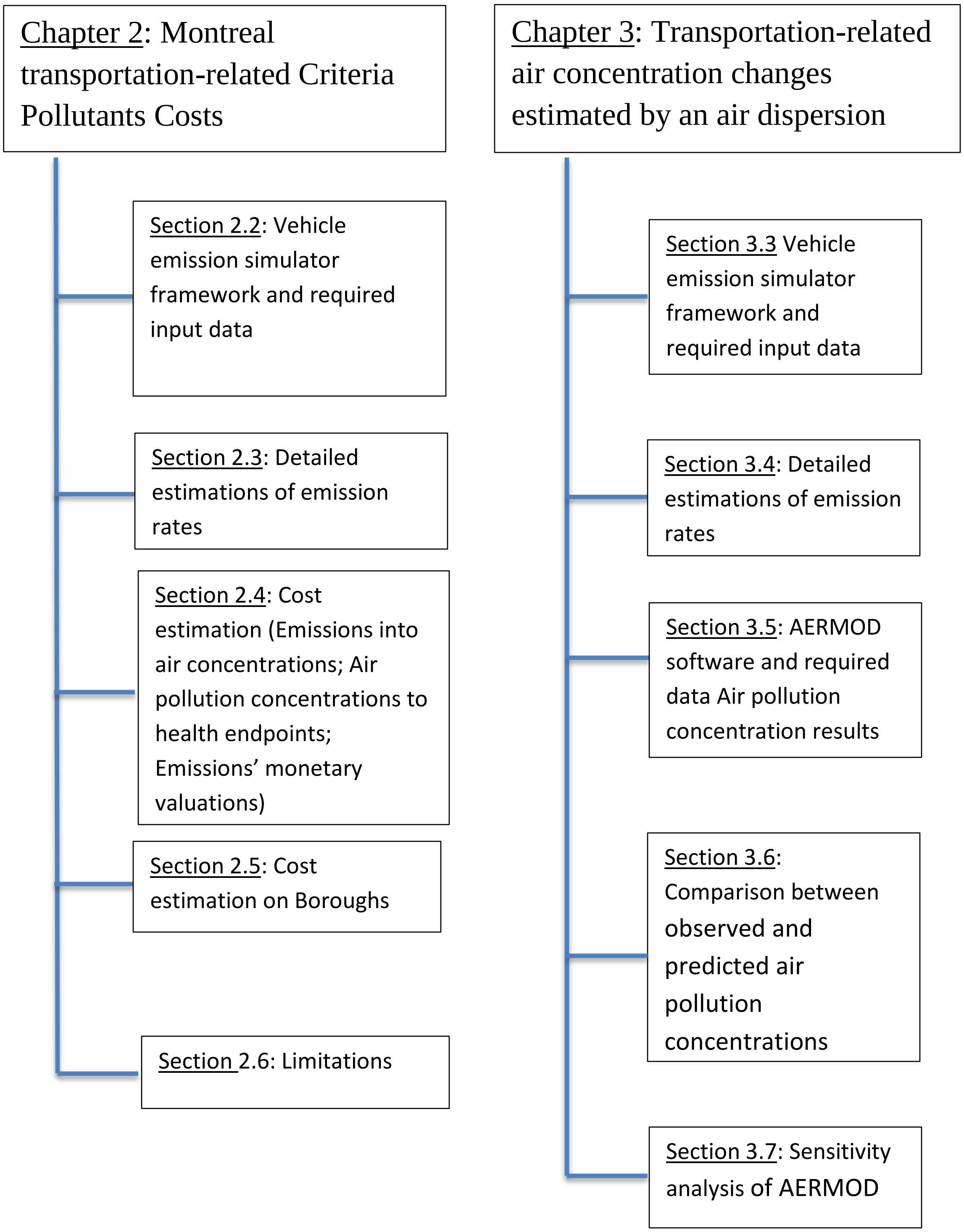


Figure 1.2 Research Outline

Chapter 2: Traffic-related Emissions and Costs Estimation

2.1. Introduction

Vehicular emissions contribute significantly to the deterioration of air quality and public health in urban areas. In order to estimate transportation-related emissions, traffic emission simulation models are used to estimate emission factors, based on attributes such as the vehicular fleet, the traffic flow volumes, the vehicle operating characteristics (e.g., the speed profile), and the meteorological data for the case study. In this chapter, I estimate and quantify variable emissions generated in the Montreal island road network based on the EPA software, MOtor Vehicle Emission Simulator (MOVES).

However, according to previous studies (Daher et al., 2018; Lorenzoni & Pidgeon, 2006), transport users do not perceive their travel-related emissions meanwhile they are interested in receiving emission information in monetary values (Daher et al., 2018). To estimate the health-related costs of emissions, I transform the emissions rates estimated from MOVES into air pollution concentrations, then convert the concentrations into health outcomes, and finally valuate these health outcomes in monetary terms. The monetary valuation is based on a value of life estimate from the survey conducted in Montreal (Daher et al., 2018) for mortality, and based on a willing-to-pay value, borrowed from the lecture review (Sawyer & Stiebert, 2007) and adjusted for Montreal, to avoid health problems for morbidity.

This chapter is divided into two parts that estimate emissions rates and valuate emissions costs in monetary values. In the first part, I apply the MOVES software to estimate emissions in Montreal explaining all necessary models, data and assumptions required to quantify the emission rates. In addition, I discuss the correlation between emissions rates and average speeds. Next, I transform the estimated emission rates in Montreal into monetary units to determine emissions costs and its geographical distribution along 41 Montreal boroughs.

2.2. Emission Estimation

Although the production, distribution, and combustion of gasoline and diesel introduce a variety of harmful chemicals into the air, land and water (Wang, et al., 2008; Mccubbin & Delucchi, 2003), my analysis is limited to $PM_{2.5}$, CO and NO_x emissions. The MOVES software used to calculate emissions, the collected data, and the analysis results are discussed later in this section.

2.2.1. Study Area

My estimation is based on a representation of the Montreal island road network consisting of more than 40,000 links focusing on the main highways and arterials. Figure 2.1 represents the road network considered in this study on the base map of the 41 Montreal boroughs.

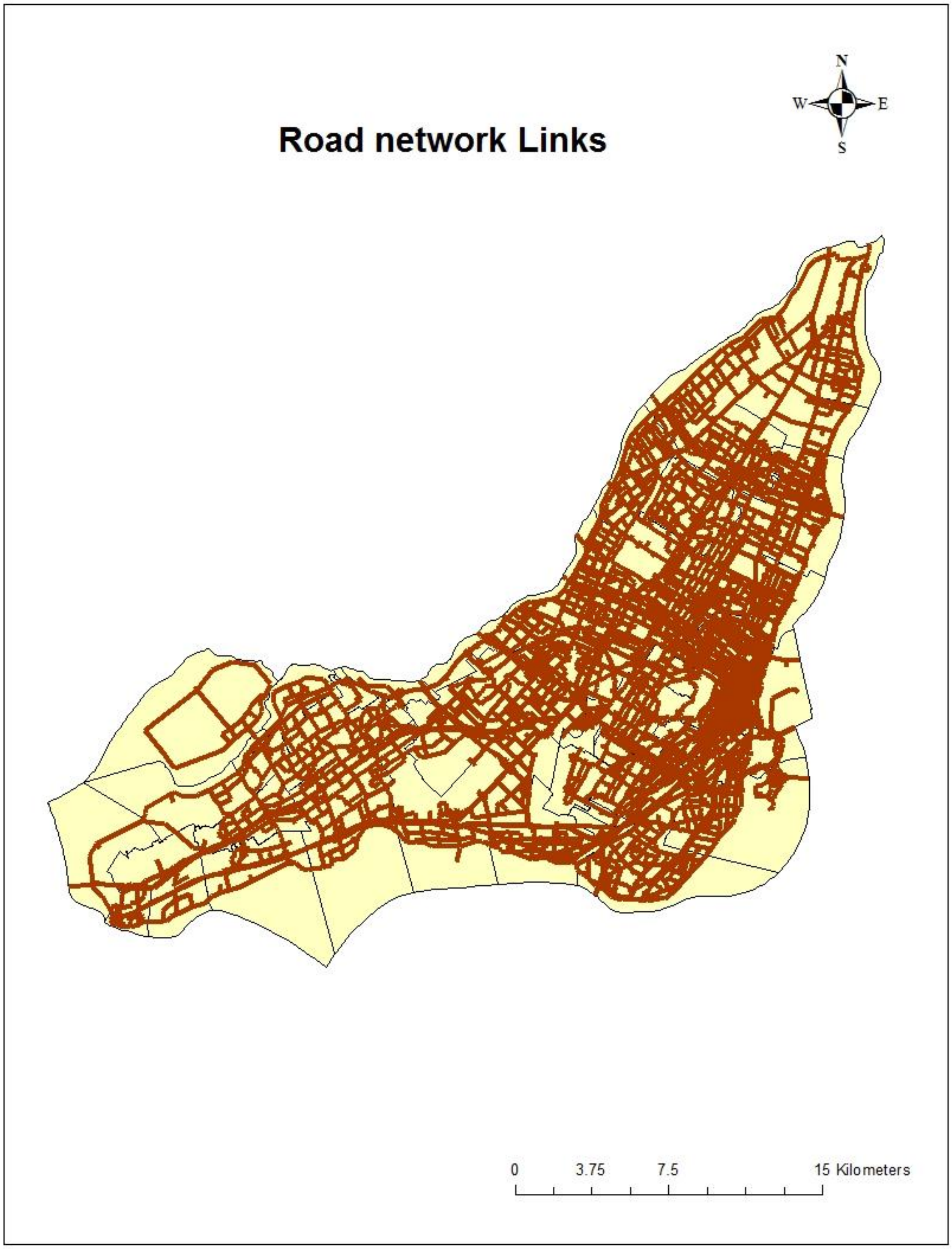


Figure 2.1 Montreal Road Network's Representation

2.2.2. MOVES County Scale

I use the MOVES software to calculate the vehicle emissions rates for Montreal. MOVES is a Java-based software that estimates vehicle emissions on three different analysis scales: national, county and project (Geroliminis & Skabardonis, 2006; Koupal et al., 2018). For the first part of this chapter, regarding the city of Montreal case study, I use the county scale to simulate emissions rates. Since the MOVES software is calibrated for US regions, I use the MTQ's assumptions to choose the Hennepin County that have the most similar geometry to Montreal. The MOVES estimates emissions rates mainly based on average speed bins (ranges) and assign an emission rate to every bin considering “Source” binning, “Age Group” binning and “Operating Mode” binning (Papson, et al., 2012). “Source” binning includes the travel activity in terms of vehicle-kilometer traveled (VKT) according to different vehicle types and fuel types. “Age Group” binning represents the vehicle’s age and model year. “Operating Mode” binning indicates the speed of each vehicle type considering different road types. The total emissions are calculated by multiplying the adjusted emission rates (e.g., grams/Vehicle-km) by the appropriate activity levels (VKT), where the adjustments are based on temperature, humidity, and fuel information.

An adapter is then used to transfer simulated volumes, speeds, and road types from the MTQ’s model based on O-D survey from 2008. First, the meteorology, fuel type(s), vehicle configuration and emissions’ types required as inputs for MOVES are prepared and inputted into the adapter. Next, road links and centroids from the Montreal road network (the EMME model) are added into the adapter. Finally, the inputs required for the MOVES are exported to a database management system (MySQL) to generate the "Runspec" document and run MOVES. Finally, MOVES results are stored in MySQL for further analysis. Figure 2.2 illustrates the procedure.

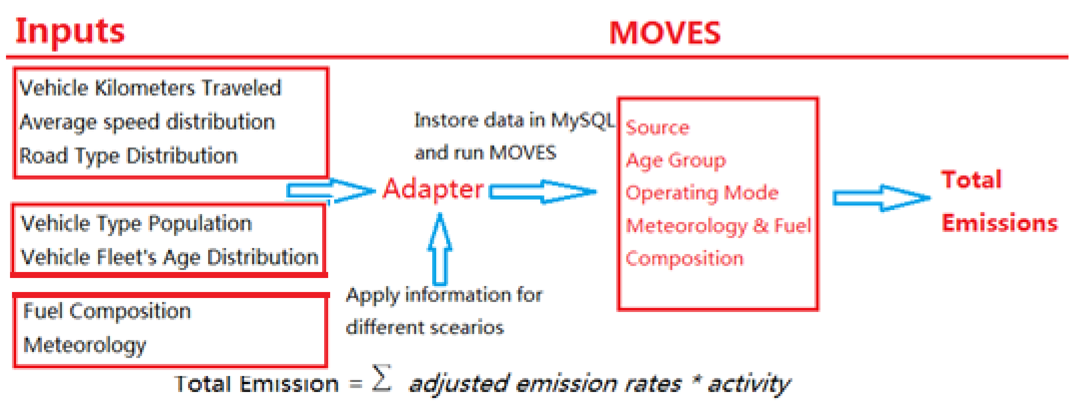


Figure 2.2 The Framework of MOVES and Adapter Methodology

2.2.3. Data Collection

The data required to run MOVES can be categorized into seven inputs: the vehicle type population, vehicle fleet's age distribution, vehicle kilometers traveled (VKT), average speed distribution, road type distribution, meteorology and fuel composition (Papson et al., 2012). The traffic volumes and average speeds on all links of the Montreal road network are available from MTQ's Montreal model (MOTREM08) and other required data are provided by SAAQ (the vehicle type population, vehicle fleet's age distribution data) and Environment Canada (meteorological data). Table 2.1 represents the data required for running the MOVES.

Table 2.1 Data Sources for MOVES's Inputs

Data Input	Description	Source
Vehicle type population	Number of vehicles by category operating in Montréal	SAAQ; Provided by MTQ
Vehicle fleet's age distribution	Age distribution of vehicles based on model year or age	SAAQ; Provided by MTQ
Vehicle kilometers traveled	Total kilometers traveled by each vehicle type/category	MTQ's Montreal Model (MOTREM08)
Average speed distribution	Average speed of each vehicle type on different road types during a period of time	MTQ's Montreal Model (MOTREM08)
Road type distribution	VMT distribution according to different road types	Quebec's Ministry of Transport (MTQ)
Meteorology	Average hourly temperature and the humidity	Environment Canada; Provided by MTQ
Fuel	Fuel type information	Environment Canada

2.3. Results and Discussion

2.3.1. Montreal Road Network

After inputting the vehicular information (from EMME), meteorology, and fuel data for various scenarios into the adapter, several MOVES simulations were conducted to obtain the emissions rates (g/vehicle-km) of the $PM_{2.5}$, CO, and NO_x on all Montreal road network's links. The emissions rates will then be analyzed during AM peak hours (6 AM to 9 AM) and off-peak hours (midnight to 4 AM), for two different weather conditions (January and October). Figures 2.3 to 2.5 illustrate the estimated $PM_{2.5}$, CO and NO_x emissions rates across the Montreal network for AM peak hours in October. Compare among these three emissions types, NO_x has the highest emission rate (up to 17.29 g/km), followed by CO (up to 4.58 g/km) and $PM_{2.5}$ (up to 0.91 g/km). In addition, the

Downtown and Plateau areas seem to have the highest air pollution rates for all emission types.

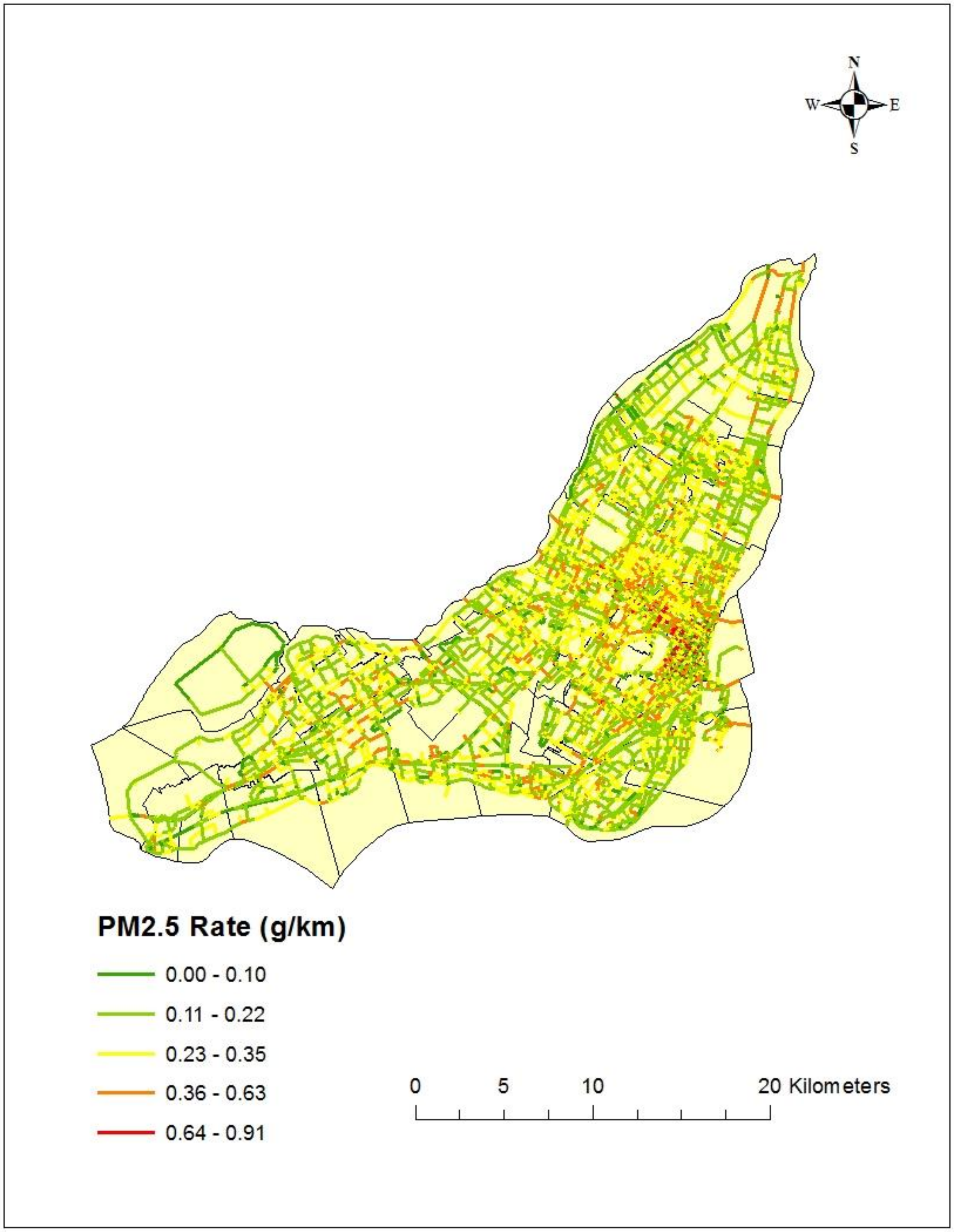


Figure 2.3 $PM_{2.5}$ Emissions Rates across the Montreal Road Network

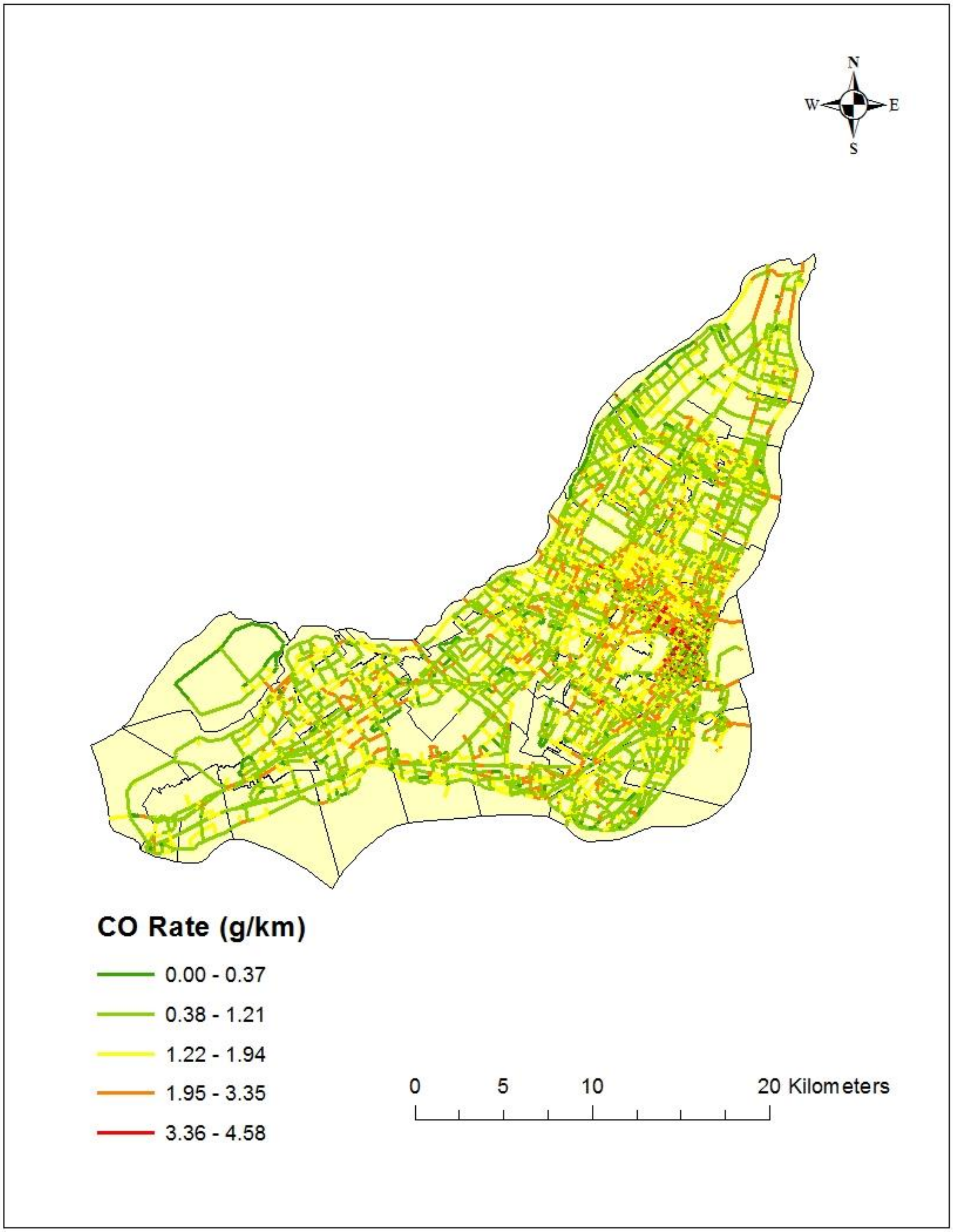


Figure 2.4 CO Emissions Rates across the Montreal Road Network

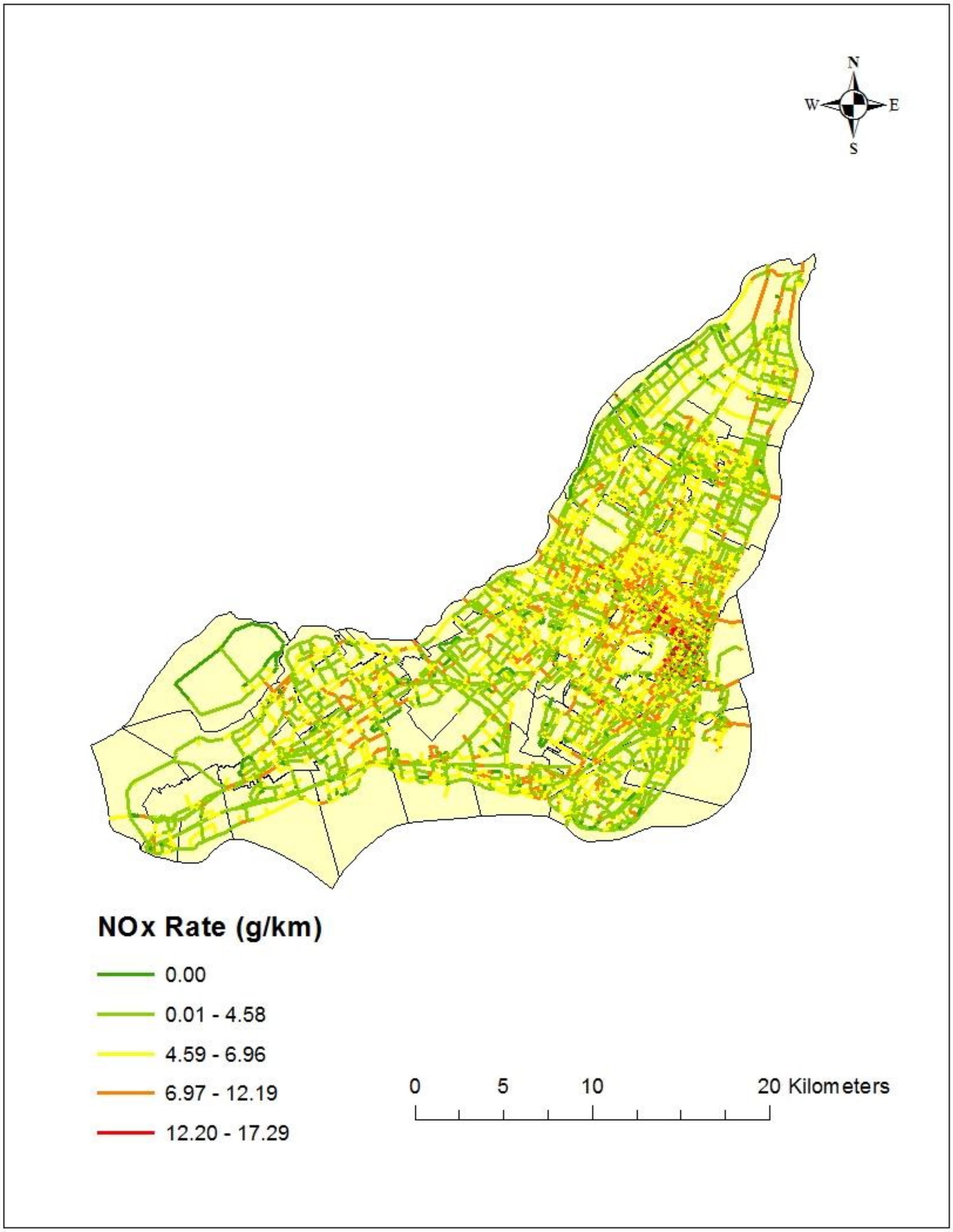


Figure 2.5 NO_x Emissions Rates across the Montreal Road Network

2.3.2. Emissions vs Speed on Links

Because the vehicle speed is the significant factor determining emissions rates (Kean et al., 2005), first, I plot the link emissions rates against the link speeds in Figures 2.6 to 2.8 to study their correlations. The rates are the average emissions rates on links based on the traffic mix (vehicle types) on each link. The speed levels are the average speed of all vehicles on each link, assuming all vehicles travel at the same speed.

