# The Healthiest vs. Greenest Path: Comparing the Effects of Internal and External Costs of Motor Vehicle Pollution on Route Choice

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**Abstract**

On-road emissions, a dominant source of urban air pollution, damage human health. The *healthiest path* and the *greenest path* are proposed as alternative patterns of traffic route assignment to minimize the costs of pollution exposure and emission, respectively. As a proof-of-concept, the framework of a link-based emission cost analysis is built for both internal and external environmental costs and is applied to the road network in the Minneapolis - St. Paul Metropolitan Area based on the EPA MOVES and RLINE models. The healthiest and the greenest paths are skimmed for all work-trip origin-destination pairs and then aggregated into work trip flows to identify the healthier or greener roads in a comparative statics analysis. The estimates show that highways have higher emission concentrations due to higher traffic flow, on which, but that the internal and external emission costs are lower. The emission cost that commuters impose on others greatly exceeds that which they bear. In addition, the greenest path is largely consistent with the traditional shortest path which implies that highways tend to be both greener and shorter (in travel time) for commuters than surface streets. Use of the healthiest path would generate more detours, and higher travel times.

Keywords: Route choice, Traffic assignment, Shortest path, Pollution, Emissions, Exposure, Intake.

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# 1 Introduction

Outdoor urban air pollution is a major risk to health. According to the World Health Organization, urban air pollution is one of the top 15 causes of death globally, and one of the top 10 causes in medium- and high-income countries. Health effects of urban air pollution include respiratory and cardiovascular disease, and adverse birth outcomes. Exposure to high concentration of airborne particle matter (PM) correlates with many adverse respiratory and cardiovascular health problems, as revealed through epidemiological and toxicological studies (e.g. (Dockery, 2001, Pope III et al., 2002)).

Motor vehicles are a dominant source of urban air pollution. As a result of incomplete combustion of fossil fuels, a number of contaminants are released into the environment, including carbon monoxide, hydrocarbons, smog-forming constituents, and particulate matter (PM).

The switch to hybrid, and ultimately electric vehicles, improves the situation, particularly tailpipe emissions, but does not eliminate the pollution problem. With full electrification of the fleet decades away, the need to mitigate the effects of automobile tailpipe pollution remains especially salient. Further, all vehicles also generate particulates where the rubber meets the road, from abrasion processes like tires and brake wear, and road dust resuspension (Charron and Harrison, 2005, Gillies et al., 2001, Lee et al., 2003). Thus, even with electrification, automobile pollution will not disappear, and depending on the types of electric power generation, some pollution may be relocated.

Once emitted into the atmosphere, air pollutants undergo mixing, diffusion, or chemical reactions, the degree of which depends on background concentration, meteorological and geographical conditions, and other local characteristics. Since exposure to significant levels of contaminants harms human health, regulations on air quality and vehicle emissions are employed in many countries. In the United States, metropolitan areas must certify that transportation plans conform to air quality standards which set maximum allowable levels of criteria pollutants (failure to do so results in suspension of federal highway funds).

On-road emissions are economically costly to human health (Mayeres et al., 1996) including both internal costs due to air pollution intake and external costs, that is, the health damage cost from emitted pollutants imposed on others. These costs depend on the economic value (due to morbidity and mortality) of pollution emissions. The full costs combine the internal and external costs.

There remains uncertainty about the operating characteristics of vehicles which minimize emissions, as this depends on the nature of the vehicle and the driving conditions. There is less uncertainty about exposure, where pollution intake occurs, as traffic counts and individual travel routes are readily employed.

The economic measure of environmental externalities of travel would be lower if travelers took alternative routes with reduced pollution generation and the exposure of others, or personal intake or exposure (Ahn and Rakha, 2007, Lena et al., 2002). In this paper, the *healthiest* path minimizes personal exposure, while the *greenest* path minimizes external pollution costs (due to emissions and general population exposure). We find traffic routing patterns which minimize the costs of air pollution exposure and emissions for individual trips. This kind of analysis could subsequently be iterated with an equilibrium or other traffic assignment procedure to discover routing for all trips, subject to others also using such a routing logic (Daganzo and Sheffi, 1977, Wardrop, 1952). As a proof-of-concept, this study proposes a framework of link-based emission cost analysis, based on the EPA MOVES and RLINE models for on-road and off-road concentration estimates and measures the internal and external emission costs for each link segment on the scale of road network in metropolitan area. Pollution produced by travelers and travelers' pollution intake along various routes could then be estimated as a function of endogenous traffic levels.

Applying the framework