Comparing the emissions rates with speed levels, I find a strong correlation during both peak and off-peak hours, as shown in Figures 2.6 to 2.8. We can observe that $PM_{2.5}$, CO, and NOx emissions rates decrease with speed until the speed reaches 100km/h, where emissions rates increase slightly with higher speed. In addition, comparing peak and off-peak emissions rates, I find that the average off-peak hours $PM_{2.5}$ and NO_x emissions rates (0.045 g/vehicle-km for $PM_{2.5}$, 0.950 g/vehicle-km for NOx) are around 3 times greater than those of peak hours (0.0186 g/vehicle-km for $PM_{2.5}$ and 0.398 g/vehicle-km for NO_x). This can be explained by the vehicle mixture in each time period since trucks represent a relatively higher percentage in the mixture during off-peak hours. However, for the CO emission, the average rate for peak hours is higher than the off-peak hours rate (1.63 g/vehicle-km for peak hours and 1.35 g/vehicle-km for off-peak hours) it might because of diesel fuel combustion engines produce lower levels of carbon monoxide than gasoline engines as heavy trucks (diesel fuel combustion) represent 8% of the vehicle mix during off-peak hours as opposed to 3% during peak hours. Therefore, higher passenger car mixture (gasoline engines) during peak hours results to a higher CO emission rate during peak hours (Geneva: World Health Organization, 2015).

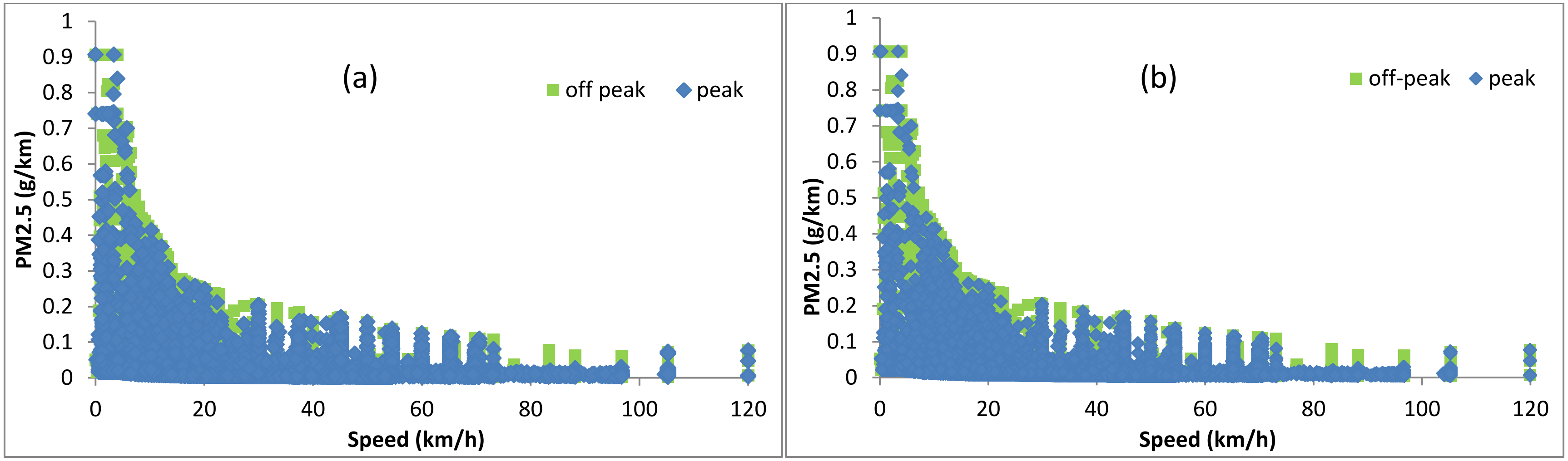


Figure 2.6 $PM_{2.5}$ Emission Rates for: (a) October; (b) January

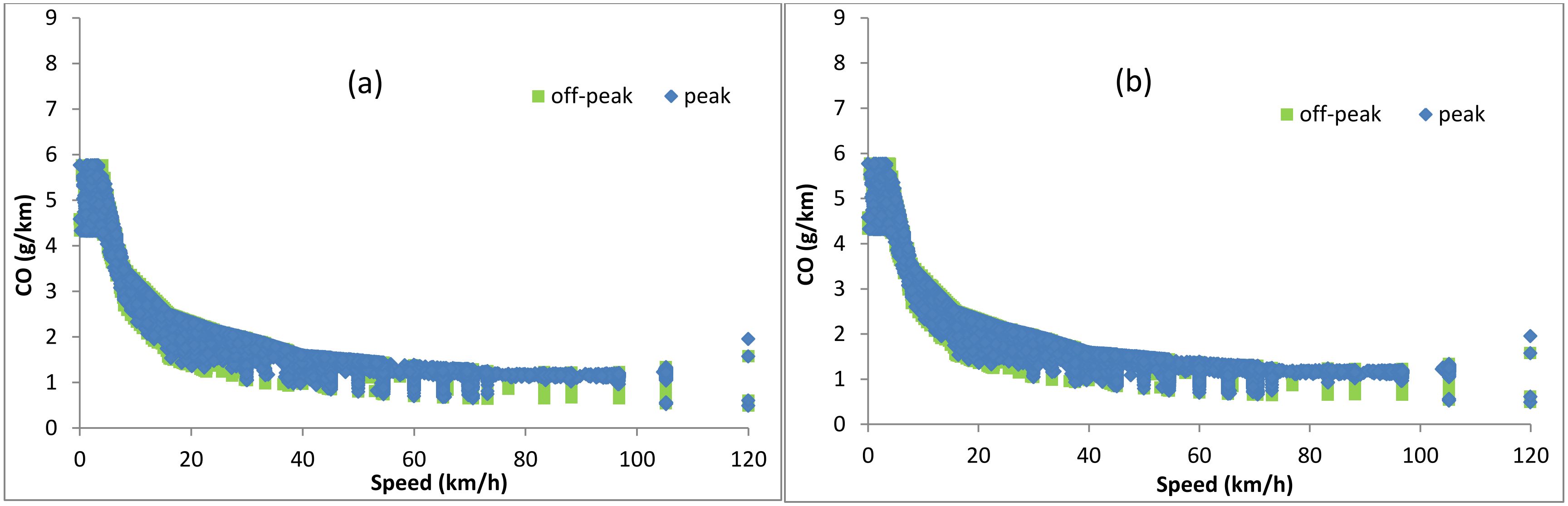
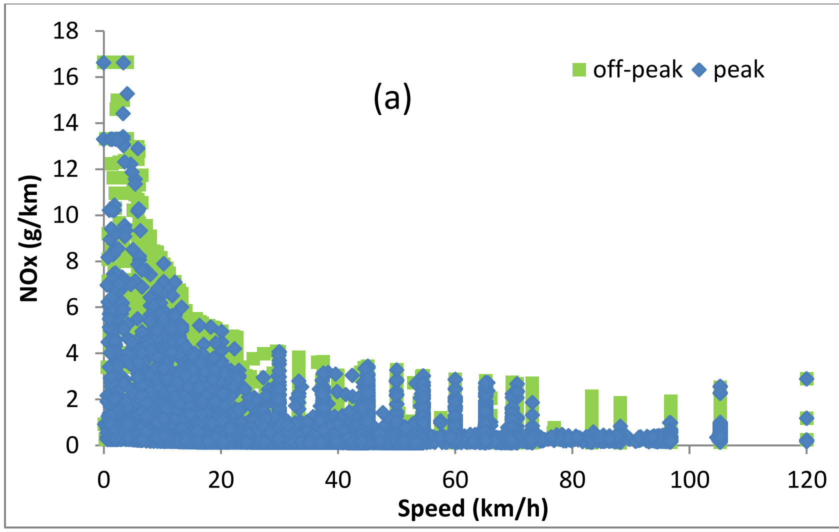


Figure 2.7 CO Emissions Rates for: (a) October; (b) January



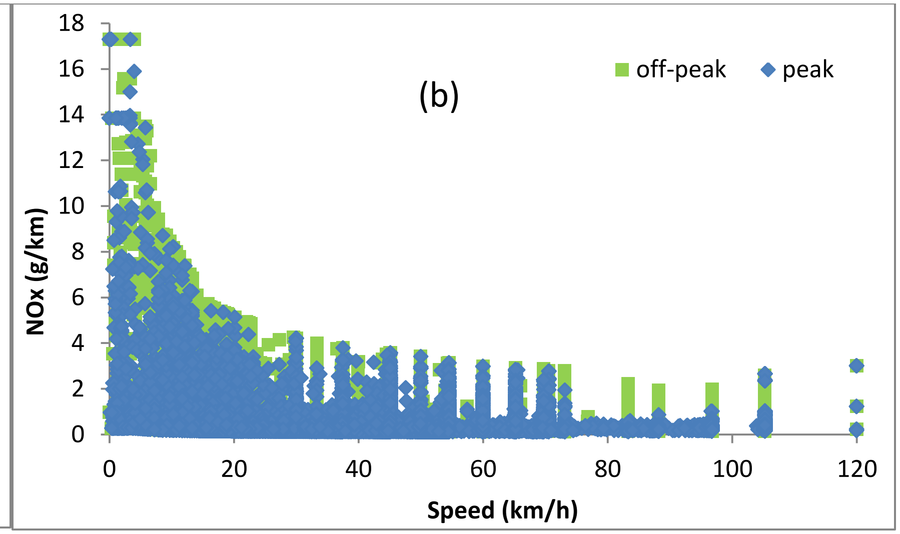


Figure 2.8 NO_x Emissions Rates for: (a) October; (b) January

As weather could act as another essential factor to impact emissions rates (Frey et al., 2003), I compare the emissions rates of January (a) and October (b) in Figures 2.6 to 2.8. The emissions rates in January are expected to be higher than those of October (Marshall & Eccleston, 1980) for several reasons. First, users drive relatively slower on icy roads and in snowy weather, which results to relatively higher emissions rates. Second, many research studies indicate that the cold-start in winter in low ambient temperatures generates a higher level of emissions (Weilenmann et al., 2005). Finally, the use of heaters increases emissions, especially when the average ambient temperature is less than -10 °C (Zhao et al., 2009). However, my results show that $PM_{2.5}$, CO, and NO_x emissions rates are very similar in January and October. This is partly due to the simulation for both months use the exact same traffic demand data. All other data regarding the fleet, age of vehicles, average speeds, volumes on the road, etc. are the same between the two simulations. During peak hours, the average CO emissions rate is 1.49 g/vehicle-km in both January and October, and the average NO_x emissions rate is 0.70 g/vehicle-km for both months. Only for $PM_{2.5}$, the average emission rate is 0.0316 g/vehicle-km in October while the rate is relatively higher, 0.0323 g/vehicle-km, in January. The slight change in the $PM_{2.5}$ emission rate is mainly due to emissions generated by passenger cars as the average emission rate for passenger cars is 0.008 g/vehicle-km in October and slightly higher, 0.01 g/vehicle-km, in January. Table 2.2 represents the peak hours emissions rates comparison for January and October.

Table 2.2 Emissions rates for October and January during peak hours

Emission Type	January	October
CO	1.49 g/vehicle-km	1.49 g/vehicle-km
NOx	0.70 g/vehicle-km	0.70 g/vehicle-km
$PM_{2.5}$	0.0323 g/vehicle-km	0.0316 g/vehicle-km

2.4. Cost Estimation

2.4.1. Methodology

Using the emissions rates calculated from MOVES as discussed in Section 2.2, in this section, I estimate the 2015 monetary value of vehicle-related criteria pollutants for Montreal using 3 modeling steps:

1. Change Emissions (in tons) to air pollution concentrations (in $\mu g/m^3$);
2. Calculate the health outcomes/risks (mortality, morbidity, etc.) associated with those concentrations; and
3. Estimate the health costs in welfare money using value-of-life and willingness-to-pay measures.

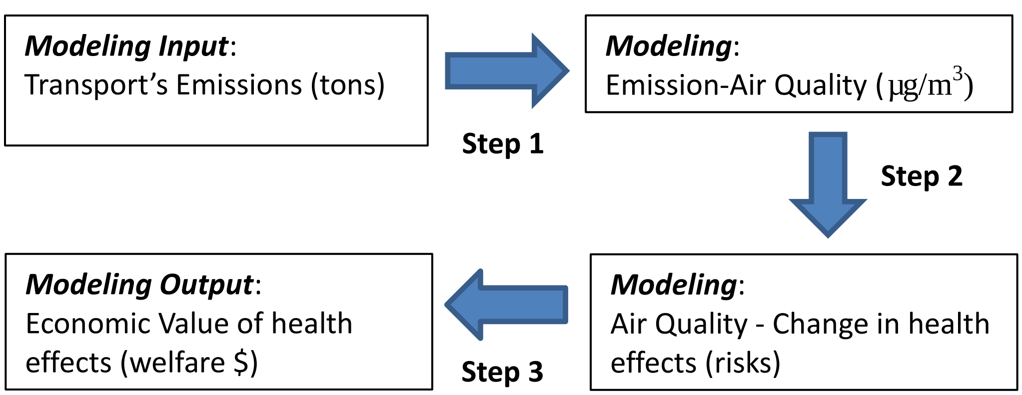


Figure 2.9 Cost Estimation Modeling Procedure

Figure 2.9 illustrates the key steps taken in estimating emission costs. The emissions derived from the MOVES model were used as the inputs. I calculate each one-day emission for a specific emission type summing up the link-based emissions rates multiplied by its traffic volume for October 2015 in order to provide the total annual emissions.

For the first step in Figure 2.9, I estimate the incremental (change in) air pollution concentration associated with transportation-related emissions based on the relationships between emissions levels and the air pollution concentrations related to transportation in 2000. For the Montreal case study, I calculate the concentration change in 2015 by multiplying the 2000 ratio of the average air pollution concentration (in μg/m^3) to the total annual emissions (in tons), for each specific emission type, which is the input of the three-step model. For each emission type, the relationship is explained in Equation 1:

$$Concentration\left(Year\ 2015, \frac{\mu g}{m^3}\right) = \frac{Concentration\left(Year\ 2000, \frac{\mu g}{m^3}\right)}{Total\ emissions\ (Year\ 2000, tons)} * Emissions\ (Year\ 2015, tons) \qquad (1)$$

As shown in Table 2.2, I obtain the above 2000-year ratio of air pollution concentration over emissions from the (Sawyer & Stiebert, 2007) study to transform 2015 emissions in tons to air pollution concentrations (μg/m^3).

Table 2.3 Relationships between Air Pollution Concentration and Emissions Levels

	Ratio-Transportation (%)
Emission types	**Quebec, 2000**
$PM_{2.5}$	1.1
NO_x	31
CO	18

For the second step, knowing the change in the air pollution concentration from the previous step, I transform the ambient air pollution concentration changes into health outcomes using Health Canada's Air Quality Benefits Assessment Tool (AQBAT) (Government of Canada, 2017). AQBAT prescribes Concentration-Response Functions (CRF) that determines the number (risk) of health endpoints' occurrences in the population size of the area as a result of changes in the ambient air quality in a specific year to Table 2.3 specifies CRFs for a variety of emission types on health endpoints/outcomes.

For instance, cardiac emergency rooms visit is one of the health problems caused by $PM_{2.5}$ pollution. In order to link $PM_{2.5}$ concentration to health outcomes, daily average concentrations of $PM_{2.5}$ were obtained from monitoring stations within the study area (Burnett et al., 2004). Hospital discharge records were obtained from the Ontario Ministry of Health for residents of the study area and hospitals located in the study area. Generalized additive models (Hastie & Tibshirani, 1990) were used to determine daily variations in $PM_{2.5}$ concentration and its relationship to daily fluctuations in hospital admissions with Poisson variation to link a series of hospital admission counts to air pollution. From this, several characteristics (for example, the mean) can be provided to estimate cardiac emergency rooms visit counts from $PM_{2.5}$ concentration.

Table 2.4 Concentration Response Functions (CRF's) in AQBAT

Health Endpoint	Pollutant	Distribution Type	Mean Value
Acute exposure Mortality	NO_x	Poisson	2.49E-04
Chronic exposure mortality	$PM_{2.5}$	Poisson	1.50E-03
Acute respiratory symptom days	$PM_{2.5}$	Linear	1.39E-03
Adult chronic Bronchitis Cases	$PM_{2.5}$	Poisson	6.80E-03
Asthma Symptom Days	$PM_{2.5}$	Linear	5.13E-04
Cardiac Emergency Rooms Visits	$PM_{2.5}$	Linear	1.70E-04
Child Acute Bronchitis Episodes	$PM_{2.5}$	Poisson	1.68E-02
Respiratory Emergency Room Visits	$PM_{2.5}$	Linear	1.32E-04
Restricted Activity Days	$PM_{2.5}$	Poisson	1.01E-03
Cardiac hospital admission	CO	Linear	2.76E-04

The last step for the health-related emissions-cost estimation is to monetarize the welfare economic value of health outcomes estimated from the previous step. I find the welfare costs associated with urban travel emissions using two figures: (i) value of life for mortality and (ii) willingness to pay for morbidity. Table 2.4 shows the average value of life for mortality costs, estimated from a survey conducted in Montreal (Daher et al., 2018). The estimated value of life for Montreal residents was $16 million, on average. I borrow the monetary cost of morbidity according to people's willingness to accept/pay for the risk of illness based on a study in Canada -2000 (Sawyer & Stiebert, 2007) and adjusted it for Montreal-2015 by multiplying the 2000's value with an inflation rate of 1.44 (Bank of Canada, 2019).

Table 2.5 Welfare Measures to Determine Mortality and Morbidity Social Costs

health endpoint		Emission Types	Monetary Value (2015 Canadian Dollar)		
			Low	Median	High
Acute exposure Mortality	VOL	NOx	/	16000000	/
Chronic exposure mortality	VOL	$PM_{2.5}$	/	16000000	/
Acute respiratory symptom days	WLP	$PM_{2.5}$	19.6	19.6	19.6
Adult chronic Bronchitis Cases	WLP	$PM_{2.5}$	245000	372400	651000
Asthma Symptom Days	WLP	$PM_{2.5}$	9.8	39.2	168
Cardiac Emergency Rooms Visits	WLP	$PM_{2.5}$	6160	6160	6160
Child Acute Bronchitis Episodes	WLP	$PM_{2.5}$	210	434	644
Respiratory Emergency Room Visits	WLP	$PM_{2.5}$	2800	2800	2800
Restricted Activity Days	WLP	$PM_{2.5}$	67.2	67.2	67.2
Cardiac hospital admission	WLP	CO	4570	9140	13711

Finally, I estimate the social (welfare) cost for each pollutant type. Equation 2 represents the welfare value of changes in health outcomes for a pollutant, multiplying the changes in the ambient air quality (concentration) by the associated response function (CRF), the case study population, and the unit cost of that pollutant type.

$$\Delta VH_{p,r} = \underset{\substack{\uparrow \\ \text{Step 1}}}{\Delta A_{p,r}} * \underset{\substack{\uparrow \\ \text{Step 2}}}{CRF_{p,h}} * P_r * \underset{\substack{\uparrow \\ \text{Step 3}}}{V_{p,h}} \qquad (2)$$

Where $\mathbf{\Delta VH_{p,r}}$ is the welfare value of a health outcome changes for each pollutant p living in that region r; $\mathbf{\Delta A_{p,r}}$ is the change in ambient air quality resulting from pollutant p in region r; $\mathbf{CRF_{p,h}}$ is the concentration response function for pollutant p and health or environmental outcome h; $\mathbf{P_r}$ is the population in region r and $\mathbf{V_{p,h}}$ is the welfare unit cost of pollutant p of environmental endpoint h for pollutant p.

2.4.2. Results and Discussion

Based on the three steps discussed in Section 2.3.1, I calculate the emissions costs in Montreal for 2015. Note that for the first case study (Montreal), I simply consider constant ratios to transform emissions to air pollution concentrations. As inputs for the three-steps-modelling procedure, I use the emissions rates for $PM_{2.5,}$ NOx, and CO as shown in Table 2.5 comparing total emissions for Quebec, 2000 and Montreal, 2015.

Table 2.6 Emission Rates for Quebec and Montreal

Emission Types	Quebec, 2000 in tons		Montreal,2015 in tons	
	Total emissions	Transportation emissions	Total emissions	Transportation emissions
$PM_{2.5}$	171000	4300	210599	2249
NO_x	459000	168000	223547	68560
CO	4559460	546782	1519820	273391

I use the air concentration ratios (tons to $\mu g/m^3$) and apply the estimated concentrations into the AQBAT model to estimate resulting health outcomes. The calculated air pollution concentration changes due to transportation-related emissions are provided in Table 2.6 for the corresponding health endpoints to be used in Step two.

Table 2.7 Air Concentration Changes for Health Outcomes

Health Endpoint	Emission Types	Unit	Concentration
Acute Exposure Mortality	NO_X	$\mu g/m^3$	9.61
For All Outcomes	$PM_{2.5}$	$\mu g/m^3$	7.16
Cardiac Hospital Admissions	CO	ppm	0.26

Based on the 2017 Environmental Assessment Report (Environmental Assessment Report, 2017), the measured $PM_{2.5}$ air pollution concentration is 8.6μg/m^3 on average, while I estimate $PM_{2.5}$ air pollution concentration at 7.2μg/m^3 in 2016. For NOx, the measured concentration is 18.8μg/m^3 and my estimate is 9.61μg/m^3 in 2016. The difference results from the fact that I estimate the air pollution concentration based on transportation emissions only, not all emissions since my focus is to estimate the health impacts/costs of transportation activities.

Then, I estimate the number of occurrences (risks) of each health outcome based on the mean value of concentration-response function (Table 2.3) Table 2.7 shows the resulting outcome for each health problem type.

Table 2.8 Number of Health Outcomes

Health Endpoint	Emission Types	Count
Acute Exposure Mortality	NO_X	36
Chronic Exposure Mortality	$PM_{2.5}$	24
Acute Respiratory Symptom Days	$PM_{2.5}$	68635
Adult Chronic Bronchitis Cases	$PM_{2.5}$	35
Asthma Symptom Days	$PM_{2.5}$	19183
Cardiac Emergency Rooms Visits	$PM_{2.5}$	3
Child Acute Bronchitis Episodes	$PM_{2.5}$	702
Respiratory Emergency Room Visits	$PM_{2.5}$	10
Restricted Activity Days	$PM_{2.5}$	36845
Cardiac Hospital Admissions	$PM_{2.5}$	150

Finally, the monetary value is estimated based on the mortality and morbidity unit costs borrowed from literature review and listed in Table 2.4. Table 2.8 reports the final estimated welfare monetary values/costs associated with each ton of emissions. Considering the distributions, I provide low, median and high estimated values of the three most impactful emission types in the table.

Table 2.9 Monetary Welfare Costs of Emissions

Health Endpoint	Cost (1000'$/ton)[1]								
	NOx			$PM_{2.5}$			CO		
	L	M	H	L	M	H	L	M	H
Acute exposure Mortality	9	60	111	/	/	/	/	/	/
Chronic exposure mortality	/	/	/	51	359	668	/	/	/
Acute respiratory symptom days	/	/	/	1	1	1	/	/	/
Adult chronic Bronchitis Cases	/	/	/	8	9	15	/	/	/
Asthma Symptom Days	/	/	/	0.1	0.5	2.2	/	/	/
Cardiac Emergency Rooms Visits	/	/	/	0.002	0.009	0.015	/	/	/
Child Acute Bronchitis Episodes	/	/	/	0.1	0.2	0.3	/	/	/
Minor Restricted Activity Days	/	/	/	/	/	/	/	/	/
Respiratory Emergency Room Visits	/	/	/	0.01	0.02	0.03	/	/	/
Restricted Activity Days	/	/	/	2	2	2	/	/	/
Cardiac hospital admission	/	/	/	/	/	/	0.003	0.021	0.054
Total	9	60	111	59	371	688	0.003	0.021	0.054

[1] L represents the lower bound while M represents mean and H represents higher bound of the monetary value of emissions.

In Table, 2.9, I summarize the total unit social welfare cost associated with CO, $PM_{2.5}$, and NO_x ($/ton) based on above all health costs.

Table 2.10 Final Calculated Unit Costs

Cost Parameters	Estimates		
	High	**Base (mean)**	Low
CO unit cost [1] ($/ton)	54	**21**	3
$PM_{2.5}$unit cost [1] ($/ton)	688,000	**371,000**	59,000
NO_x unit cost [1] ($/ton)	111,000	**60,000**	9,000

2.5. Emissions cost Distribution on Borough

I examine the emissions cost geographical distributions in the Montreal area. I calculate the total health-related emissions cost for each borough based on the three-step modelling procedure discussed in Section 2.3 by sum up the costs for $PM_{2.5}$, CO, NO_x. I included the emissions costs into GIS software to illustrate $PM_{2.5}$, CO, NO_x, total health-related emission and CO_2 emission costs in each borough for different periods of the day and under two weather conditions.

Figure 2.10 provides the distribution of emission cost in January during peak hours for $PM_{2.5}$, $NO_{x,}$ and CO for all vehicle types. Compare among three health-related emissions costs, NO_x has the highest emission cost (up to 0.38 $/km), followed by PM2.5 (0.31 $/km) and CO (0.0074 $/km) during peak hours. In addition, downtown and Plateau areas have the highest emissions cost for all these emission types. The emissions costs (0.3$/km) in these areas are almost 40 times the costs of driving in the east-western boroughs of Montreal (0.0074$/km).

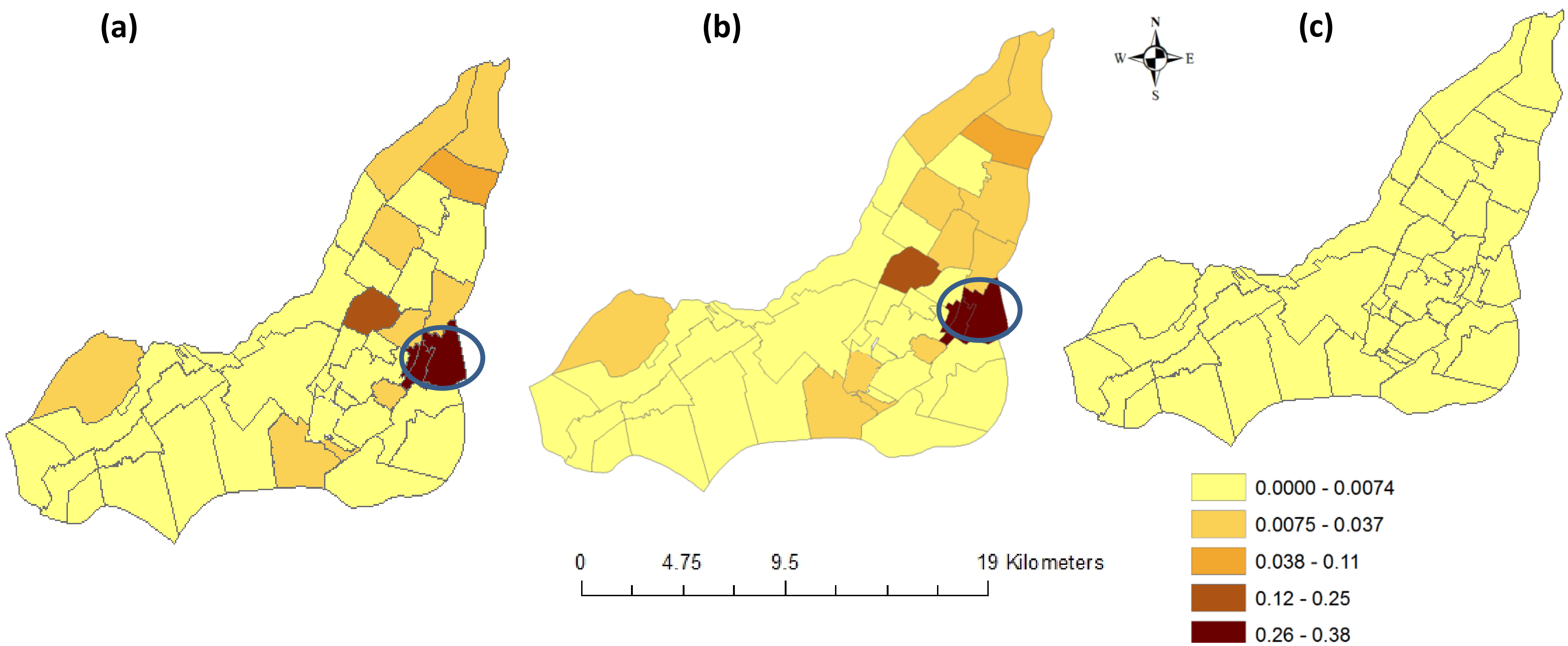


Figure 2.10 Emissions Costs ($/km) in January for (a) $PM_{2.5}$; (b) NO_x; (c) CO

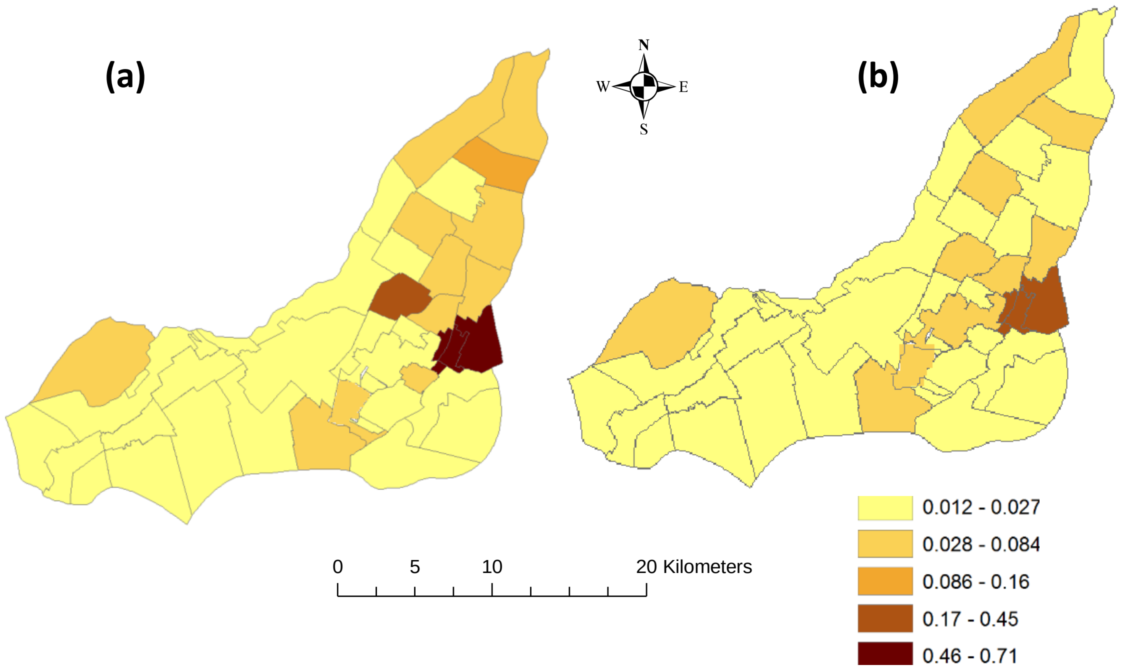


Figure 2.11 Emissions Cost ($/km) during Peak Hours of (a) Total health-related emission cost; (b) CO_2 emission cost

Figure 2.11 compares the geographical distribution of peak-hours total health-related emission cost ($PM_{2.5}$, NO_x and CO) with climate change costs (CO_{2eq}) in January 2017 in Montreal. CO_{2eq} emission cost is calculated by multiplying emissions rate with social cost of carbon of ($41/ton), according to Environment and Climate Change Canada. The health-related emission cost (up to 0.71 $/km) is relatively higher than CO_{2eq} emission cost (up to 0.45 $/km). However, my results show that the overemphasis on climate change implications of transportation seems to be misleading, especially because I excluded many other vehicular air pollution types (CO, VOC, etc.) from my analysis, and those would widen the gap.

2.6. Limitations

The estimated emissions rate from the MOVES software for both January and October are based on a fixed travel demand which cannot represent the variations in emissions completely. Therefore, the next research study should consider the variations in demand (summer months are generally more congested in Montreal). In addition, my estimations are based on an average person, an average value of travel time, and an average passenger car feature. All these numbers would be different using personalized characteristics/features (e.g., the car model). In addition, MOVES is developed and calibrated for the US counties and does not represent the vehicle fleet in Montreal. MOVES's limitations could be investigated by comparing the emissions from MOVES with the emissions measured from real on-road driving. However, generally, MOVES's results should be lower than older-age vehicles' emissions and higher than those of fuel efficient vehicles in Montreal.

For the air-pollution-concentration estimations, my assumption regarding constant ratios is simple but effective in calculating the changes in concentrations in Montreal. However, the concentration changes could vary not only due to emissions generated in that area but also due to a variety of other factors such as land use configurations, wind speed, humidity, etc. Therefore, a more detailed analysis is required to determine a more precise geographical distribution of the air pollution concentration change. This is one of my study's limitations that I will address in the next chapter for the Colombia case study using software.

In order to determine the welfare costs associated with travel-related emissions, I used the AQBAT concentration-response functions for the year 2000, which might require updates/adjustments to determine the health endpoints in 2015 precisely. Therefore, a more up-to-date air-quality-benefit-assessment tool could provide more reliable estimates. In addition, some of the unit cost values are adopted from national (Canada) or Provincial (Quebec)-based studies, therefore, using these values could lead to emissions costs that are lower than real values/impacts.

Chapter 3: Air Pollution Dispersion Modelling: the Case Study of four Intersections in Bucaramanga, Colombia

3.1. Introduction

As previously mentioned in Chapter 2, I transform emissions into the air pollution concentration based on the ratio approach (the constant ratio of concentration over emission I tons). However, the results from Chapter 2 cannot provide correct results since the concentration varies with conditions. Therefore, a dispersion model is required to simulate the movements of air pollutants. Since 2005, the EPA has adopted the AMS/EPA Regulatory Model (AERMOD) as the regulatory model for estimating air pollutant concentrations, emitted from sources such as industrial plants and vehicular traffic (Environmental Protection Agency, 2012).

In this chapter, using the MOtor Vehicle Estimation Simulator (MOVES), I apply a dispersion model (AERMOD) to estimate the dispersion of traffic-related air pollution concentrations on four intersections in Bucaramanga, Colombia. The road-level hourly mobile sources are obtained from the MOVES project-scale module based on a vehicle data collection. The air pollution concentrations are estimated by the AERMOD based on the emissions from vehicles in grams from the MOVES. Finally, the air pollution concentration outputs are compared with the observed air pollution concentration based on the emission-concentration-measurement devices installed on the buildings' roofs in the four neighborhoods.

3.2. Study Area

I estimate traffic-related emissions and air pollution concentrations are conducted in four neighborhoods (La Concordia, La Joya, La Provenza and La AltoViento) in the city of Bucaramanga, Colombia. Figure 3.1 shows the neighborhoods in ArcGIS. The city is the second most populated city in Colombia with a population size of 521,857 in the year 2017 (World population review, 2019) and suffers from heavy traffic congestion and highly-polluting motor vehicle problems typical to developing countries.

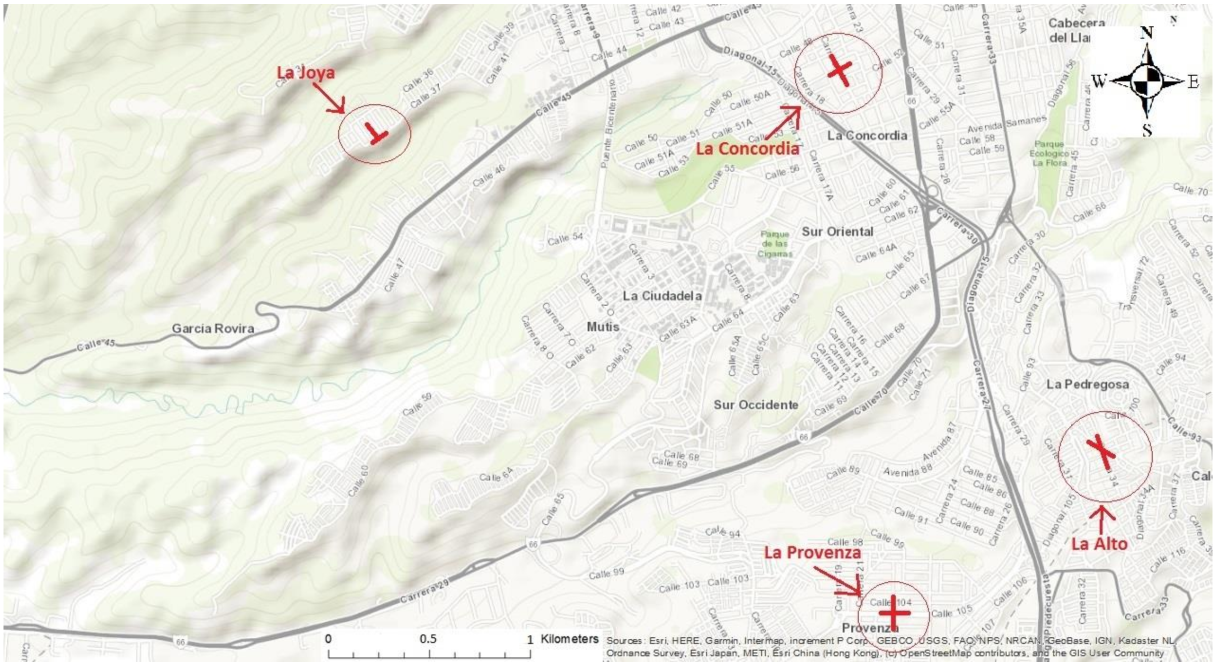


Figure 3.1 Locations of Four Studied Neighborhoods (Gómez et al., 2015)

Figure 3.2 demonstrates all associated link configurations. Figure 3.2 (a) represents the first intersection; the Calle 51 Street and Carrera 21 Street intersection located at the La Concordia neighborhood. On this intersection, the Calle 51 Street is a two-way one-lane road (excluding one parking lane) and the Carrera 21 Street is a 3-lane one-way road. Figure 3.2 (b) represents the second intersection, the Calle 37 Street and Carrera 9 Street intersection in La Joya neighborhood. The Calle 37 Street is a two-way two-lane road and the Carrera 21 Street is a one-lane one-way road (excluding one parking lane). Third, the Calle 105 Street and Carrera 22 Street (signalized) intersection is located in neighborhood La Provenza, Bucaramanga as shown in Figure 3.2 (c). The Calle 105 Street is a two-way four-lane road while the Carrera 21 Street is a two-lane one-way road. Finally, the Diagonal 33 Street and Carrera 34 Street intersection is located at the neighborhood of La AltoViento, Bucaramanga, as shown in Figure 3.2 (d). The Diagonal 33 Street is a two-way two-lane road and Carrera 34 Street is a two-lane one-way road. Our research team selected these four distinct neighborhoods in order to study the impacts of variations in the traffic level and the intersection type on the air pollution concentrations. I study these four intersections and estimate their associated traffic-related emissions and air pollution concentrations from travel activities in the surrounding areas.

Figure 3.2 Links in four Intersections (a) La Concordia; (b) La Joya; (c) La Provenza; (d) La Alto

3.3. Emissions Estimation

3.3.1. MOVES Project Scale

For this case study, I use the MOVES's project scale module to simulate and estimate the traffic-related emissions and their dispersions. Modeling microscale analysis, the MOVES project scale is designed to evaluate individual projects. Inputs for MOVES are the link-specific traffic data, to be used in the Project Data Manager (PDM). The MOVES estimation is mainly based on two key inputs: vehicles' speed and link's grade. Examining the video-data collected, I determine the speed of vehicles by studying the detailed second-by-second speed profiles of cars and motorcycles traveling through the 4 intersections during a peak hour (9am-10am) and an off-peak hour (12am-1am). I separate the intersections into several links and estimate the second by second vehicle speeds based on links' lengths and vehicles' travel time records passing through the intersection using the recorded videos with one additional link that represents the off-network activities (vehicles stopped at each intersection with "zero speed"). Emissions for intersections can be estimated from the MOVES using the framework shown in Figure 3.3.

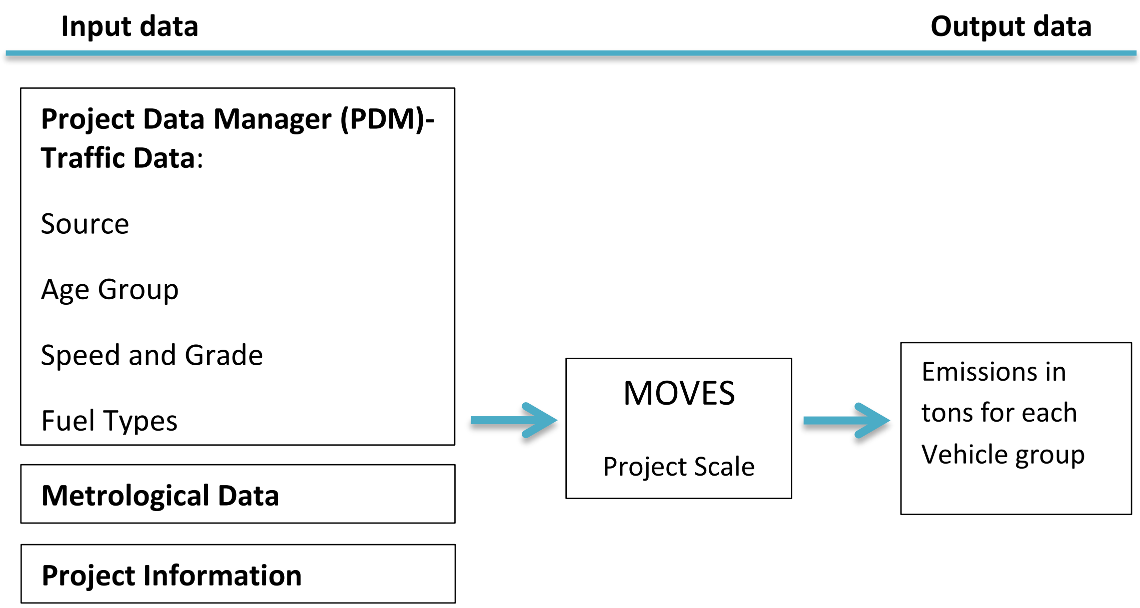


Figure 3.2 MOVES Project Scale's Framework

3.3.2. Data Collection

Since MOVES software is calibrated for U.S. counties, not Canada, I select the Leon County, Florida that has the most similar conditions to those of Bucaramanga (in terms of weather conditions and Longitude).

Our research team conducted the vehicle data collection in June 2018 for the La Concordia & La Joya and July 2018 and La Provenza & La Alto intersections. We installed cameras on buildings' roofs to record videos for further analysis. Next, I count vehicles in four different vehicle type categories: passenger cars, motorcycles, light trucks and heavy trucks. All vehicles are accounted based on 5-minute intervals. Then, I determine the traffic volume and vehicle type distribution databased on the vehicle counting data.

Since most vehicles in Bucaramanga are shipped from close-by large cities including Floridablanca or Giron, I use the vehicle age distribution for Floridablanca as input into MOVES. Also note that the vehicle fleet in Bucaramanga is different from the vehicle fleet in the U.S., which MOVES is built upon on that. As the last input, I obtain the meteorology data for Bucaramanga using the historical data of temperature and wind (Time and data, 2018).

In order to provide more accurate emission estimates for each intersection, I apply second-by-second speed profiles instead of average speeds. This is one of the most important steps that most studies to estimate emissions have neglected. As video records can show each intersection within a 50-meter radius, only, I assume traffic volumes and speeds will remain the same after moving out of the 50-meter radius. Figures 3.4 to 3.11 represent the second-by-second speed profiles on all links in each intersection during peak and off-peak hours within 50-meter, 100-meter and 200-meter radiuses (circled).

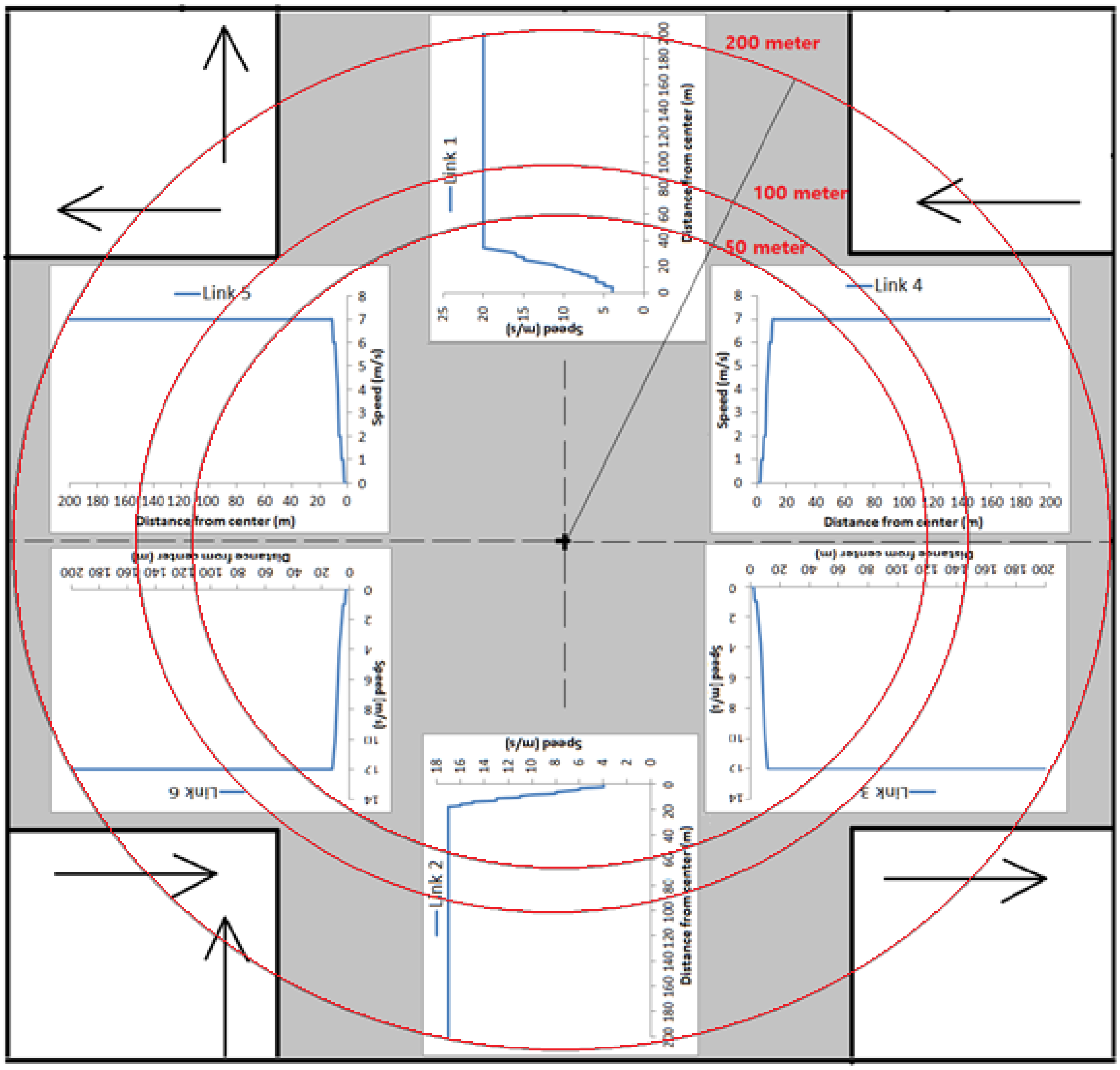


Figure 3.3 Speed Profiles- La Concordia during Peak Hours

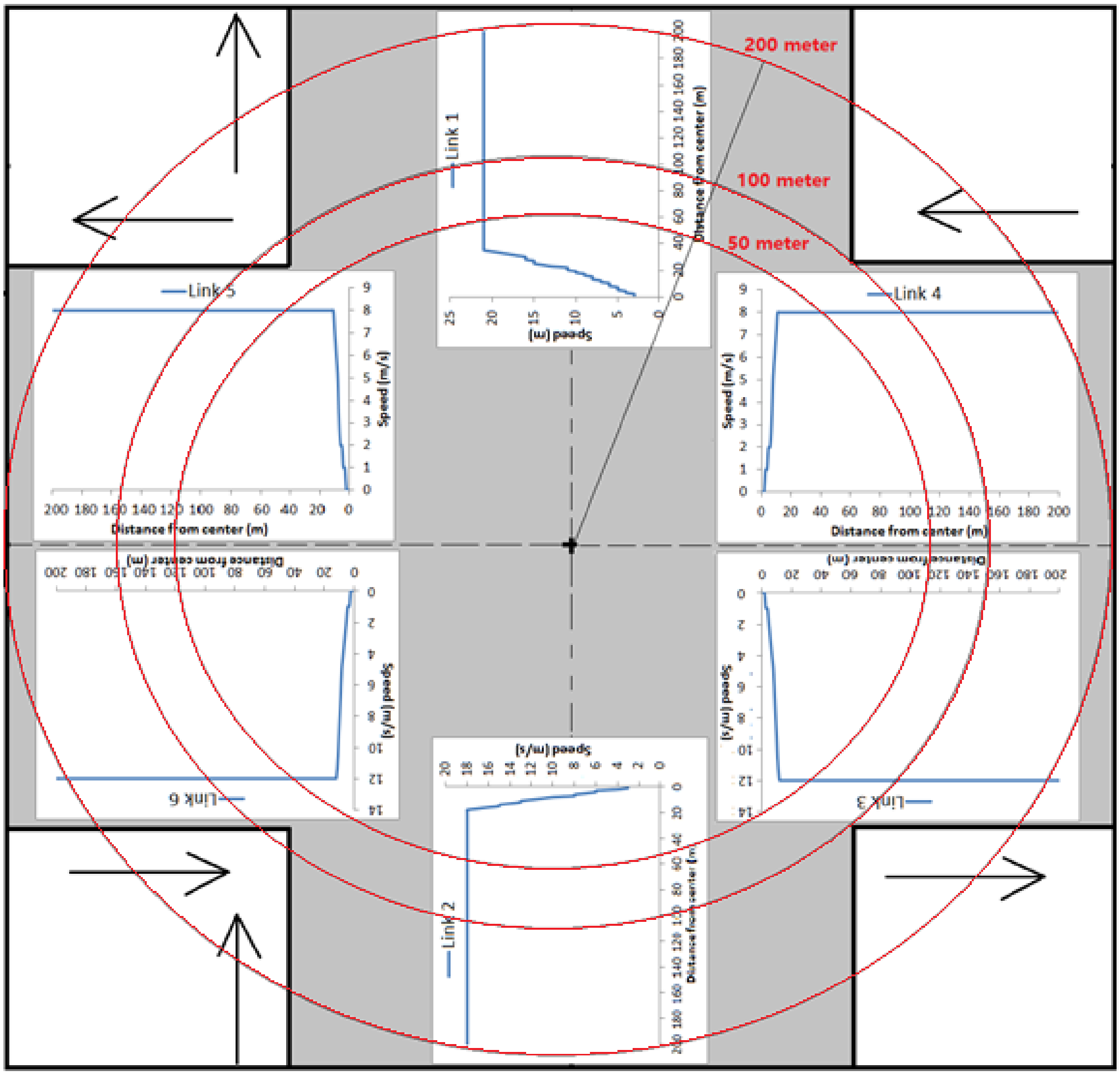


Figure 3.4 Speed Profiles-La Concordia during Off-peak Hours

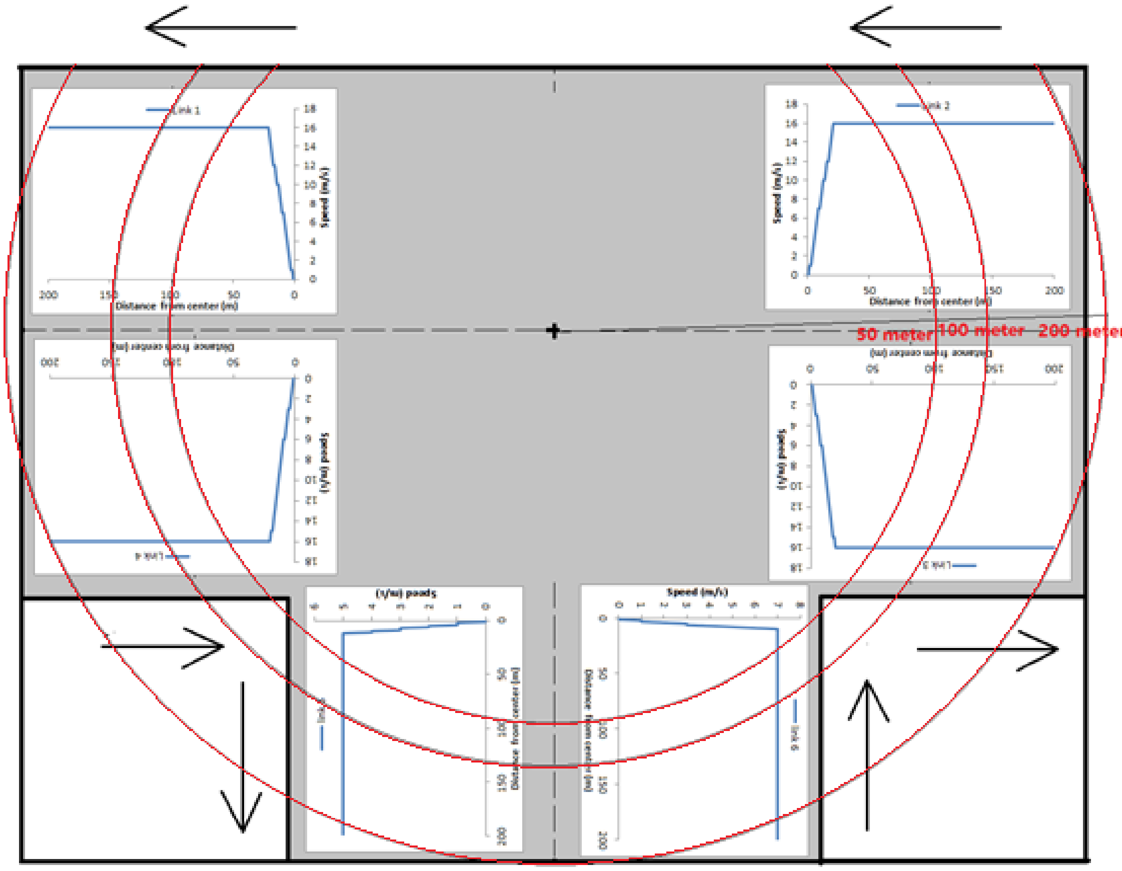


Figure 3.5 Speed Profiles-La Joya for Peak Hours

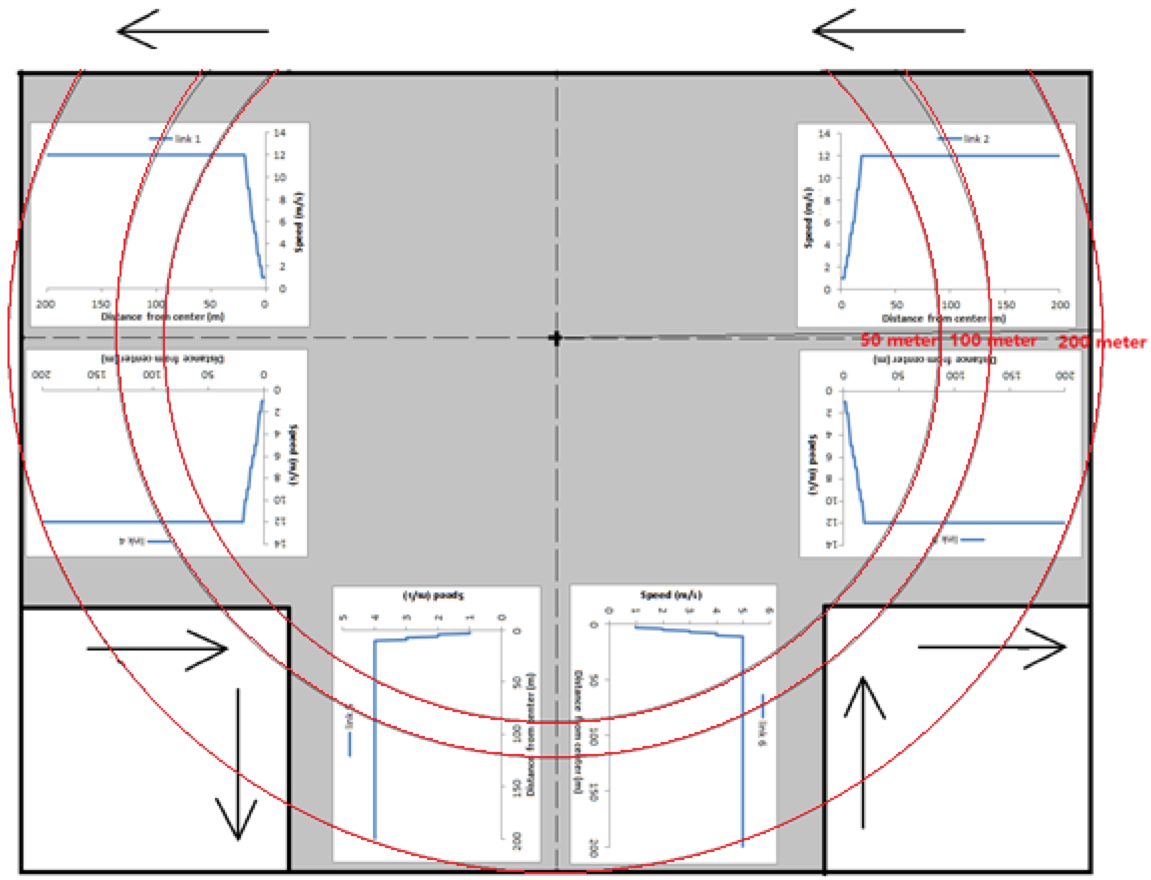


Figure 3.6 Speed Profiles-La Joya during Off-peak Hours

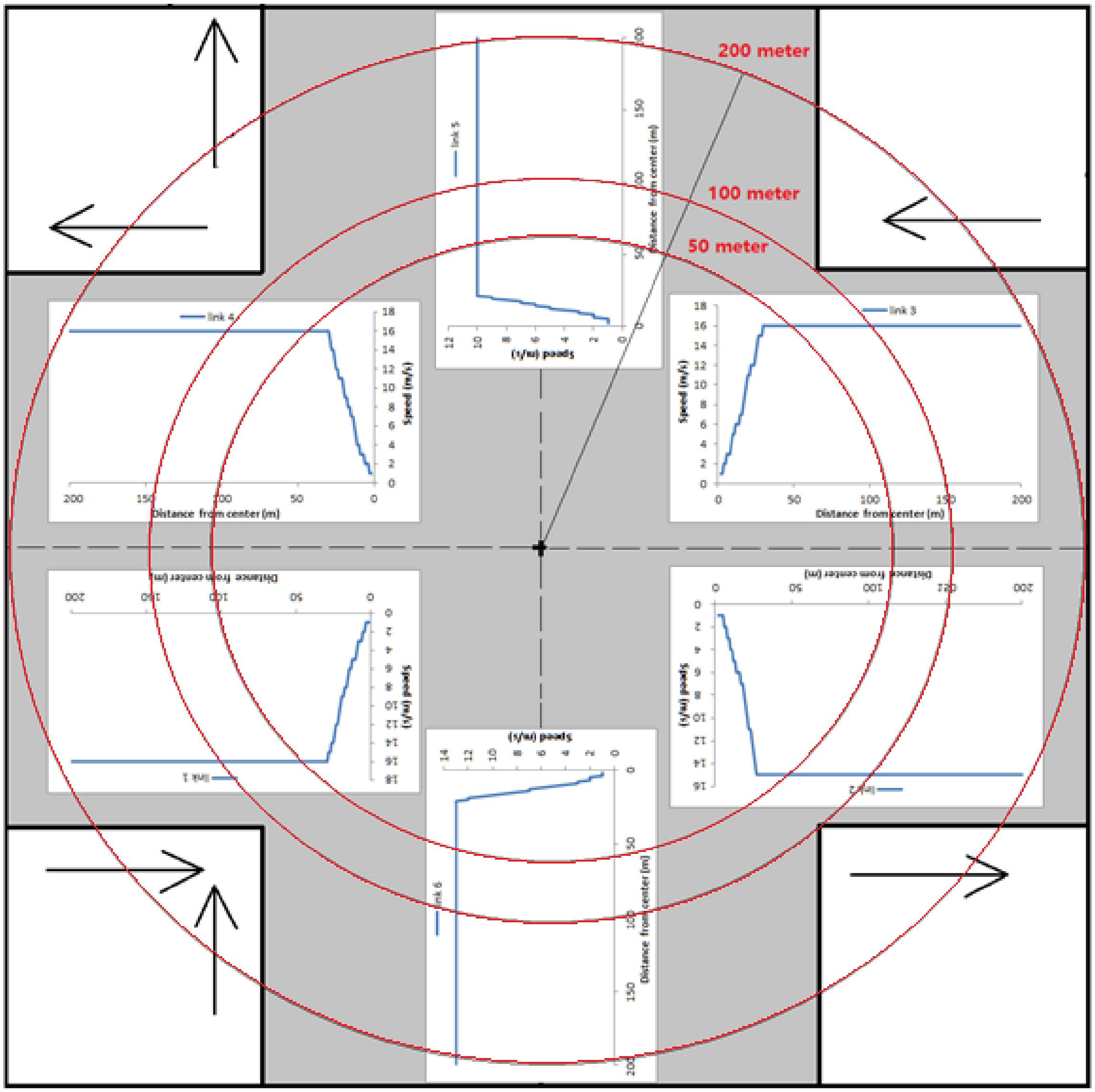


Figure 3.7 Speed Profiles-La Provenza during Peak Hours

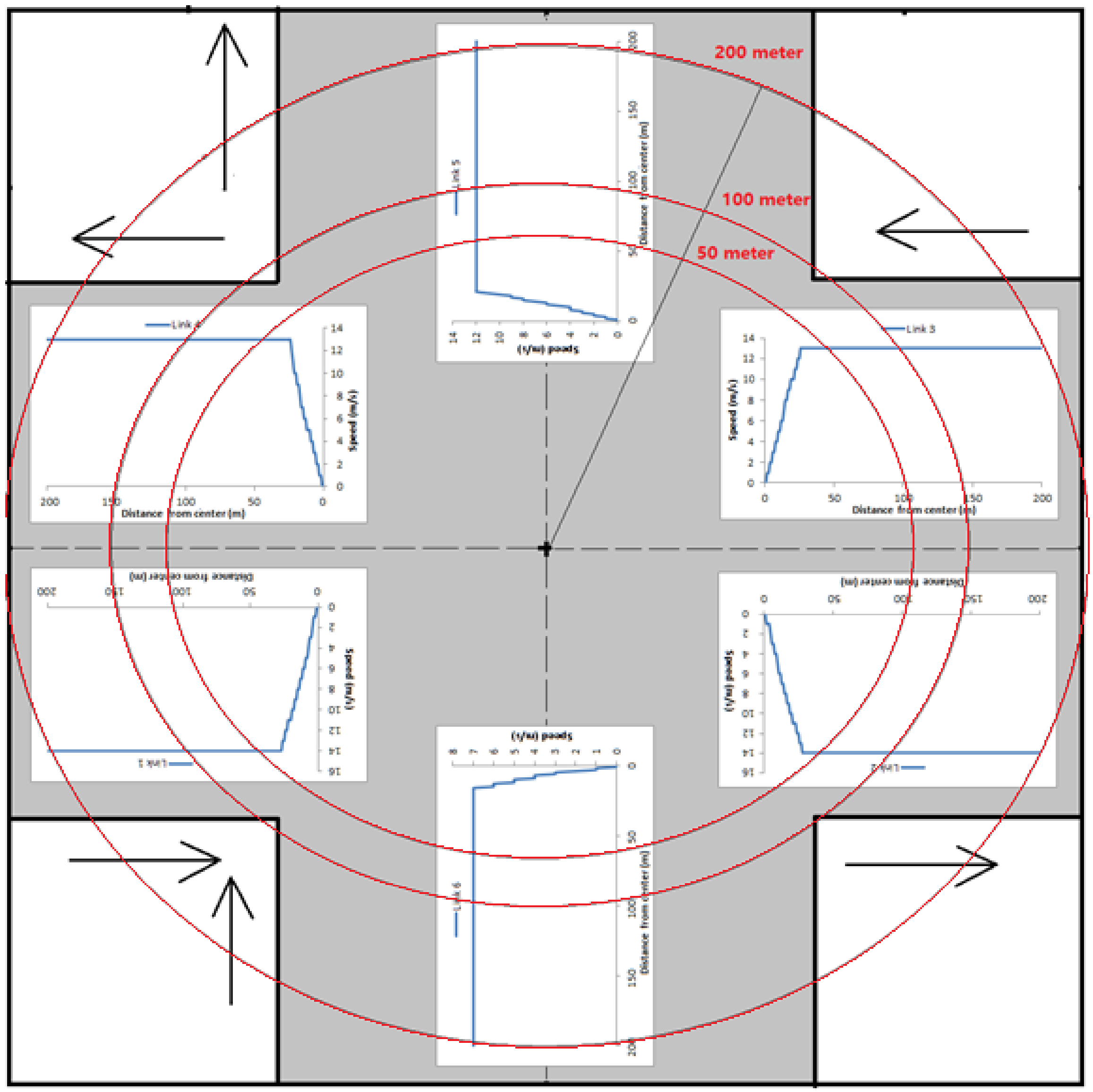


Figure 3.8 Speed Profiles-La Provenza during Off-peak Hours

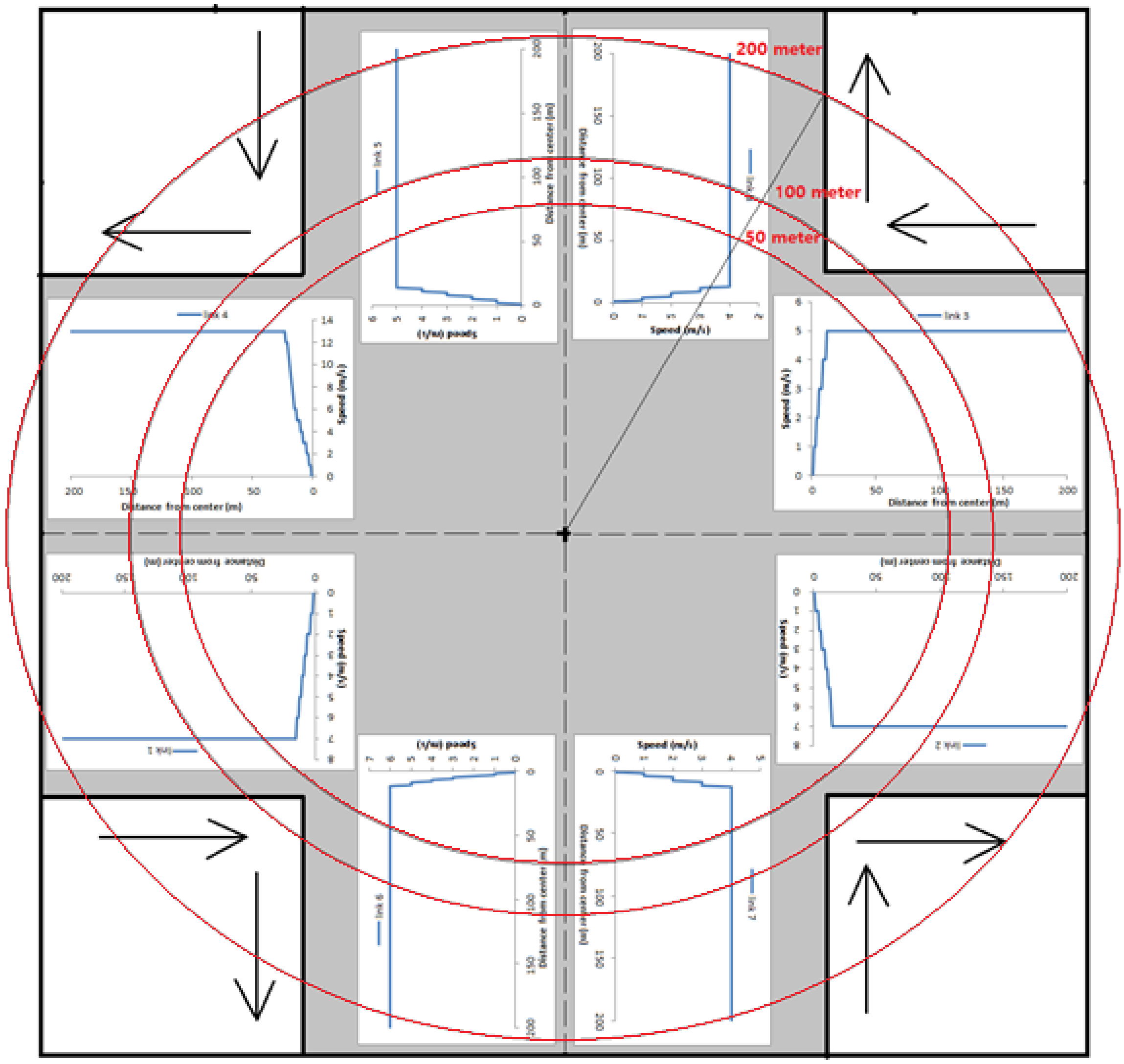


Figure 3.9 Speed Profiles-La Alto during Peak Hours

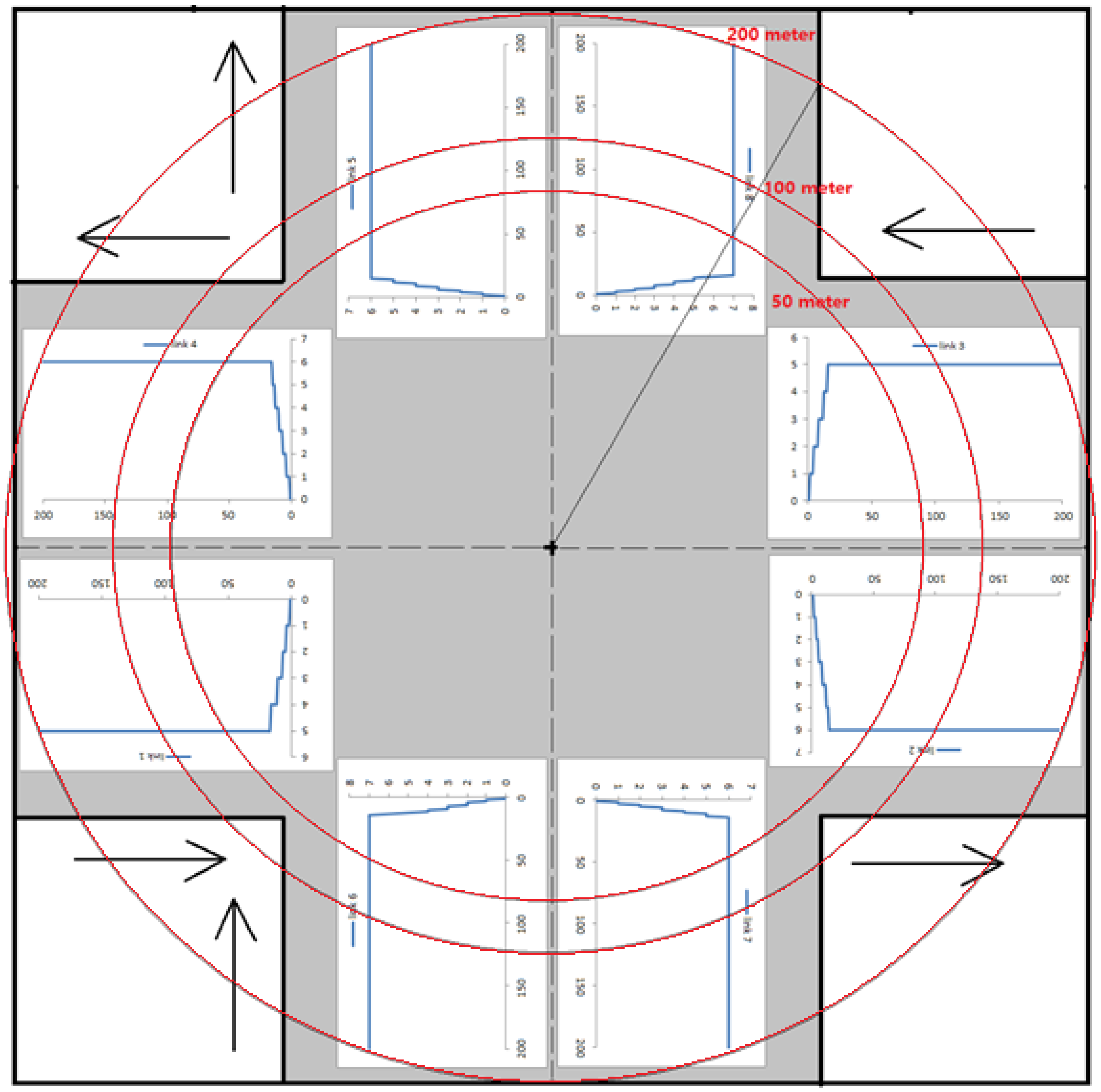


Figure 3.10 Speed Profiles-La Alto during off-peak Hours

In addition, links' grades for all four intersections are borrowed from the publicly-available Google Earth data as shown in Table 3.1.

Table 3.1 Road Grades for Each Intersection

Intersection	Grade
La Concordia	±3.5%
La Joya	±12.8%
La Provenza	±1.3%
La Alto	±23.4%

I gather other information from several other sources. All the necessary data required to run the MOVES project scale and their sources are listed in Table 3.2.

Table 3.2 Data Sources as Inputs for the MOVES Project Scale

Data Input	**Description**	**Source**
Vehicle type population	Number of local vehicles operating in the area	Field video collection (by our research team)
Vehicle fleet's age distribution	Vehicle age distribution based on vehicle model year or age	Floridablanca vehicle registration data (Direccion de transito, 2018)
speed profile	Speed profile of each vehicle type on travelling along intersections	Field video collection (by our research team)
Road Type Distribution	Fraction of a vehicle type volume for different road types	Vehicle counting based on videos (by our research team)
Meteorology	Average hourly temperature and the humidity inputs	Colombia climate (Time and Data, 2018)
Fuel	Fuel information	Based on county vehicle information (MOVES default fuel data)

3.4. Emissions Results from MOVES

After inputting all required data into MOVES, I estimate the emission rates for $PM_{2.5}$ and Black Carbon (BC) for the four intersections during two different time periods. Figures 3.12 to 3.15 show the estimated emission rate (g/h) based on the traffic volumes for each intersection during peak/off-peak hours.

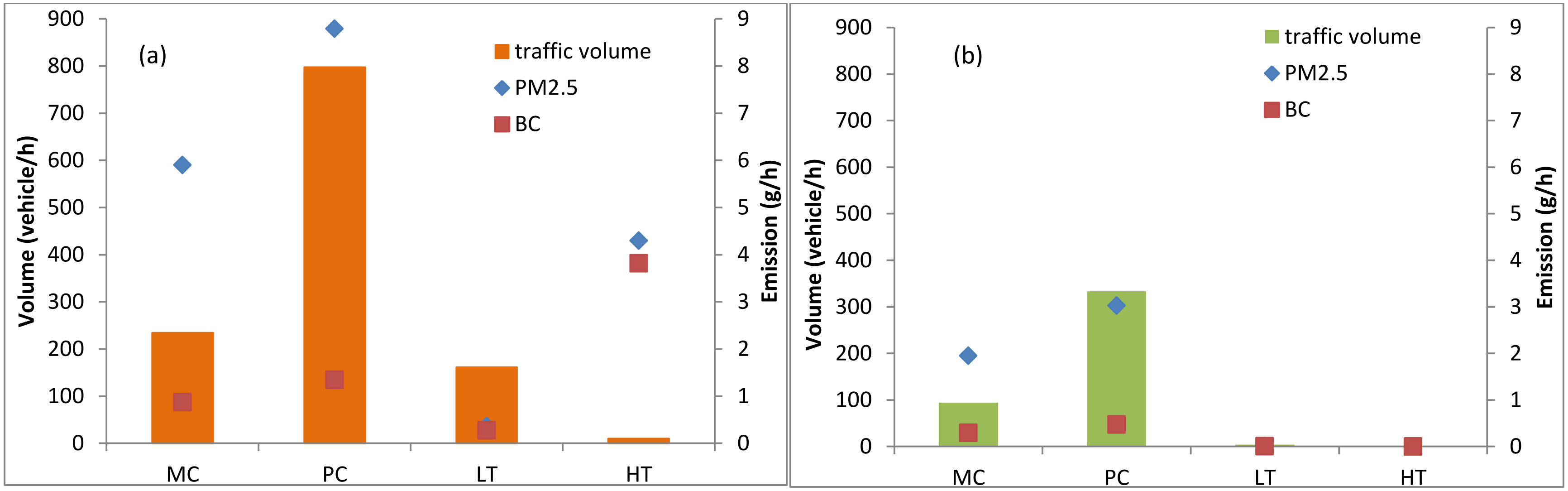


Figure 3.11 La Concordia Intersection (200-meter radius) Emissions vs Volumes for (a) Peak Hours; (b) Off-peak Hours

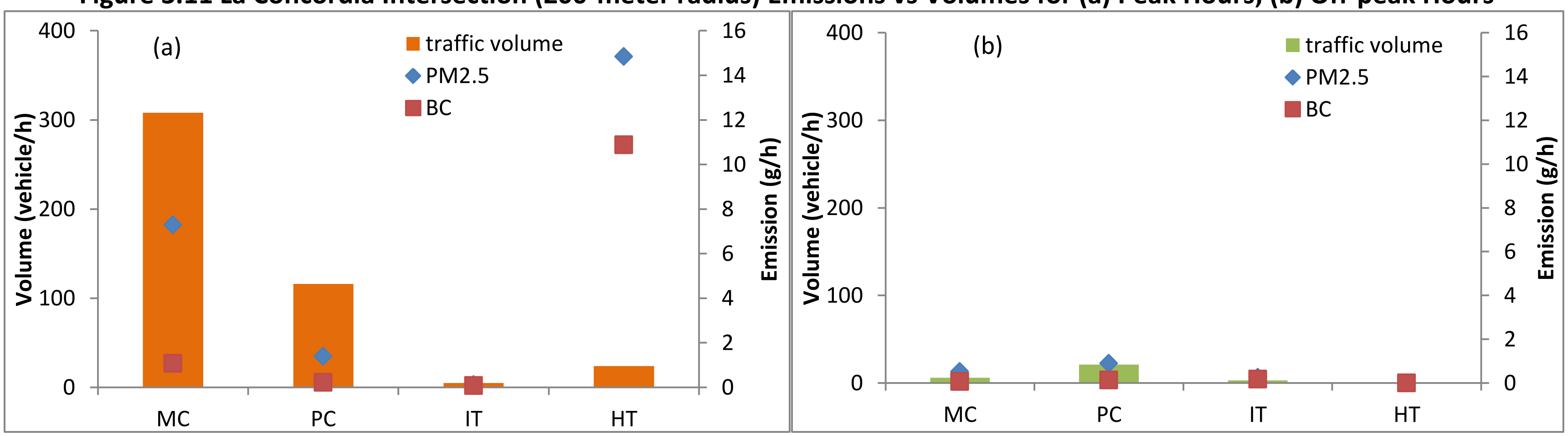


Figure 3.12 La Joya Intersection (200-meter radius) Emissions vs Volumes for (a) Peak Hours; (b) Off-peak Hours

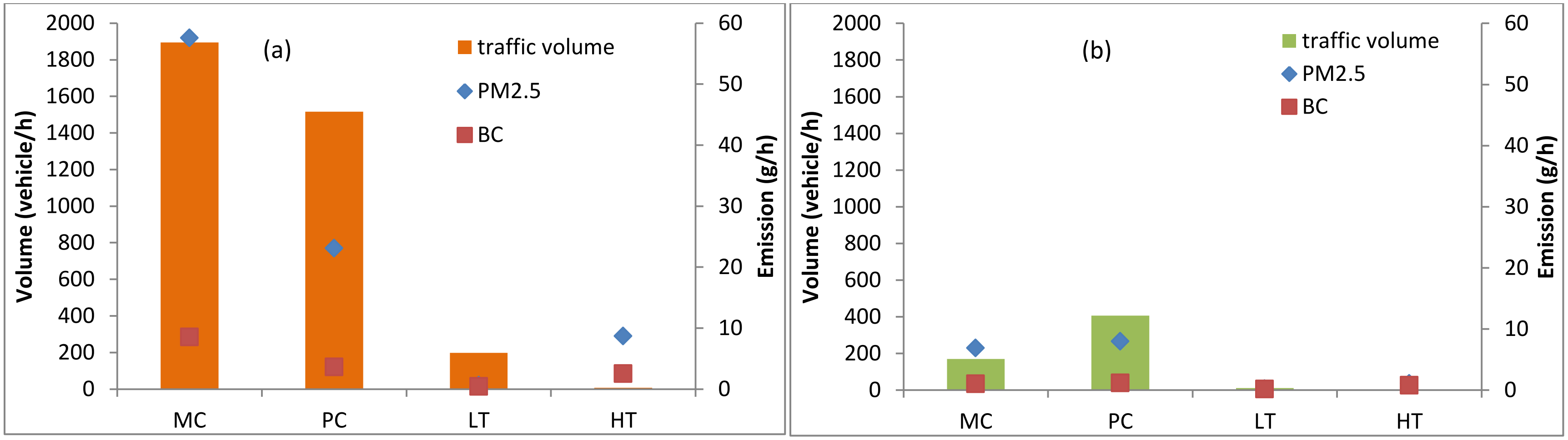


Figure 3.13 La Provenza Intersection (200-meter radius) Emissions vs Volumes for (a) Peak Hours; (b) Off-peak Hours

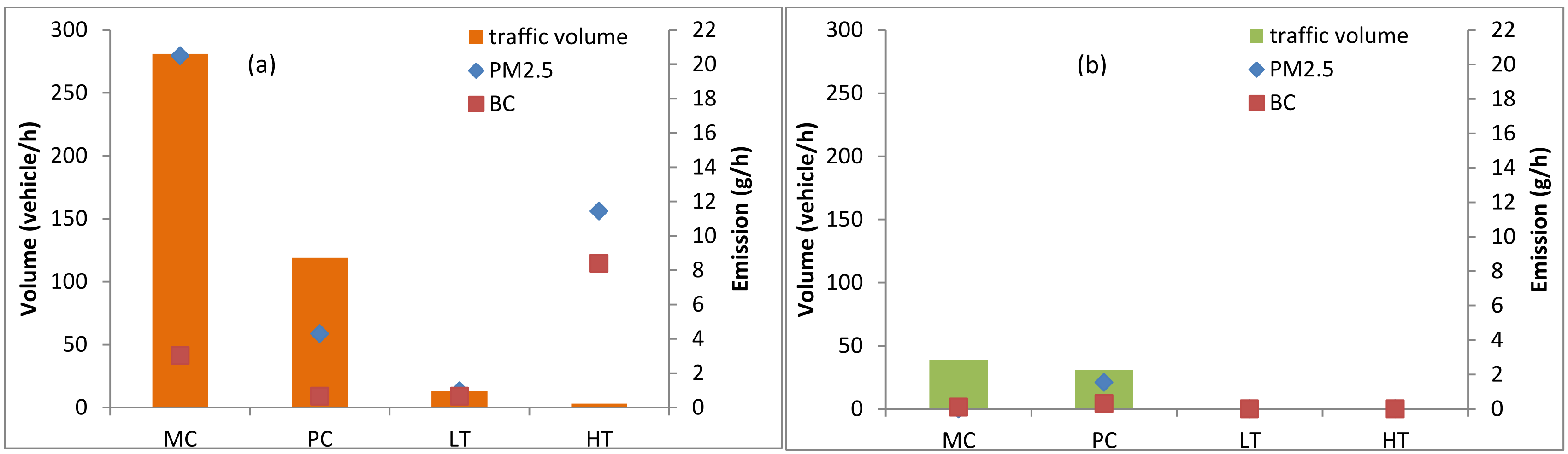


Figure 3.14 La Alto Intersection (200-meter radius) Emissions vs Volumes for (a) Peak Hours; (b) Off-peak Hours

Figures 3.12 to 3.15 demonstrate that the higher the traffic volume the higher the $PM_{2.5}$ and Black Carbon emissions rates. Also note that heavy trucks generate high emission rates with a relatively small traffic volume. In addition, emissions are higher during peak hours compared to off-peak hours, which is mainly due to larger peak-hours traffic volumes.

We can observe in Figure 3.12 that passenger cars emit the highest $PM_{2.5}$ rates during peak hours (9g/h) and off-peak hours (3g/h) for intersection in neighborhood La Concordia. For Black Carbon, heavy trucks, although small in numbers, generate the highest rate during peak hours (3.8 g/h) while passenger cars result in the highest emission rate during off-peak hours (0.5g/h). For the La Joya intersection, the rates are generally higher; heavy trucks generate $PM_{2.5}$ rates of 15g/h and Black Carbon rates of 11g/h while light trucks generate the lowest rates for $PM_{2.5}$ (0.3g/h) and Black Carbon (0.1g/h) during peak hours, as shown in Figure 3.13 (a). For the La Provenza and La Alto intersections, motorcycles have the highest $PM_{2.5}$ emission rates during peak hours (58g/h for La Provenza and 21g/h for La Alto) since there are many while passenger cars have the highest emission rate during off-peak hours (8g/h for La Provenza and 12g/h for La Alto). Similarly, motorcycles have the highest Black Carbon emission rates during peak hours (7g/h) for La Provenza and La Alto intersections, while heavy trucks generate the highest rates (8g/h).

Figure 3.16 represents total emission rates against total passenger-car-equivalent volumes. Intersections located in La Provenza generates the highest $PM_{2.5}$ (90g/h) during peak hours and (16g/h) during off-peak hours and Black carbon (15g/h during peak hours and 3g/h during off-peak hours) both during peak and off-peak hours with highest traffic volume (2700vehicle/h during peak hours and 600 vehicle/h during off-peak hours) compared to other three intersections.

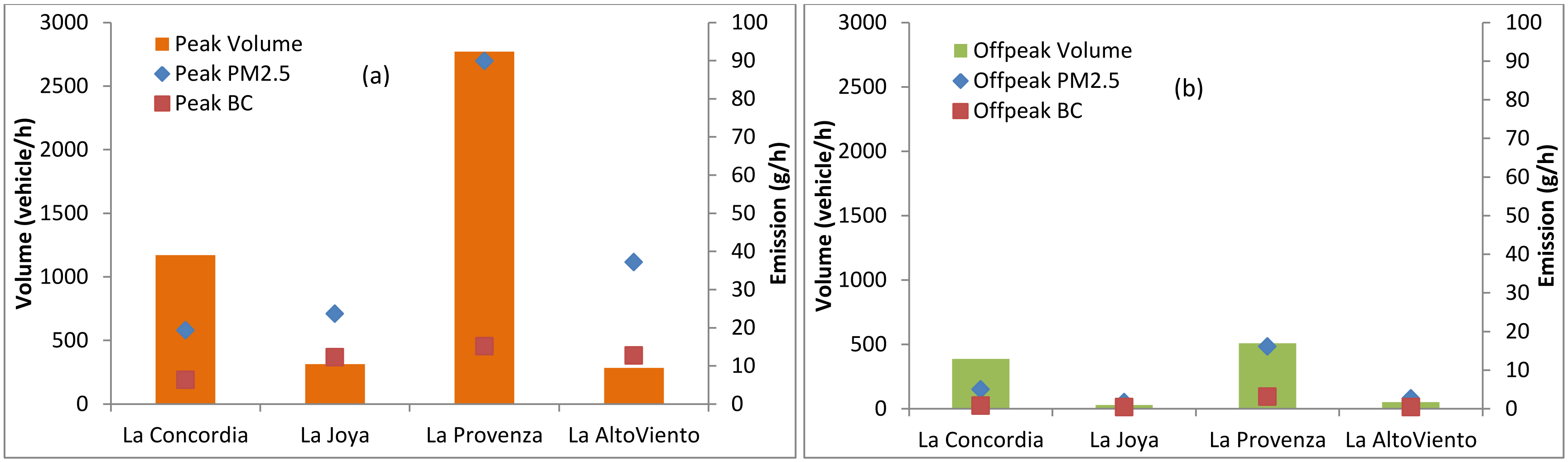


Figure 3.15 Total Emissions vs Volumes on Four Intersections (200-meter radius) for (a) Peak Hours; (b) Off-peak Hours

3.5. Air Pollution Concentration's Estimation

3.5.1. AERMOD Framework

In this study, I use the AERMOD View software, which is developed by Lakes Environmental Software (Lake Environment, 2019). The software provides a user-friendly Graphical User Interface as shown in Figure 3.17 below.

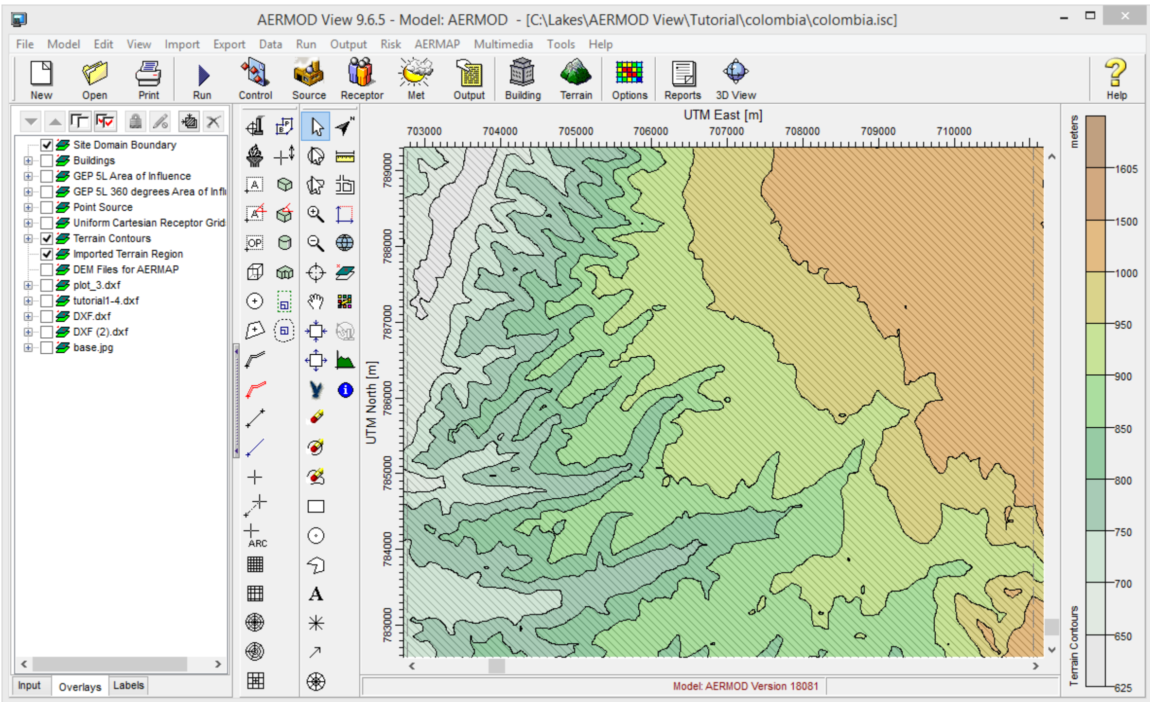


Figure 3.16 AERMOD-View's Graphical User Interface

In addition, the AERMAP and AERMET View models are applied to process and view the terrain and meteorological data. Figure 3.18 represents the general framework of AERMOD.

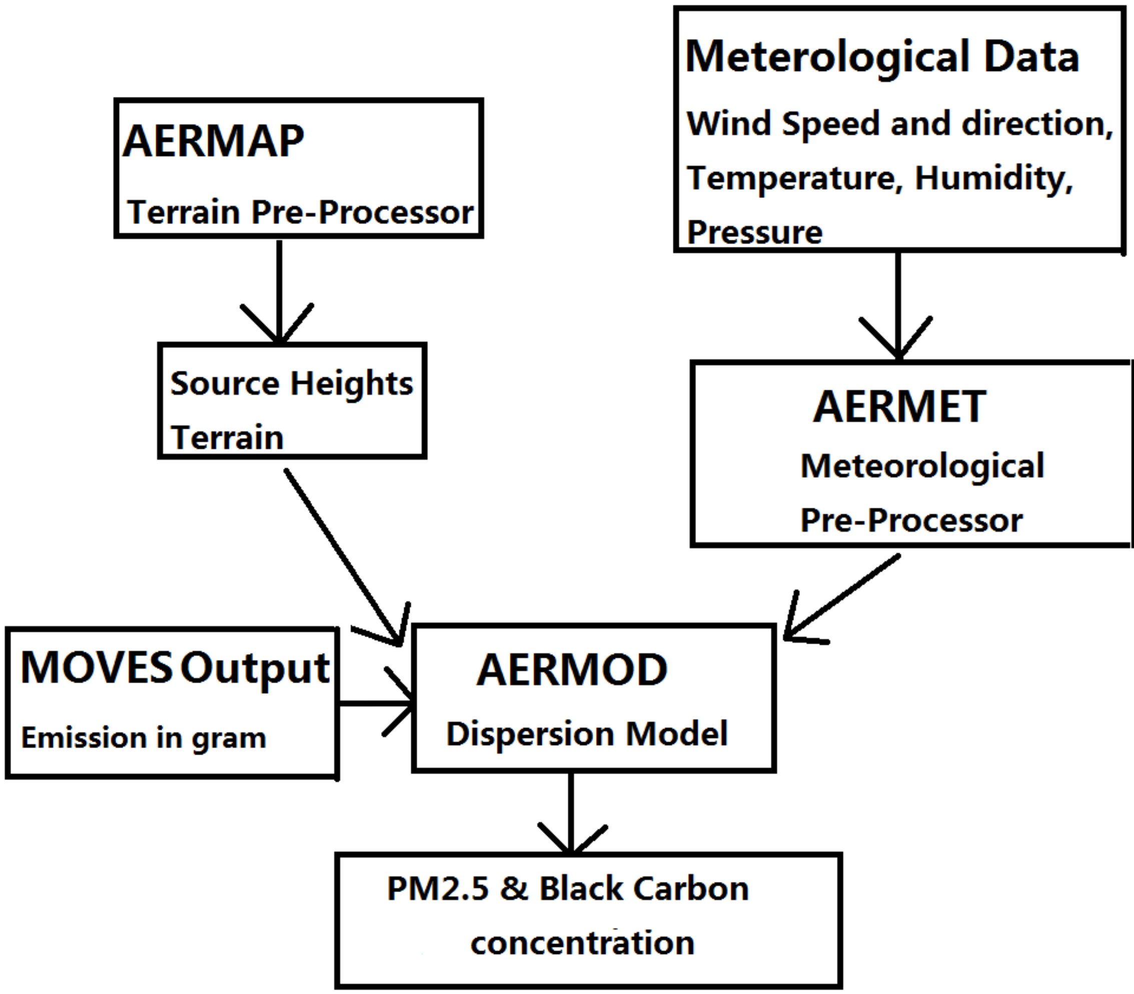


Figure 3.17 General Framework of AERMOD

The typical meteorological data set can be developed from historical climate data for the studied area (Time and data, 2018). The already-available meteorological dataset provides the following hourly inputs to AERMOD: wind direction, wind speed, ground-level ambient temperature, relative humidity and pressure. Table 3.3 below shows the meteorological data to represent the hourly information.

Table 3.3 Sample Meteorological Data- Inputs for AERMOD Modelling

Year	Month	Day	Hour	Dry Bulb Temperature	Relative Humidity	Station Pressure	Wind Direction	Wind Speed
				deg C	%	mb	deg	m/s
2018	Jun	1	1	22	83	1014.2	0	1.11
2018	Jun	1	2	22	83	1014.2	0	1.11
…	…	…	…	…	…	…	…	…
2018	Jun	1	18	19	100	1013.5	330	4.72
2018	Jun	1	19	19	100	1014.2	340	1.94
2018	Jun	1	20	20	100	1014.9	0	1.11
2018	Jun	1	21	20	100	1016.3	0	1.11
2018	Jun	1	22	19	100	1017.3	330	3.61
2018	Jun	1	23	19	100	1017.6	310	1.94
2018	Jun	1	24	19	100	1017.6	340	1.67

I then convert the above information into AERMET's Samson format and use it to generate the WARPLOT, which has the wind-rose plot for the AERMOD use, as shown in Figure 3.19. The wind speed and direction influence the transport and dispersion of emissions in the atmosphere. Then, I use the outputs of AERMET directly in the AERMOD.

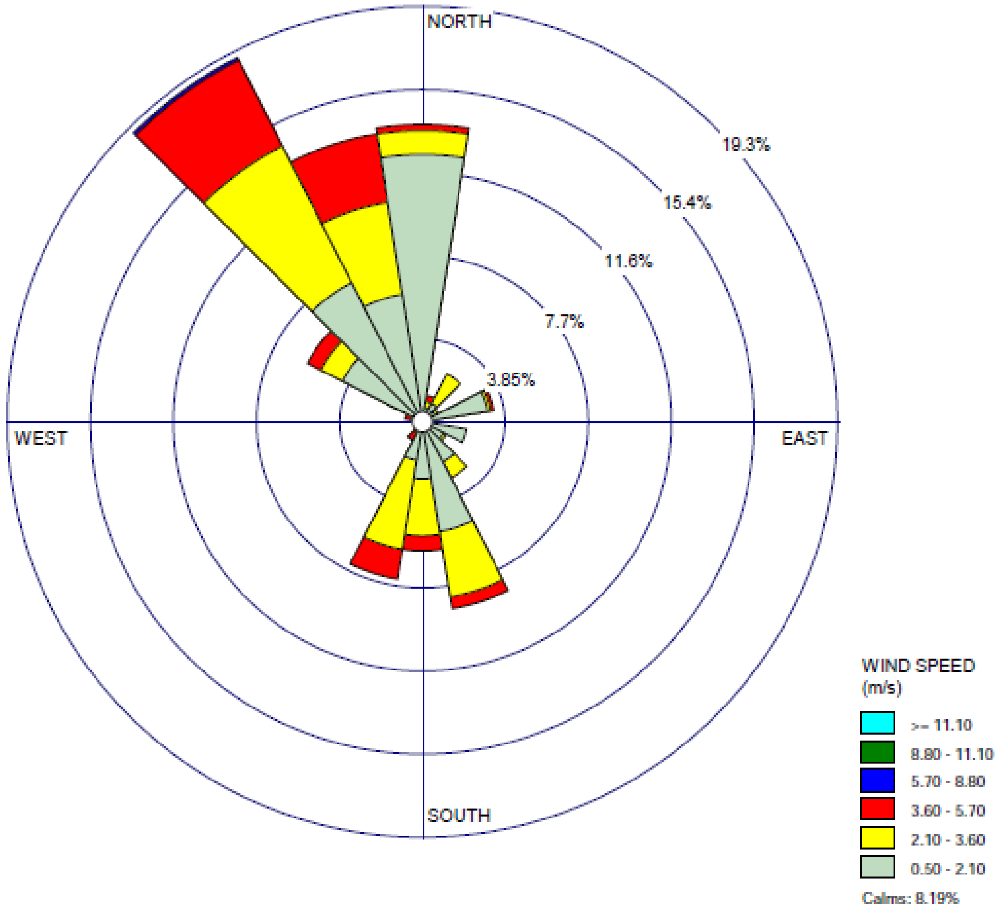


Figure 3.18 Wind Speed and Direction from WARPLOT

In addition, terrain characteristics could affect air quality concentrations. The AERMAP model first determines the base elevation using the WebGIS module, which is already installed in the AERMOD View software, to provide the terrain data for the studied areas. Finally, I include 12 industrial sources that generate $PM_{2.5}$ and Black Carbon in Bucaramanga (Azuero Díaz, 2016) and listed them in Table 3.4.

Table 3.4 Industrial Sources in Bucaramanga

Product	Location
Lubricating oils	Carrera 15 # 20-33
Chicken producer	Anillo Vial #2-46
Chicken producer	Cra 14 # 4-13 Bucaramanga
Service for hotel and industrial	Cra 4 # 5 -04
Cheese producer	Cra 19 # 5 -21 Bucaramanga
Manufacture of mechanical metal products	Cra 15 # 7-29
Rubber products supplier	Calle 23 # 13-35
processing cocoa, coffee and cereal	Calle 33 #13-37
Food manufacturer	Parque Industrial de Bucaramanga I
Bird pig food	Parque Industrial de Bucaramanga I
Pasta manufacturer	Calle 20# 12-50
Construction equipment supplier	Calle 21 # 11-41

3.5.2. Air Concentration Distribution

After running AERMET and AERMAP and inputting all required data into AERMOD, I estimated the air pollution concentration distributions of $PM_{2.5}$ and Black Carbon (BC) in the four intersections during peak hours, off-peak hours, and over a day. Figures 3.20 and 3.21 show the air pollution concentration distributions in the 200-meter radius of the La Concordia intersection. As expected, the concentrations are the highest among the most heavily-used links. A comparison between the peak hours (a) and off-peak hours (b) emissions show that for both emission types, the peak air pollution concentrations are much higher than those of off-peak hours, in most cases more than twice. This result shows that the time of day has a significant influence on the $PM_{2.5}$ and Black Carbon concentrations.

Figures 3.22 to 3.25 illustrate the estimated $PM_{2.5}$ and Black Carbon concentrations considering the distance from the centerline of intersections. In addition, the concentration curves indicate the $PM_{2.5}$ and Black Carbon concentrations drop off substantially when moving away from the intersection centers, and then gradually decrease after 50 meters. The substantial drop is due to a combination of higher speed and lower traffic volumes when we move away from the center.

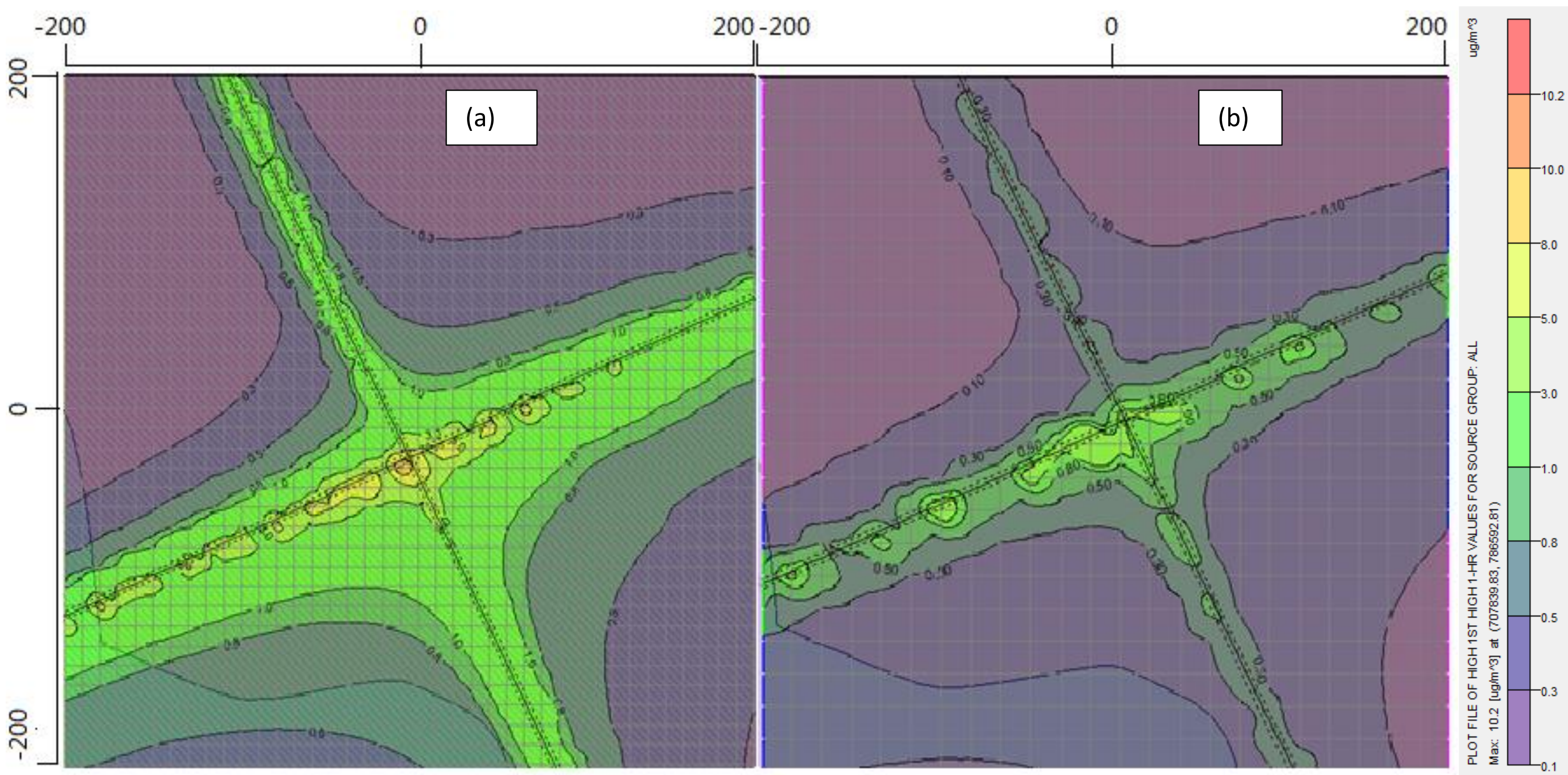


Figure 3.19 La Concordia's $PM_{2.5}$ Air Pollution Concentration Distributions (a) Peak hours; (b) off-peak hours

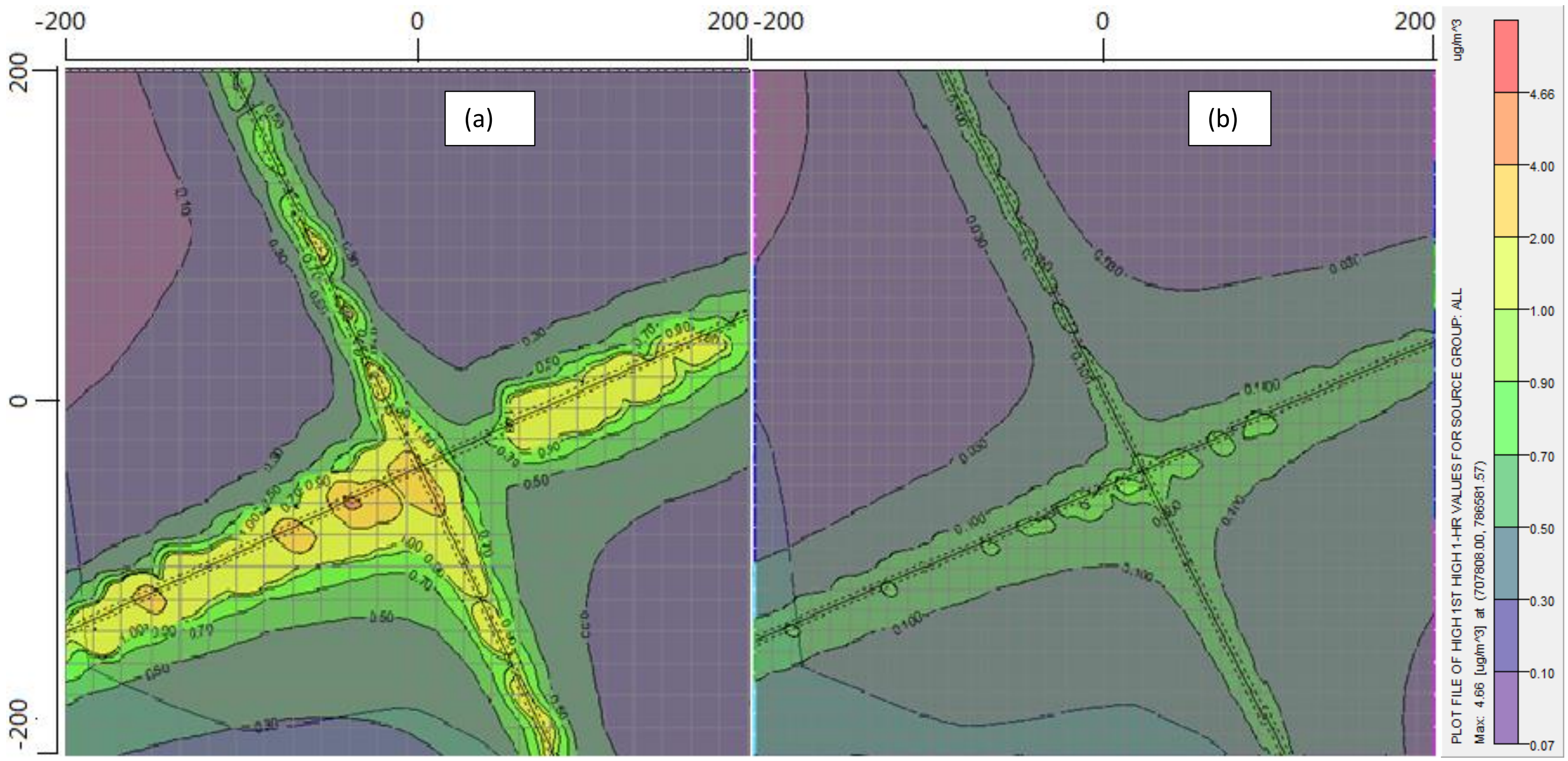


Figure 3.20 La Concordia Black Carbon Air Pollution Concentration Distributions (a) Peak hours; (b) off-peak hours

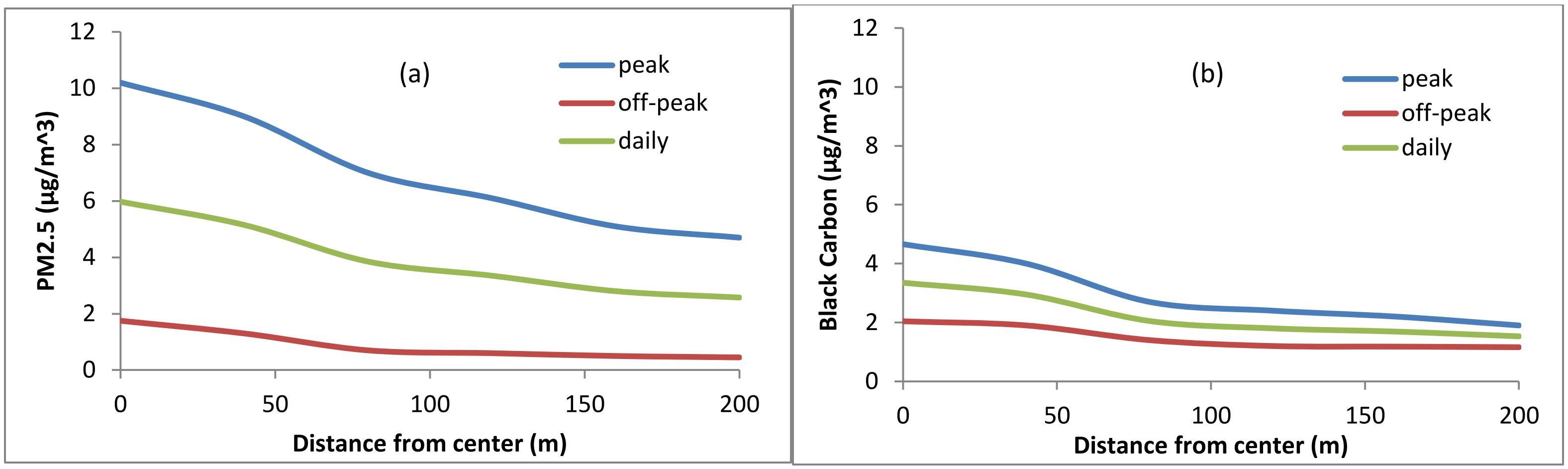


Figure 3.21 La Concordia Air Pollution Concentration based on the Distance from Intersection Center (a) $PM_{2.5}$; (b) Black Carbon

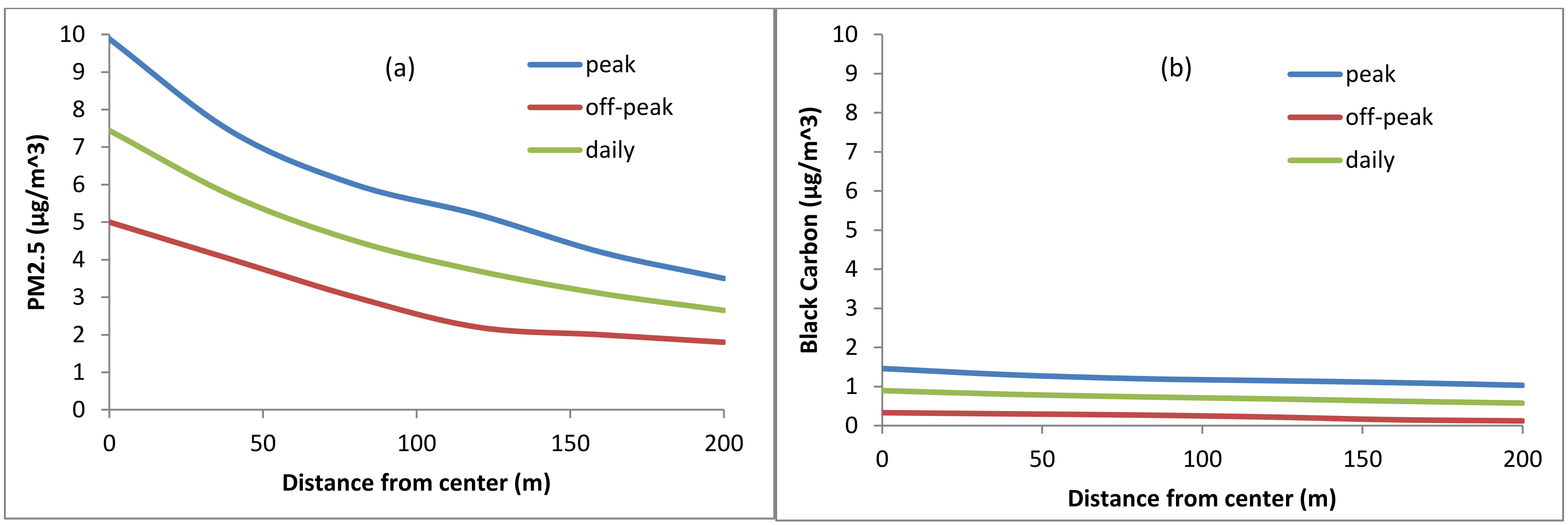


Figure 3.22 La Joya Air Pollution Concentration based on the Distance from the Intersection Center (a) $PM_{2.5}$; (b) Black Carbon

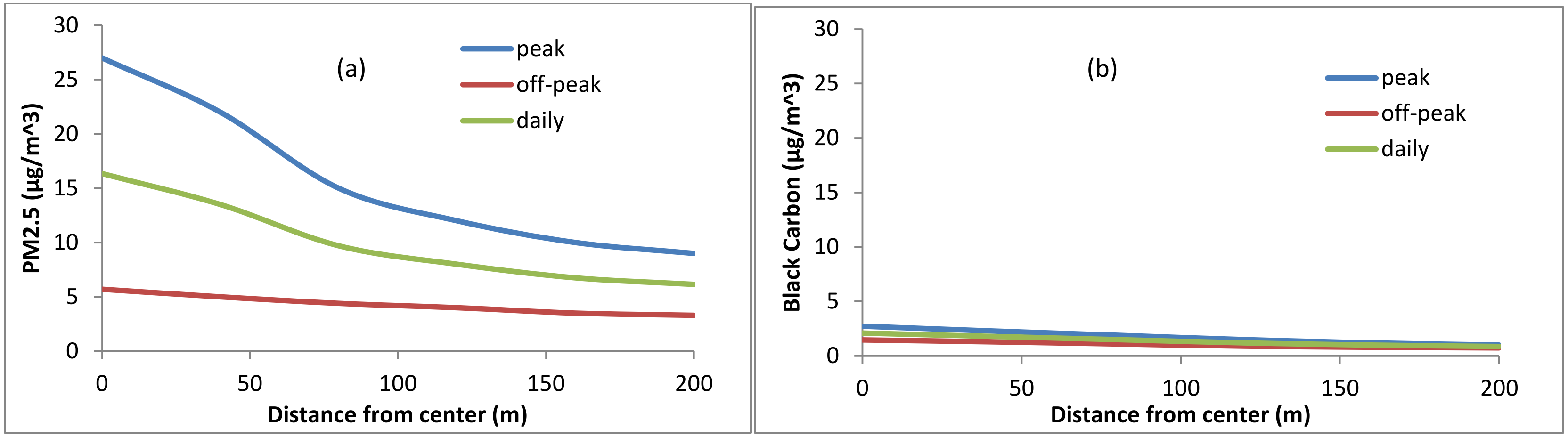


Figure 3.23 La Provenza Air Pollution Concentration based on the Distance from the Intersection Center (a) $PM_{2.5}$; (b) Black Carbon

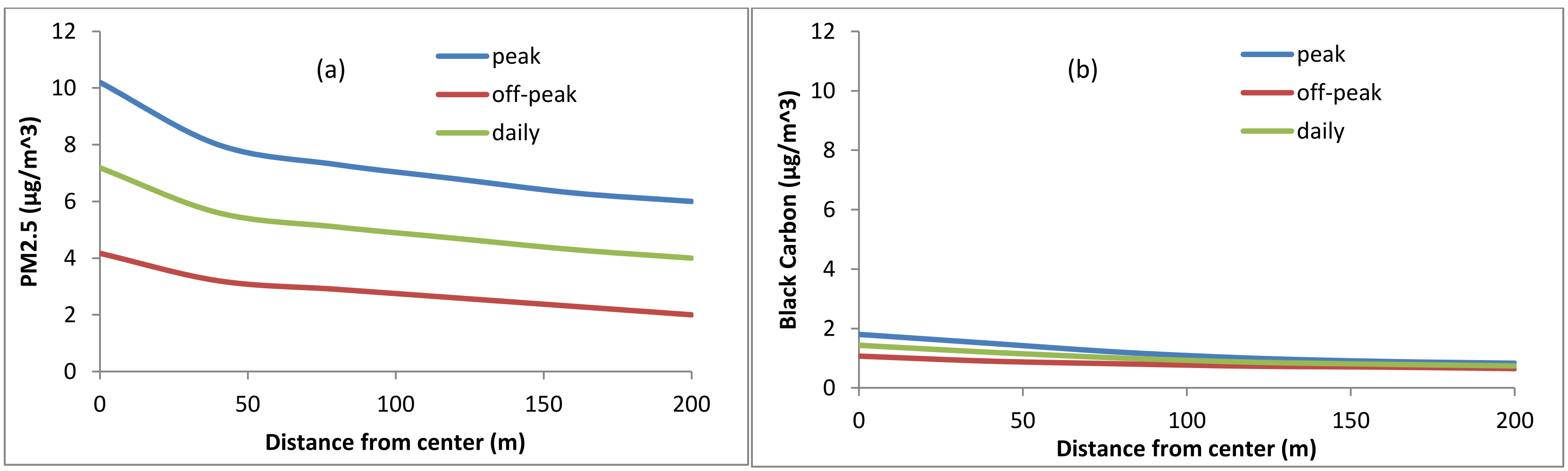


Figure 3.24 La Alto Air Pollution Concentration based on the distance from Intersection Center (a) $PM_{2.5}$; (b) Black Carbon

3.6. AERMOD Predicted Vs Observed Air Pollution Concentration

In addition, our research team measured the real-time $PM_{2.5}$ and Black Carbon air pollution concentrations using the devices located on the building roofs in all four intersections. The observed data is then used to represent the urban $PM_{2.5}$ pollution levels. The ambient concentrations are calculated by the receptors measuring such data. I compared my estimated vehicle-related $PM_{2.5}$ and Black Carbon concentrations (from AERMOD) with the observed ambient measurements.

Figures 3.26 and 3.27 show the observed and predicted peak-hours, off-peak-hours, and daily-average concentrations for a typical weekday in June 2018. To verify the reliability of the proposed modeling methodology, I compare the observed and predicted values for all four intersections. Overall, my proposed modeling captures the general trends of $PM_{2.5}$ and Black Carbon concentrations for the La Concordia, La Provenza and La Alto intersections throughout a day. However, the modelled $PM_{2.5}$ concentration in the La Joya intersection is much less than the observed values. This intersection is much closer to an industrial zone in Bucaramanga. Although I included some industrial sources in this study, the difference is significant (Figure 3.26-b). Note that the predicted concentrations are generally lower than the observations due to the fact that other factors can also affect the results including emissions generated by people’s daily activities at home/buildings, relatively less clean vehicles in Colombia than those in MOVES, etc.

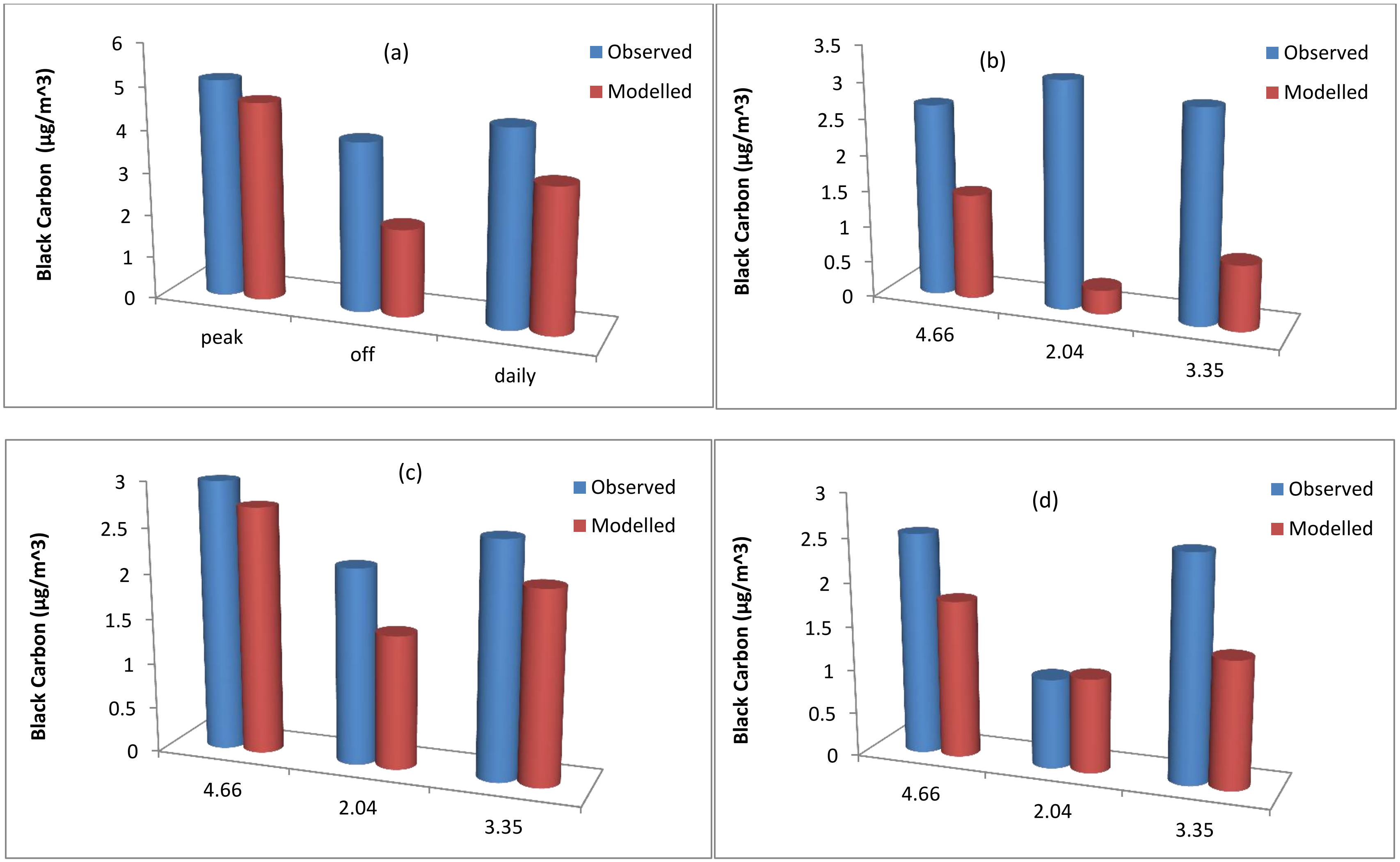


Figure 3.25 Observed vs Estimated $PM_{2.5}$ concentrations in (a) La Concordia; (b) La Joya; (c) La Provenza; (d) La Alto

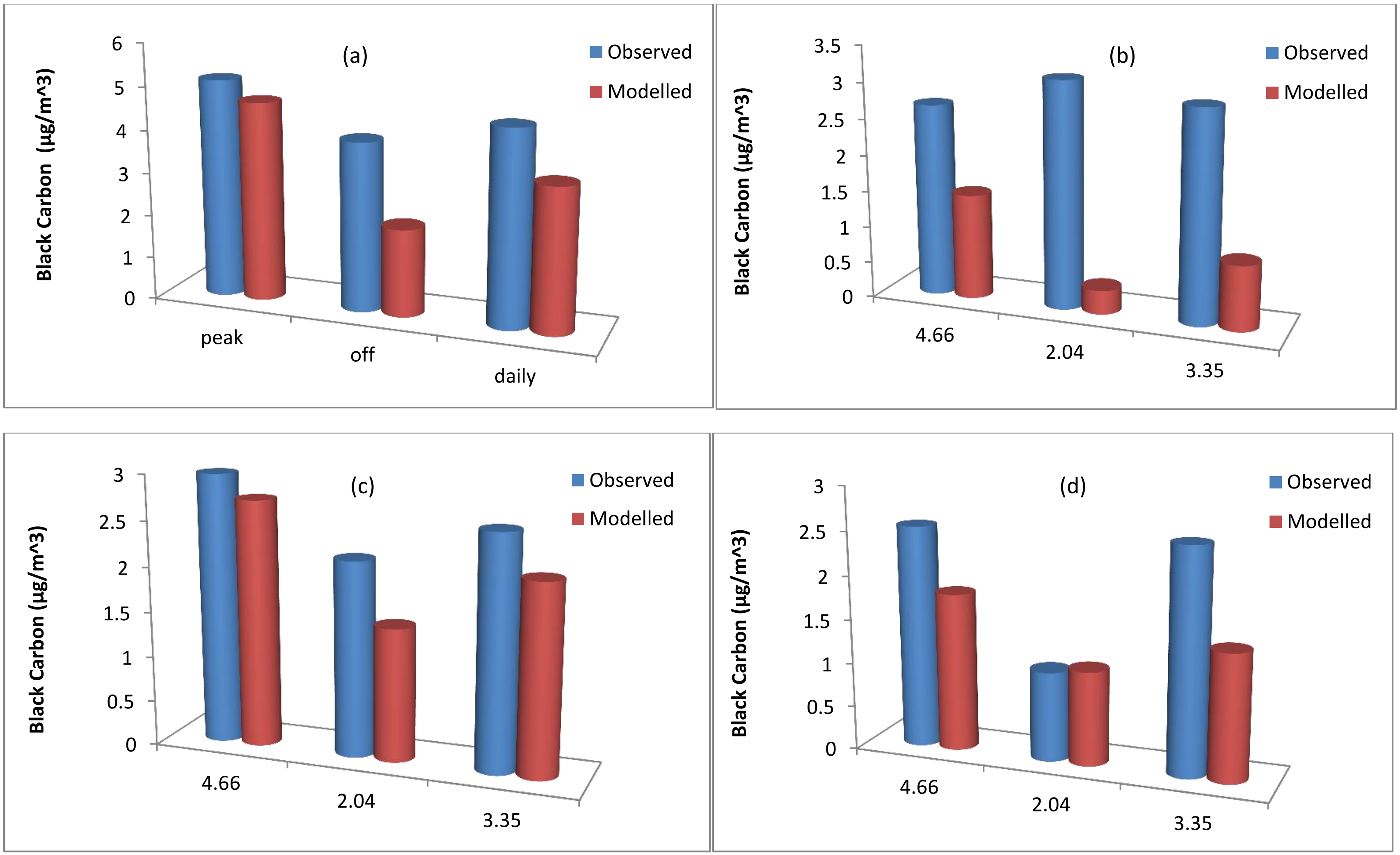


Figure 3.26 Observed vs Estimated Black Carbon concentrations in (a) La Concordia; (b) La Joya; (c) La Provenza; (d) La Alto

3.7. Sensitivity Analyses

Sensitivity analyses are undertaken in this study to better understand the behavior of the AERMOD dispersion model and observe the variation in modelled concentrations as input data are altered. Various studies have shown that meteorological conditions, including wind and temperature, can affect $PM_{2.5}$ air pollution concentration (Hien et al., 2002). In this section, the influences of wind speed and temperature on $PM_{2.5}$ concentrations are analyzed for four intersections in Bucaramanga, Colombia.

3.7.1. Wind Speed

In order to analyze the impacts of wind speed in air pollution concentration, the air pollution concentration estimated based on observed wind data is compared with the air pollution concentration estimated based on three times higher and three times lower of the observed wind data. All other input data, including traffic volume and other meteorological data, are kept constant. The results for $PM_{2.5}$ air pollution concentration obtained are shown in Figure 3.28.

As observed, AERMOD is highly sensitive to wind conditions. The air pollution concentration estimated based on observed wind data (10.21 µg/m^3 for peak hours, La Concordia) is almost four times the air pollution concentration estimated based on three times higher of the observed wind data (2.53 µg/m^3 for peak hours, La Concordia) and the air pollution concentration estimated based on three times lower of the observed wind data(13.06 µg/m^3 for peak hours, La Concordia) is almost 1.3 times the observed wind data due to the speed of transport of pollutants away from the modelling receptor location. This implies that wind speed is a critical factor in pollutant dispersion.

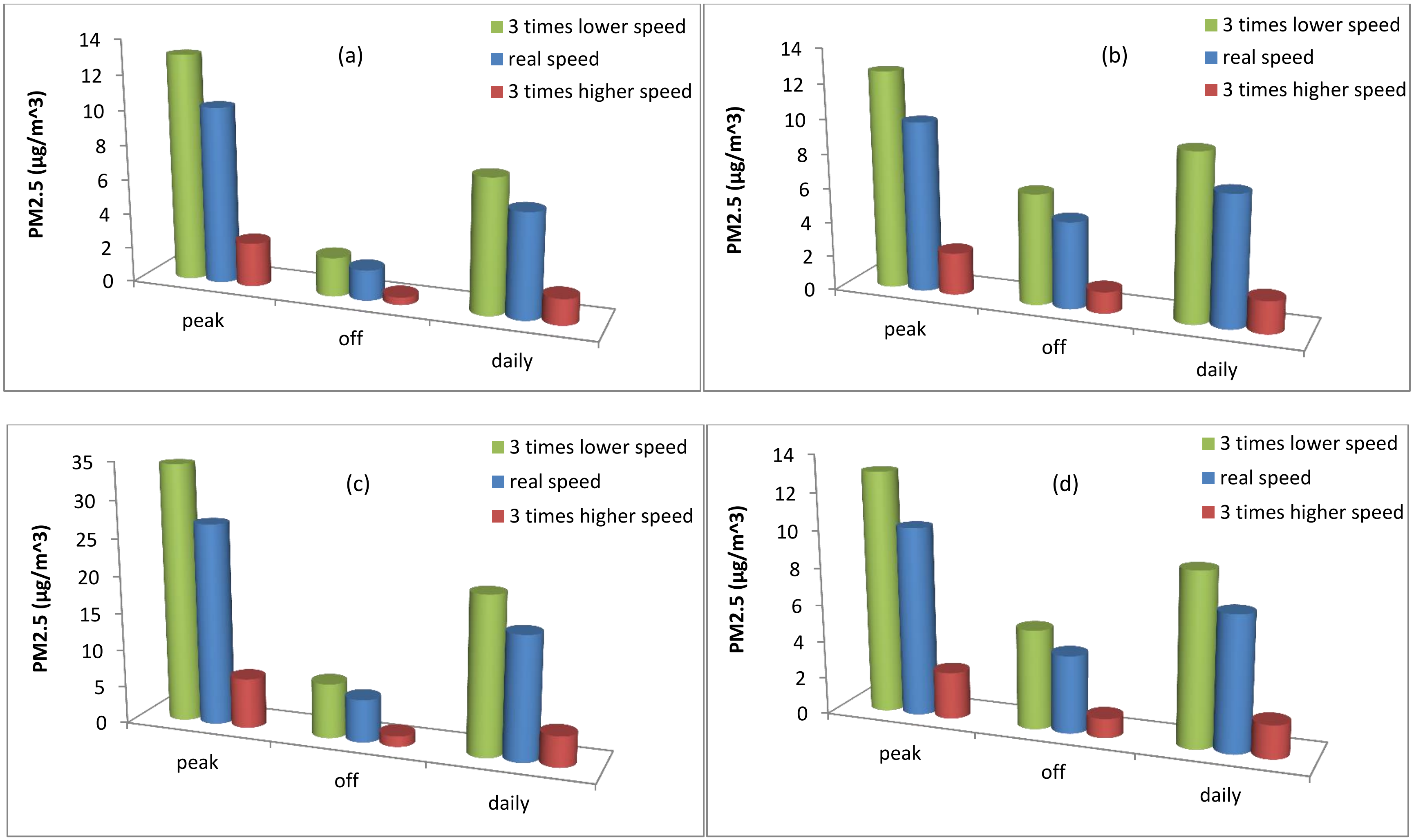


Figure 3.27 $PM_{2.5}$ Concentrations Estimated Based on Real, Three Times Higher and Three Times Lower Wind Speed in (a) La Concordia; (b) La Joya; (c) La Provenza; (d) La Alto

3.7.2. Temperature

In order to analyze the influence of temperature in air pollution concentration, I estimate the $PM_{2.5}$ air pollution concentration based on the temperature of 31°C and 17°C (highest and lowest temperature in Bucaramanga) compared to the air pollution concentration estimated based on the temperature of June 2018 (22°C on average). All other input data, including traffic volume and other meteorological data, are kept constant. The results obtained are shown in Figure 3.29.

The temperature was observed to have a slightly negative correlation with $PM_{2.5}$ concentration in this study. The air pollution concentration estimated based on real temperature (10.21 µg/m^3 for peak hours, La Concordia) is around 1.002 times the air pollution concentration estimated based on the temperature of 17°C (10.23 µg/m^3 for peak hours, La Concordia) and the air pollution concentration estimated based on the temperature of 31°C (10.17 µg/m^3 for peak hours, La Concordia) is around 1.004 times the air pollution concentration estimated based on real temperature. However, some studies have shown that temperature was positively correlated with $PM_{2.5}$ (Wang & Ogawa, 2015). Therefore, further research on the correlation of temperature on $PM_{2.5}$ concentrations should be carried out.

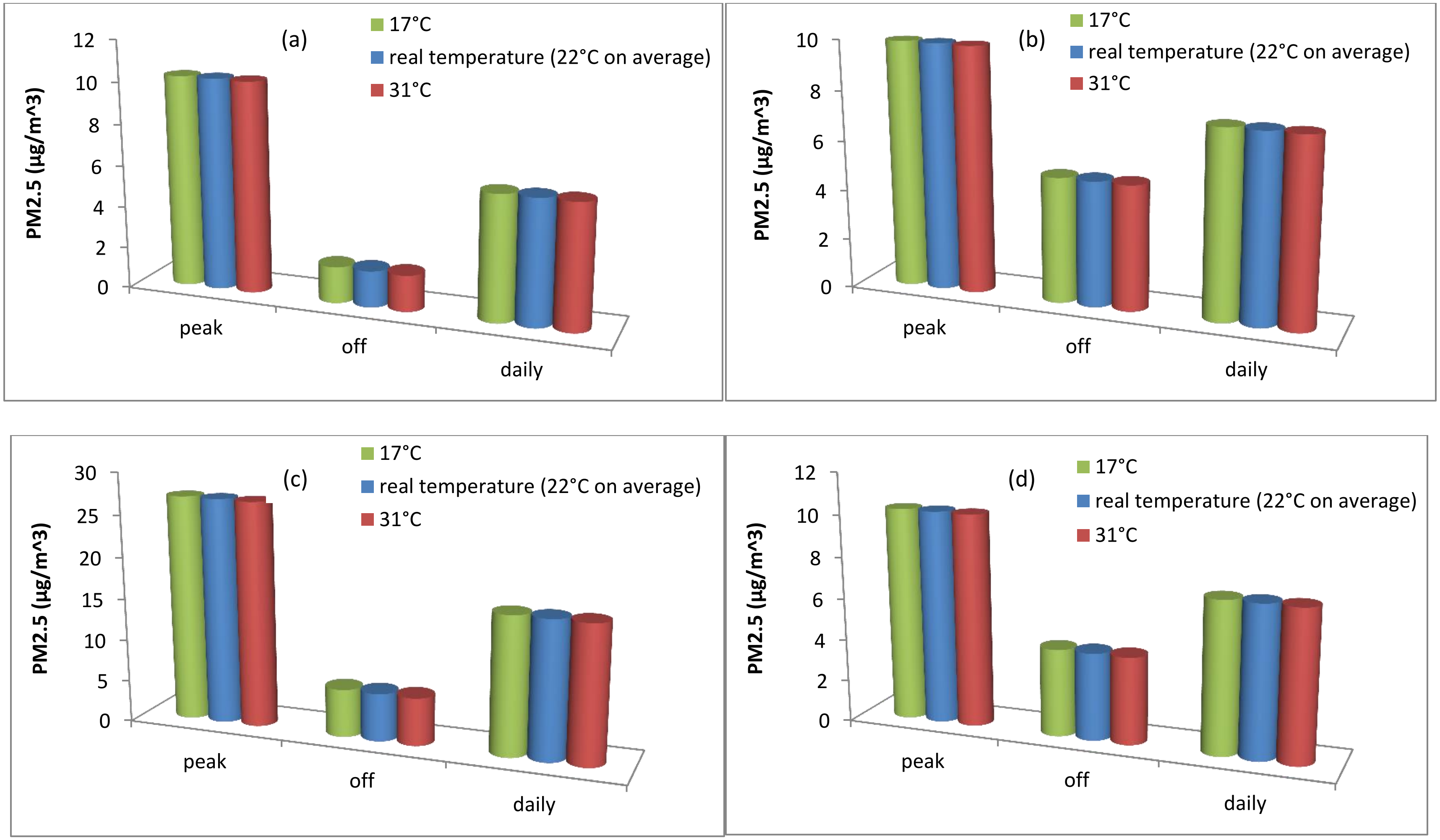


Figure 3.28 $PM_{2.5}$ Concentrations Estimated Based on Real temperature (22°C on average), 17°C and 31°C in (a) La Concordia; (b) La Joya; (c) La Provenza; (d) La Alto

Chapter 4: Conclusion

4.1. Traffic-related Emissions and Costs Estimation

As shown in the literature, vehicular emissions contribute significantly to air quality as well as public health in urban areas (Satran et al., 2006; Mavroidis & Chaloulakou, 2010; Sawyer et al., 2007). However, previous studies (Daher et al., 2018; Lorenzoni & Pidgeon, 2006) have shown that transport users do not perceive their travel-related emission as out of pocket costs. However, travelers prefer emissions' information in monetary values rather than in their own units (tons/grams) (Daher et al., 2018). In the second chapter, I estimated and quantified emissions generated in the Montreal road network for the Montreal transport users. To estimate the health-related costs of emissions, I transformed the emissions rates estimated from MOVES into air pollution concentrations, then converted the concentrations into health outcomes, and finally valuated these health outcomes in monetary terms.

I found several interesting results. First, comparing the emissions rates with speed levels, a strong correlation exists during both peak and off-peak hours, where $PM_{2.5}$, CO and NOx emissions rates decrease with speed until the speed reaches 100km/h, where emissions rates increase slightly with higher speed. In addition, I found that the average off-peak hours $PM_{2.5}$ and NO_x emissions rates (0.045 g/vehicle-km for $PM_{2.5}$, 0.950 g/vehicle-km for NOx) are around three times greater than those of peak hours (0.0186 g/vehicle-km for $PM_{2.5}$ and 0.398 g/vehicle-km for NO_x). This can be explained by the composition of the vehicle fleet in each time period since trucks represent a relatively higher percentage in the mixture during off-peak hours. However, for the CO emission, the average rate for peak hours is higher than the off-peak hours rate (1.63 g/vehicle-km for peak hours and 1.35 g/vehicle-km for off-peak hours) it might because of the fact that diesel-fueled combustion engines produce lower levels of carbon monoxide than gasoline-fueled engines; heavy trucks (diesel fuel combustion) represent 8% of the vehicle mix during off-peak hours as opposed to 3% during peak hours. Therefore, the higher passenger car mixture (gasoline engines) during peak hours results in a higher CO emission rate during peak hours (Geneva: World Health Organization, 2015).

I also compared the emissions rates of January with those of October as the Montreal weather could act as another important factor in affecting emissions rates (Frey et al., 2003). My results show that $PM_{2.5}$, CO and NO_x emissions rates are very similar in size for both months. This is partly due to the only difference between the two cases is the average weather inputs. The travel demand data is assumed the same for all months, based on an O-D survey conducted in fall 2008.

Moreover, I also examined the geographical distributions of emissions (and their costs) in the Montreal area. Among three health-related emissions costs, NO_x has the highest emission cost (up to 0.38 $/km), followed by $PM_{2.5}$ (0.31 $/km) and CO (0.0074 $/km) during peak hours. In addition, the downtown and Plateau areas have the highest emissions cost for all these emission types. The emissions costs (0.3$/km) in these areas are almost 40 times the costs of driving in the east-western boroughs of Montreal (0.0074$/km).

In addition, I compared the geographical distribution of peak-hours total health-related emission costs ($PM_{2.5}$ and NO_x) with climate change costs (CO_{2eq}) in January 2017 in Montreal, and found out that health-related emission cost is relatively higher than CO_{2eq} emission cost. However, my results show that the overemphasis on climate change implications of transportation seems to be misleading, mainly because I excluded many other vehicular air pollution types (CO, VOC, etc.) from my analysis, and those would widen the gap.

4.2. Air pollution dispersion modelling

As previously mentioned in Chapter 2, my assumption for the Montreal case study was to transform emissions (tons) into air pollution concentrations based on a constant ratio approach. However, the assumption cannot provide accurate results. Therefore, a dispersion model is required to simulate the movement of air pollutants in a given region. In the third chapter, I applied a dispersion model (AERMOD) along with MOtor Vehicle Estimation Simulator (MOVES) to estimate the traffic-related air pollution concentration distribution for four intersections in Bucaramanga, Colombia.

Several interesting results emerge. First, the higher vehicle volume, the higher the emission rates for both $PM_{2.5}$ and Black Carbon, except when heavy trucks are high in numbers. In addition, emissions are higher during peak hours compare to off-peak hours, which is mainly due to the larger vehicle volume observed during peak hours. Furthermore, Black Carbon emissions are lower in size than $PM_{2.5}$ emissions. The intersection located in La Provenza generates the highest $PM_{2.5}$ (90g/h during peak hours and 16g/h during off-peak hours) and Black Carbon (15g/h during peak hours and 3g/h during off-peak hours).

Considering the air pollution concentration estimated from AERMOD, I found that the concentrations are highest along the most heavily traveled links among the intersections. Peak-hours traffic volumes generate a relatively higher air pollution concentration than those of off-peak hours for both $PM_{2.5}$ and Black Carbon, in most cases more than twice. Moreover, the $PM_{2.5}$ and Black Carbon concentrations drop off substantially when moving away from the intersection centers, and then gradually decrease after 50 meters.

In addition, the real-time $PM_{2.5}$ and Black Carbon air pollution concentrations are measured using the equipment located on the second-floor balcony or the roof of buildings in four intersections. Using such measurements, I compared the real observations with my modelled estimations for four intersections. Overall, the proposed set of models captures most of the general trends in $PM_{2.5}$ and Black Carbon. However, the estimated $PM_{2.5}$ concentration for one intersection in La Joya is much less than the observation. This intersection is close to the industrial zone in Bucaramanga even though I included some industrial sources in this study. Also note that the predicted concentrations are less than the observations, and this is due to the fact that not only on-road mobile sources and industrial sources can affect air pollution concentration, many other factors can also affect the results including emissions generated by people's daily activities, the relatively old vehicle fleet in Colombia (different from MOVES's fleet), etc.

Sensitivity analyses are undertaken in this study to better understand the behavior of the AERMOD dispersion model in estimating $PM_{2.5}$ concentrations when input data altered. As observed, AERMOD is highly sensitive to wind conditions. The air pollution concentration estimated based on observed wind data (10.21 µg/m^3 for peak hours, La Concordia) is almost four times the air pollution concentration estimated based on three times higher of the observed wind data (2.53 µg/m^3 for peak hours, La Concordia) and the air pollution concentration estimated based on three times lower of the observed wind data(13.06 µg/m^3 for peak hours, La Concordia) is almost 1.3 times the observed wind data due to the speed of transport of pollutants away from the modelling receptor location. The temperature was observed to have a slightly negative correlation with $PM_{2.5}$ concentration in this study. The air pollution concentration estimated based on real temperature (10.21 µg/m^3 for peak hours, La Concordia) is around 1.002 times the air pollution concentration estimated based on the temperature of 17°C (10.23 µg/m^3 for peak hours, La Concordia) and the air pollution concentration estimated based on the temperature of 31°C (10.17 µg/m^3 for peak hours, La Concordia) is around 1.004 times the air pollution concentration estimated based on real temperature. However, some studies have shown that temperature was positively correlated with $PM_{2.5}$ (Wang & Ogawa, 2015). Therefore, further research on the correlation between temperature and $PM_{2.5}$ concentrations should be carried out.

4.3. Research Contributions, Limitations and Future Work

My study suffers from several incomplete assumptions. Both case studies (Montreal, Bucaramanga) could be improved in the future. Regarding the Montreal case study, the estimated emissions rate from the MOVES software for both January and October are based on a fixed travel demand which cannot represent the variations in emissions completely. Therefore, a next research study should consider the variations in demand (summer months are generally more congested in Montreal). In addition, my estimations are based on an average person, an average value of travel time, and an average passenger car feature. All these numbers would be different using personalized characteristics/features (e.g., the car model) In addition, MOVES is developed and calibrated for the US counties and does not represent the vehicle fleet in Montreal. MOVES's limitations could be investigated by comparing the emissions from MOVES with the emissions measured from real on-road driving. However, generally, MOVES's results should be lower than older-age vehicles' emissions and higher than those of fuel efficient vehicles in Montreal.

In order to determine the welfare costs associated with travel-related emissions, in Chapter 2, I used the AQBAT concentration-response functions for the year 2000. The functions should be updated to determine the health endpoints in 2015, precisely. In addition, some of the unit cost values are adopted from national (Canada) or Provincial (Quebec)-based studies, therefore, using these values could lead to emissions costs that are lower than real values/impacts.

For the air-pollution-concentration estimation in Chapter 2, my assumption regarding a constant ratio is simple but effective. However, the concentration changes could vary not only due to emissions generated in that area, but also due to a variety of other factors such as land use configurations, wind speed, humidity, etc.

Therefore, in the third chapter, I applied the AERMOD air pollution dispersion model to estimate the air pollution concentration for Bucaramanga, and compared the concentration with the observed air pollution concentration measured by equipment. In order to map the second-by-second speed profile of each link in the studied intersections, I assumed some links to have a fixed speed profile after moving out of the camera vision, since these links' speed profiles cannot be estimated from the video records. Moreover, one key lesson from my study is that we should use MOVES and similar other software programs with cautious. MOVES is calibrated for the counties located in the United States and not Bucaramanga, Columbia, i.e., the make and model of cars are different. In addition, a detailed locally-calibrated model does not exist. My $PM_{2.5}$ and Black Carbon concentration estimates (from MOVES and AERMOD) are only around 70% of the measured concentration levels by the equipment, mainly because of the relatively older vehicle fleet in Colombia than those of Leon. Furthermore, other factors that can affect air pollution concentrations are not taken into consideration, factors such as the rainfall intensity, changes in temperature/humidity (over a day), the impact of the area size (radius), etc. Further research is required to provide more accurate air pollution concentration estimations for the studied areas.

Appendix A: Emission vs Traffic Volume for Intersections in Bucaramanga (50 and 100 meter radius)

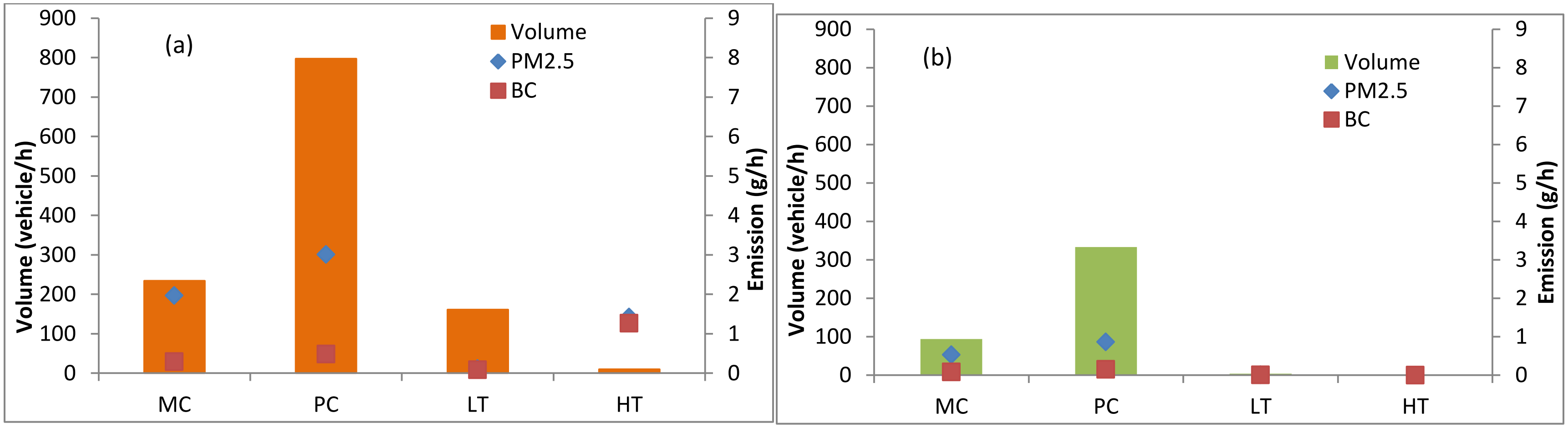


Figure 1 La Concordia Intersection (50 meter radius) Emission vs Volume for (a) Peak Hours; (b) Off-peak Hours

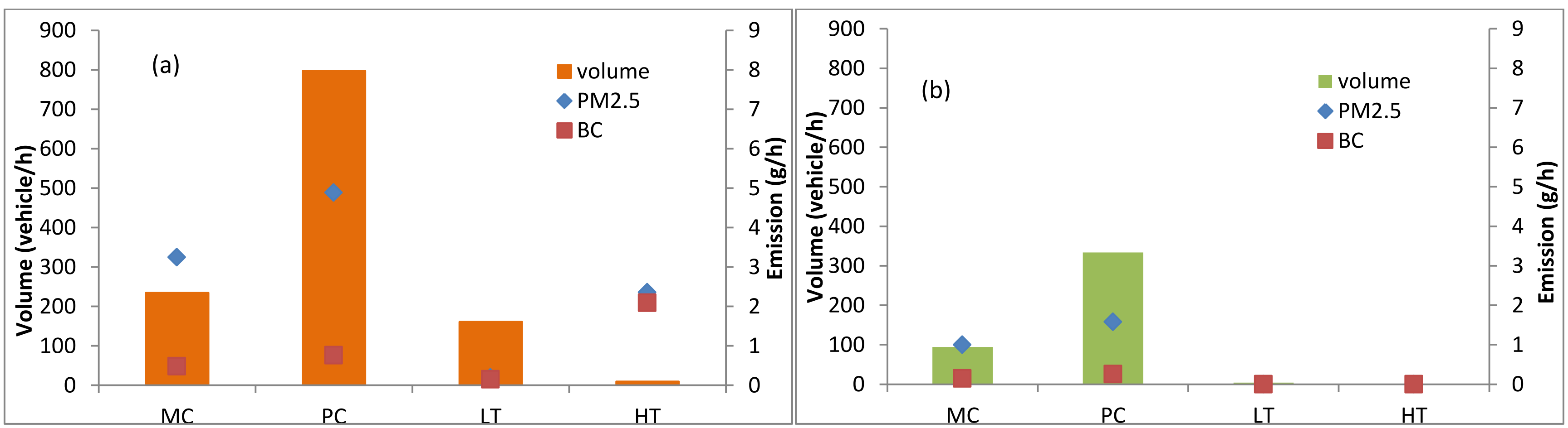


Figure 2 La Concordia Intersection (100 meter radius) Emission vs Volume for (a) Peak Hours; (b) Off-peak Hours

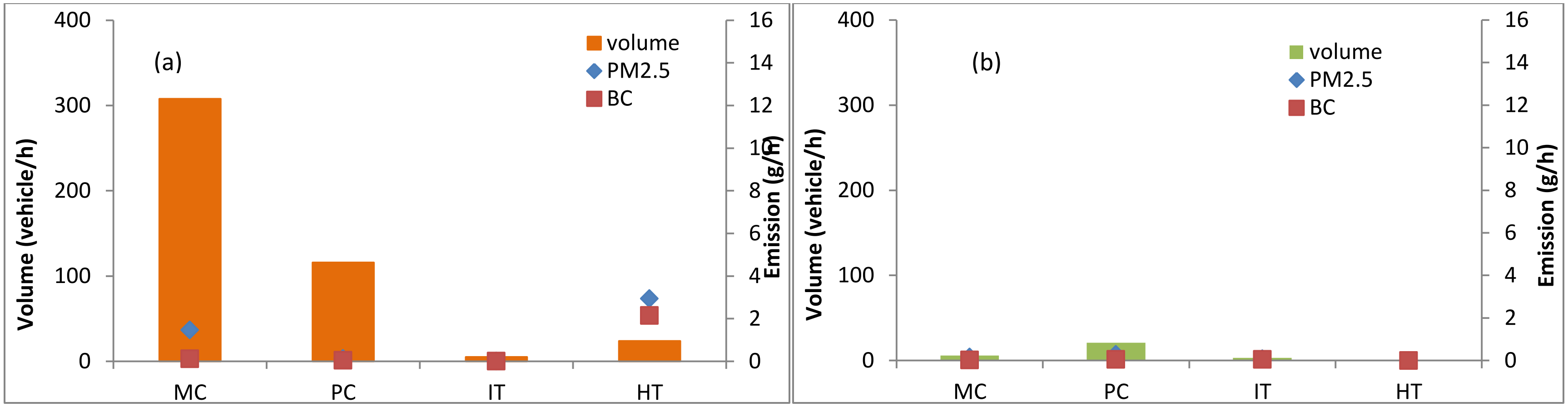


Figure 3 La Joya Intersection (50 meter radius) Emission vs Volume for (a) Peak Hours; (b) Off-peak Hours

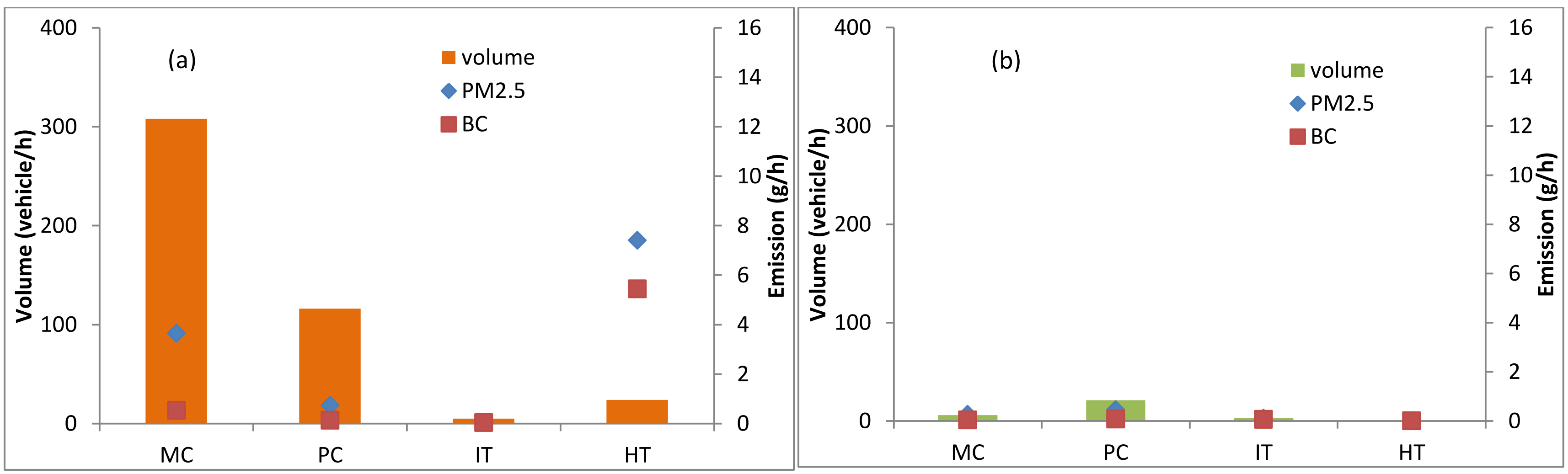


Figure 4 La Concordia Intersection (100 meter radius) Emission vs Volume for (a) Peak Hours; (b) Off-peak Hours

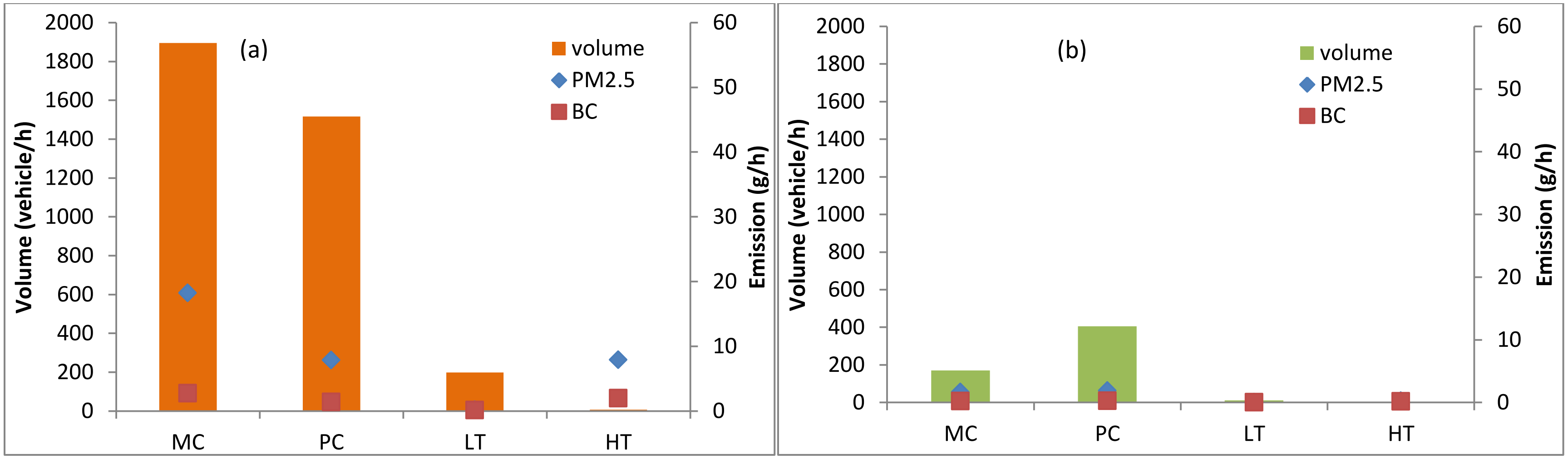


Figure 5 La Provenza Intersection (50 meter radius) Emission vs Volume for (a) Peak Hours; (b) Off-peak Hours

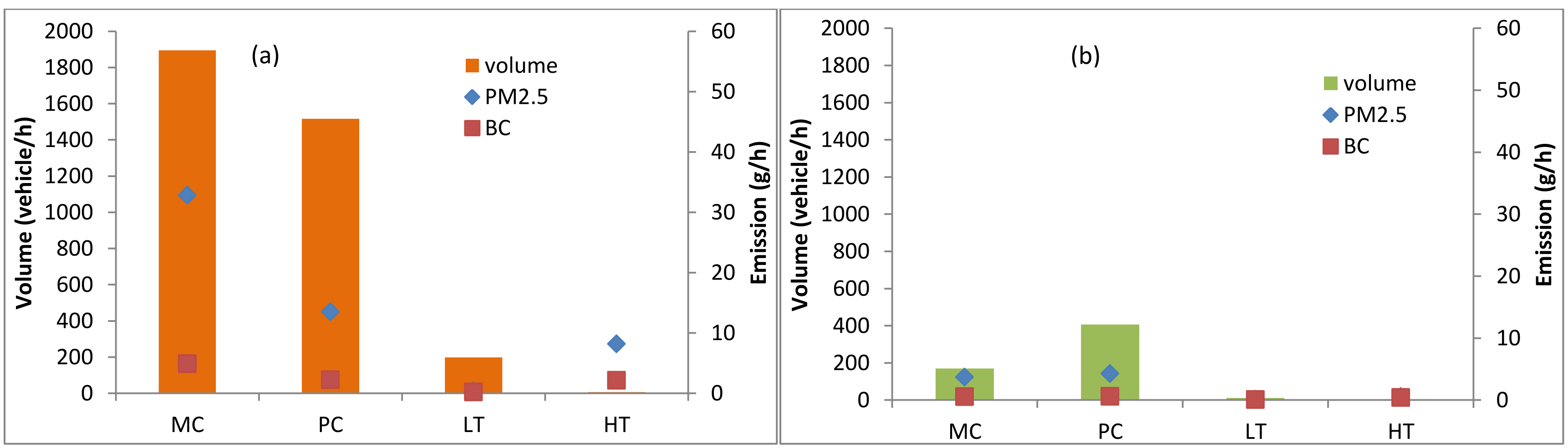


Figure 6 La Provenza Intersection (100 meter radius) Emission vs Volume for (a) Peak Hours; (b) Off-peak Hours

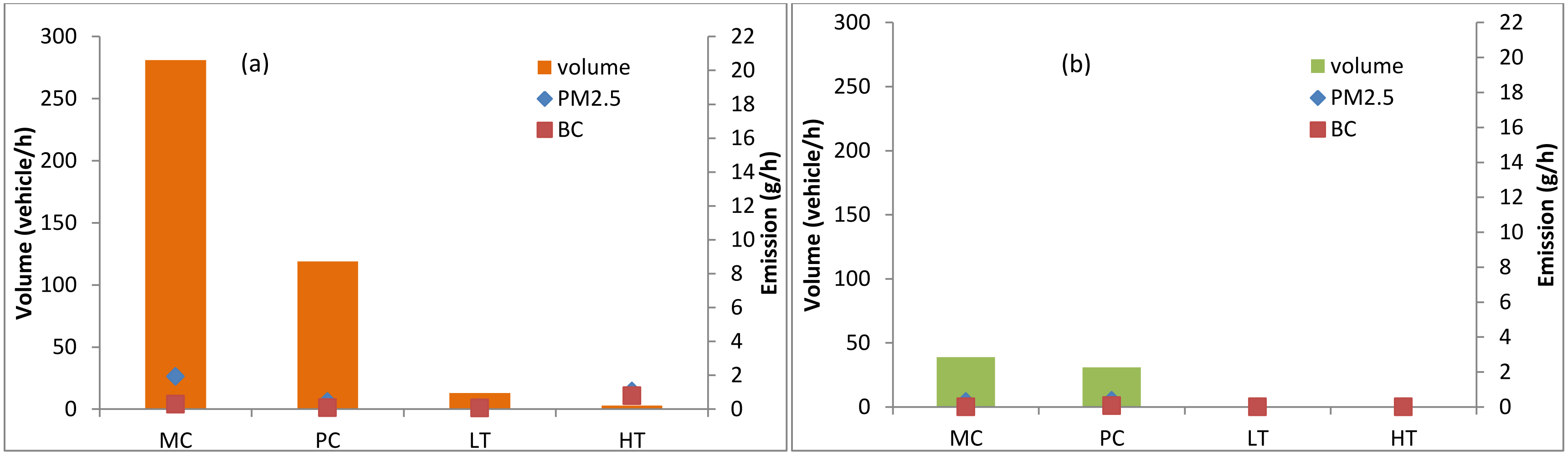


Figure 7 La Alto Intersection (50 meter radius) Emission vs Volume for (a) Peak Hours; (b) Off-peak Hours

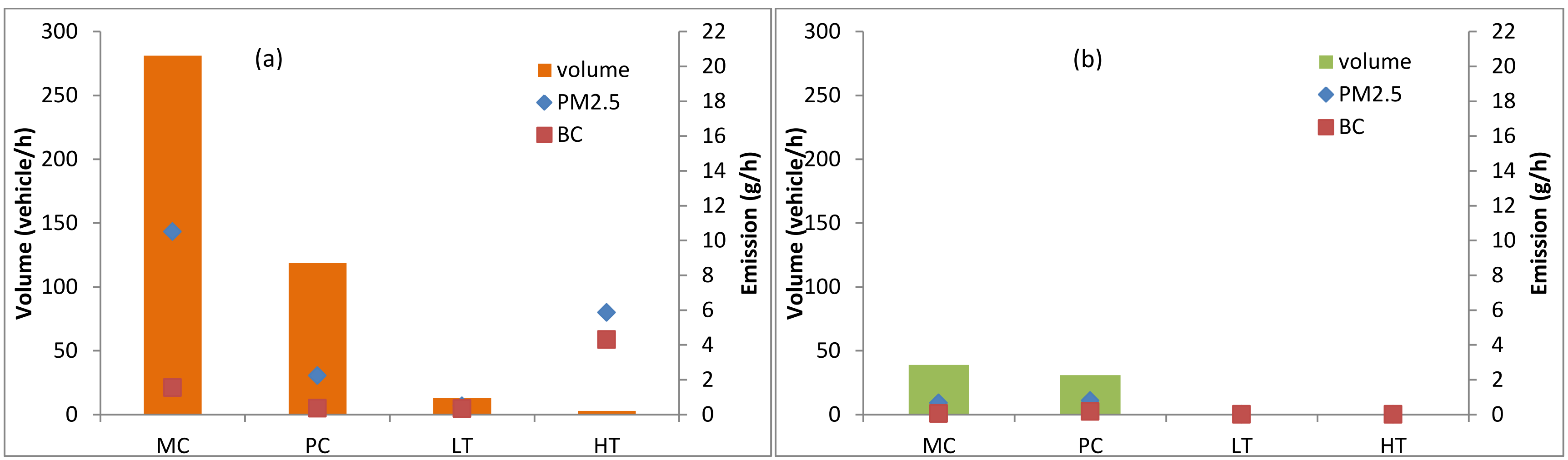


Figure 8 La Alto Intersection (50 meter radius) Emission vs Volume for (a) Peak Hours; (b) Off-peak Hours

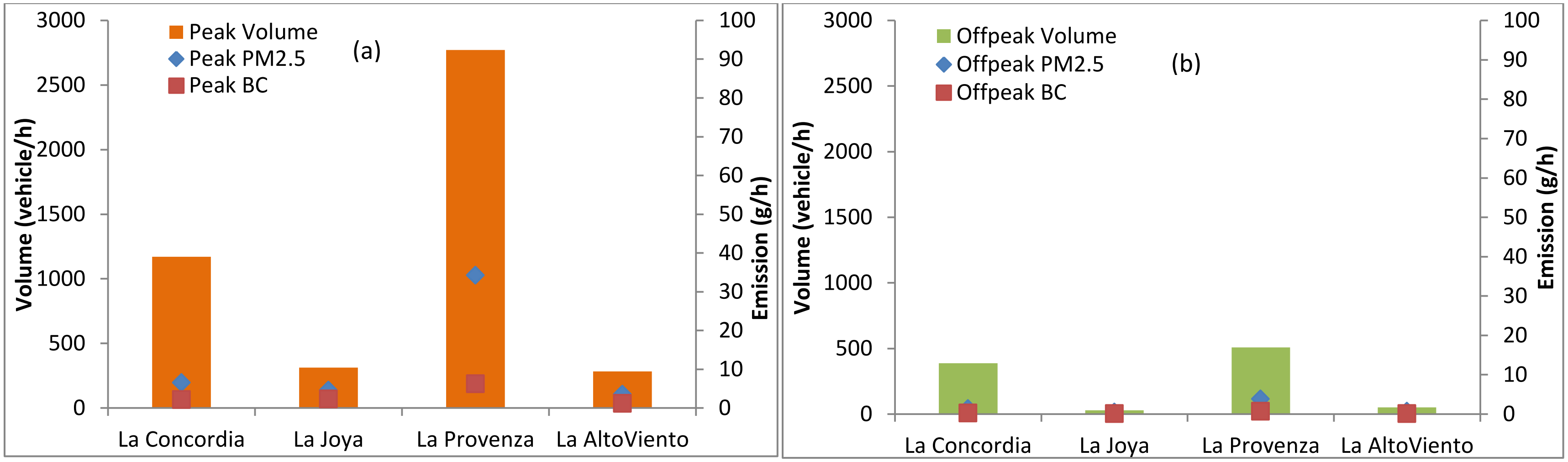


Figure 9 Total Emissions vs Volumes on Four Intersections (50-meter radius) for (a) Peak Hours; (b) Off-peak Hours

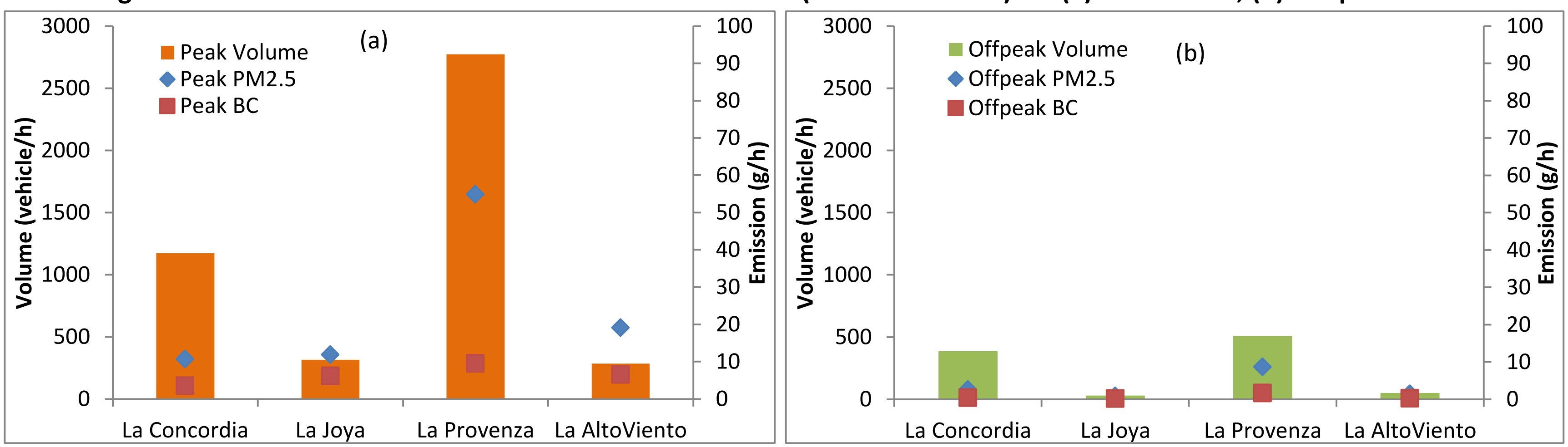


Figure 10 Total Emissions vs Volumes on Four Intersections (100-meter radius) for (a) Peak Hours; (b) Off-peak Hours

Bibliography

Abou-Senna, H., & Radwan, E. (2013). VISSIM/MOVES integration to investigate the effect of major key parameters on CO2 emissions. *Transportation Research Part D: Transport and Environment, 21, 39-46.*

Alam, A., & Hatzopoulou, M. (2017). Modeling Transit Bus Emissions Using MOVES : Comparison of Default Distributions and Embedded Drive Cycles with Local Data. *Journal of Transportation Engineering, Part A: Systems, 143(10), 04017049.*

Alvarez, J. A., Quiñones, E., & Álvarez, V. (2018). Estimating the Emission Factor For Different Vehicles In The City Of Cartagena De Indias, Columbia. *Air Pollution XXVI.*

Bank of Canada. (2019). Inflation Calculator. Retrived form https://www.bankofcanada.ca/rates/related/inflation-calculator/.

Boldo, E., Linares, C., Lumbreras, J., Borge, R., Narros, A., García-Pérez, J., & Ramis, R. (2011). Health impact assessment of a reduction in ambient PM2.5 levels in Spain. *Environment International, 37(2), 342-348.*

Bowker, G. E., Baldauf, R., Isakov, V., Khlystov, A., & Petersen, W. (2007). The effects of roadside structures on the transport and dispersion of ultrafine particles from highways. *Atmospheric Environment, 41(37), 8128-8139.*

Brode, R.W. & Anderson, B. (2008). Technical Issues Related to Use of the CALPUFF Modeling System for Near-field Applications. *Environmental Protection Agency.* Retrieved from http://www.epa.gov/scram001/7thconf/calpuff/calpuff_nearfield_technical_issues_092608.pdf.

Brook, R., Rajagopalan, S., & Pope,C.(2010). American Heart Association Council on Epidemiology and Prevention, Council on the Kidney in Cardiovascular Disease, and Council on Nutrition, Physical Activity and Metabolism. *Particulate matter air pollution and cardiovascular disease: an update to the scientific statement from the American Heart Association. Circulation. 2010, Vol. 121, P. 2331–2378.*

Brunekreef, B., & Holgate, S.T. (2002). Air pollution and health. *Lancet 2002, 360, 1233–42.*

Buckeridge, D. L., Glazier, R., Harvey, B. J., Escobar, M., Amrhein, C., & Frank, J. (2002). Effect of motor vehicle emissions on respiratory health in an urban area. *Environmental Health Perspectives, 110(3), 293-300.*

Burnett, R.T., Cakmak, S. & Brook, J.R. (1998). The Effect of the Urban Ambient Air Pollution Mix on Daily Mortality Rates in 11 Canadian Cities. *Public Health, 89, 152.*

California Environmental Protection Agency. (2010). EMFAC Release, Moving Cooler: An Analysis of Transportation Strategies for Reducing Greenhouse Gas Emissions (Executive Summary). *Cambridge Systematics I, 2009.*

Chen, H., Goldberg, M. S., Burnett, R. T., Jerrett, M., Wheeler, A. J., & Villeneuve, P. J. (2013). Long-Term Exposure to Traffic-Related Air Pollution and Cardiovascular Mortality. *Epidemiology, 24(1), 35-43.*

Chen, H., Goldberg, M., & Villeneuve, P. (2008). A systematic review of the relation between long-term exposure to ambient air pollution and chronic diseases. *Environment Health. 2008, 23, 243–297.*

Chen, K., & Yu, L. (2007). Microscopic Traffic-Emission Simulation and Case Study for

Chestnut, L. G., Rowe, R. D., & Breffle, W. S. (2011). Economic Valuation Of Mortality-Risk Reduction: Stated Preference Estimates From The United States And Canada. *Contemporary Economic Policy, 30(3), 399-416.*

Cohen, A. J., Brauer, M., Burnett, R., Anderson, H. R., Frostad, J., Estep, K., & Forouzanfar, M. H. (2017). Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: An analysis of data from the Global Burden of Diseases Study 2015. *The Lancet, 389(10082), 1907-1918.*

Daher, N., Yasmin, F., Wang, M. R., Moradi, E., & Rouhani, O. (2018). Perceptions, Preferences, and Behavior Regarding Energy and Environmental Costs: The Case of Montreal Transport Users. *Sustainability, 10(2), 514.*

Edward, C., Ang-Olson. J, Rosenbaum. A. (2014). Effects of Transportation Emissions on Air Quality in Southeast Los Angeles County, *Transportation Research Board 93rd Annual Meeting.*

Direccion de transito. (2018). Requisitos de tranmites de vehiculos. Retrieved from https://www.transitobucaramanga.gov.co/requisitos_tramites.php.

Emisia, 2011. COPERT 4, Computer programme to calculate emissions from road transport, 628. Retrieved from http://www.emisia.com/copert.

Environmental Assessment Report. (2017). AIR QUALITY IN MONTRÉAL. Retrieved from http://ville.montreal.qc.ca/pls/portal/docs/page/enviro_fr/media/documents/vdm_bilanqualiteair_2017_en.pdf.

Environment Canada. (2012). National Pollutant Release Inventory (NPRI), CAC Trends. Retrieved 2011 December, from http://www.ec.gc.ca/inrpnpri/default.asp?lang=En&n=4A577BB9-1.

Environment and Climate Change Canada. (2015). *1990-2015 Air Pollutant Emission Inventory Report.* Retrieved from https://www.ec.gc.ca/pollution/A17452DA-CFC0-4222-985F-36B12FCBAA0B/APEI2017-E-Feb%2015%202017.pdf.

Environment and Climate Change Canada. (2016). Canadian Environmental Sustainability Indicators: Air Pollutant Emissions; *Environment and Climate Change Canada: Ottawa, ON, Canada, 2016; pp. 7–22.*

Environment and Climate Change Canada. (2016a). Canadian Environmental Sustainability Indicators: Air Pollutant Emissions. Environment and Climate Change Canada Retrieved from http://www.ec.gc.ca/indicateurs-indicators/default.asp?lang=en&n=E79F4C12-.

Environment and Climate Change Canada.(2017). Canadian Environmental Sustainability Indicators: Greenhouse Gas Emissions; *Environment and Climate Change Canada: Ottawa, ON, Canada, 2017; p. 8.*

Environmental Protection Agency. (2012). Air Quality Dispersion Modeling - Preferred and Recommended Models. Retrieved from https://www.epa.gov/scram/air-quality-dispersion-modeling-preferred-and-recommended-models.

Evaluation of Traffic Control Strategies. *Journal of Transportation Systems Engineering and Information Technology, 7(1), 93-100.*

Frey, H. C., Unal, A., Rouphail, N. M., & Colyar, J. D. (2003). On-Road Measurement of Vehicle Tailpipe Emissions Using a Portable Instrument. *Journal of the Air & Waste Management Association, 53(8), 992-1002.*

Geneva: World Health Organization, (2015). Diesel and gasoline engine exhausts and some nitroarenes. Retrived from https://monographs.iarc.fr/wp-content/uploads/2018/06/mono105.pdf.

Geroliminis, N., & Skabardonis, A. (2006). Real Time Vehicle Reidentification and Performance Measures on Signalized Arterials. *2006 IEEE Intelligent Transportation Systems Conference.*

Gibson, M. D., Kundu, S., & Satish, M. (2013). Dispersion model evaluation of PM2.5, NOx and SO2 from point and major line sources in Nova Scotia, Canada using AERMOD Gaussian plume air dispersion model. *Atmospheric Pollution Research, Column. 4, P. 157-167.*

Gilangould, G. M. (2015). A new approach for evaluating regional exposure to particulate matter emissions from motor vehicles. *Transportation Research Part D: Transport and Environment, Vol. 34, Page. 307-317.*

Gómez, J., Montes, N.E., Nivia, Á. & Diederix, H., compilers. 2015. Geological Map of Colombia 2015.

Government of Canada, 2017. Air Quality Benefits Assessment Tool (AQBAT). Retrived from http://science.gc.ca/eic/site/063.nsf/eng/h_97170.html.

Grabow, M., Spak, S., Holloway, T., Stone, B., Mednick, A., & Patz, J. (2012). Air Quality and Exercise-Related Health Benefits from Reduced Car Travel in the Midwestern United States. *Epidemiology, 23, P-249.*

Hao, J., He, D., Wu, Y., Fu, L., & He, K. (2000). A study of the emission and concentration distribution of vehicular pollutants in the urban area of Beijing. *Atmospheric Environment, Vol. 34(3).*

Hastie, T., & Tibshirani, R. (1990). Generalized Additive Models*. London, U.K.: Chapman and Hall, 1990.*

Hien, P., Bac, V., Tham H., Nhan, D., Vinh, L. (2002). Influence of meteorological conditions on PM2.5 and PM2.5-10 concentrations during the monsoon season in Hanoi, Vietnam. *Atmosphere. Environment. 2002, 36: 3473-3484.*

Indra, E., Sinha, N. K., Mrinal, G., Gurdeep, S., Smriti, S., & Indranath, S. (2004). *CLASSIFICATION OF AIR POLLUTION DISPERSION MODELS: A CRITICAL REVIEW. 19-20.*

Johnson, F. R., Fries, E. E., & Banzhaf, H. S. (1997). Valuing morbidity: An integration of the willingness-to-pay and health-status index literatures. *Journal of Health Economics, 16(6), 641-665.*

Jungers, B., Kear, T., & Eisinger, D. (2006). A Survey of Air Quality Dispersion Models for Project-Level Conformity Analysis. *Prepared for The California Department of Transportation.*

Kean, A. J., Harley, R. A., & Kendall, G. R. (2003). Effects of Vehicle Speed and Engine Load on Motor Vehicle Emissions. *Environmental Science & Technology, 37(17), 3739-3746.*

Koupal, J., Michaels, H., Gumberworth, M., Bailey, C., & Brzezinski, D. (2002). EPA's plan for MOVES: a comprehensive mobile source emissions workshop. *Proceedings of the 12th CRC on-road vehicle emission workshop, San Diego, CA; 2002*.

Lake Environmet. (2019). Air dispersion modeling. Retrived from https://www.weblakes.com/products/air_dispersion.html.

Lee, G., You, S., Ritchie, S. G., Saphores, J., Jayakrishnan, R., & Ogunseitan, O. (2012). Assessing air quality and health benefits of the Clean Truck Program in the Alameda corridor, CA. *Transportation Research Part A: Policy and Practice, 46(8), 1177-1193.*

Lorenzoni, I., and N. F. Pidgeon. Public Views on Climate Change: European and USA 539 Perspectives. *Climate Change, Vol. 77, Issue 1-2, 2006, pp. 73–95.*

Louis-François Tétreault. (2018). Estimating the health benefits of planned public transit investments in Montreal. *Environmental Research,160, 412–419*.

Marshall W. F. & Eccleston B. H. (1980). Emissions at off ambient temperature. *SAE 800512. Society of Automotive Engineers, Inc., 400 Commonwealth Drive, Warrendale. PA.*

Mavroidis, I., & Chaloulakou, A. (2010). Characteristics and expected health implications of annual PM10 concentrations in Athens, Greece. *International Journal of Environment and Pollution, 41(1/2), 124.*

Mccubbin, D. R., & Delucchi, M. A. (2003). The Health Effects of Motor Vehicle-Related Air Pollution. *Handbook of Transport and the Environment Handbooks in Transport, 411-427.*

Miller, K., Siscovick, D., & Sheppard, L. (2007). Long-term exposure to air pollution and incidence of cardiovascular events in women. *The New England Journal of Medicine. 2007, 356, 447–458.*

Misra, A., Roorda, M. J., & Maclean, H. L. (2013). An integrated modelling approach to estimate urban traffic emissions. *Atmospheric Environment, 73, 81-91.*

Noland, R., & Quddus, M. (2006). Flow improvements and vehicle emissions: Effects of trip generation and emission control technology. *Transportation Research D, 11(1), 1-14.*Moulvi, I. (2010). Driver behavior variability and its effect on vehicle exhaust emissions. *Proceedings of the Air and Waste Management Association's 103rd Annual Conference and Exhibition, AWMA, 5, pp. 4121-4138. Calgary.*

Ntziachristos, L., & Samaras, Z. (2000). COPERT III Computer programme to calculate emissions from road transport. Methodology and emission factors (Version 2.1). *Technical Report, vol. 49. Copenhagen: European Environment Agency; 2000.* Retrieved from: https://www.eea.europa.eu/publications/Technical_report_No_49.

Okui, N. (2017). Estimation of Fuel Economy and Emissions for Heavy-Duty Diesel Plug-In Hybrid Vehicle with Electrical Heating Catalyst System. *SAE Technical Paper Series.*

Papson, A., Hartley, S., & Kuo, K. (2012). Analysis of Emissions at Congested and Uncongested Intersections with Motor Vehicle Emission Simulation 2010. *Transportation Research Record: Journal of the Transportation Research Board, 2270, 124-131.*

Parent, M., Goldberg, M. S., Crouse, D. L., Ross, N. A., Chen, H., Valois, M., & Liautaud, A. (2013). Traffic-related air pollution and prostate cancer risk: A case–control study in Montreal, Canada. *Occupational and Environmental Medicine, 70(7), 511-518.*

Pervin, T., Gerdtham, U. G., & Lyttkens, C. H. (2008). Societal costs of air pollution-related health hazards: A review of methods and results. *Cost effectiveness and resource allocation : C/E*, *6*, 19.

Pope, C., & Dockery, D. (2006). Health effects of fine particulate air pollution: lines that connect. *Air Waste Management Association. 2006, Vol.56, P. 709–742.*

Rouhani, O.M., Geddes, R., Gao, O., Bel, G. (2016). Social Welfare Analysis for Alternative Investment Public-Private Partnership Approaches. *Transportation Research Part A, 88, pp. 86-103,* retrived from http://dx.doi.org/10.1016/j.tra.2015.11.003.

Rowangould, G. M. (2015). A new approach for evaluating regional exposure to particulate matter emissions from motor vehicles. *Transportation Research Part D: Transport and Environment, Vol. 34, Page. 307-317.*

Sacks, J. D., Lloyd, J. M., Zhu, Y., Anderton, J., Jang, C. J., Hubbell, B., & Fann, N. (2018). The Environmental Benefits Mapping and Analysis Program – Community Edition (BenMAP–CE): A tool to estimate the health and economic benefits of reducing air pollution. *Environmental Modelling & Software, 104, 118-129.*

Satran, D., Henry, C., & Adkinson, C. (2006). Cardiovascular Manifestations of Moderate to Severe Carbon Monoxide Poisoning. *Annalysis of Emergency Medicine, 47(3), 298.*

Sawyer, D., & S. Stiebert. Evaluation of Total Cost of Air Pollution Due to Transportation in Canada. *Final Report. March 30, 2007.*

Shekarrizfard, M., Faghih-Imani, A., Tétreault, L., Yasmin, S., Reynaud, F., Morency, P., Hatzopoulou, M. (2017). Regional assessment of exposure to traffic-related air pollution: Impacts of individual mobility and transit investment scenarios. *Sustainable Cities and Society, 29, 68-76.*

Shen, X., Yao, Z., Zhang, Q., Wagner, D. V., Huo, H., Zhang, Y., & He, K. (2015). Development of database of real-world diesel vehicle emission factors for China. *Journal of Environmental Sciences, 31, 209-220.*

Statistics Canada. (2017). *Vehicle Registration*. Ottawa: Statistics Canada. Retrieved from https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=2310006701.

Time and data. (2018). Past Weather in Bucaramanga, Colombia. Retrieved from https://www.timeanddate.com/weather/colombia/bucaramanga/historic.

US Department of Transportation. (2016). Revised Departmental Guidance on Valuation of a Statistical Life in Economic Analysis from https://www.transportation.gov/office-policy/transportation-policy/revised-departmental-guidance-on-valuation-of-a-statistical-life-in-economic-analysis.

Vallamsundar, S., & Lin, J. (2011). MOVES vs MOBILE: A Comparison of GHG and Criteria Pollutant Emissions. *Transportation Research Record(2233), 27-35.*

Voorhees, A. S., Wang, J., Wang, C., Zhao, B., Wang, S., & Kan, H. (2014). Public health benefits of reducing air pollution in Shanghai: A proof-of-concept methodology with application to BenMAP. *Science of The Total Environment, 485-486, 396-405.* http://www.bv.transports.gouv.qc.ca/mono/1022480.pdf. Accessed on 3 January 2019.

Wang, H., Chen, C., Huang, C., & Fu, L. (2008). On-road vehicle emission inventory and its uncertainty analysis for Shanghai, China. *Science of the Total Environment, 398(1-3), 60-67.*

Wang, J. & Ogawa, S. (2015). Effects of Meteorological Conditions on PM2.5 Concentrations in Nagasaki, Japan. Int. J. *Environment. Resources. Public Health 2015, 12, 9089-9101.*

Weilenmann, M., Soltic, P., Saxer, C., Forss, A., & Heeb, N. (2005). Regulated and nonregulated diesel and gasoline cold start emissions at different temperatures. *Atmospheric Environment, 39(13), 2433-2441.*

World population review. (2019). Population of Cities in Colombia (2019). Retrieved from http://worldpopulationreview.com/countries/colombia-population/cities/.

Zhang, A., Boardman, A. E., Gillen, D., & Waters, W.G. (2004). *Towards Estimating the Social and Environmental Costs.*

Zhang, K., & Batterman, S. (2013). Air pollution and health risks due to vehicle traffic. *Science of The Total Environment, 450-451, 307-316.*

Zhao, X., Zhang, X., Xu, X., Xu, J., Meng, W., & Pu, W. (2009). Seasonal and diurnal variations of ambient PM2.5 concentration in urban and rural environments in Beijing. *Atmospheric Environment, 43(18), 2893-2900.*

Zou, B., Zhan, F.B., Wilson, J.G., Zeng, Y.N. (2010). Performance of AERMOD at different temporal scales. *Simulation Modelling Practice and Theory, Vol. 18, P. 612–623.*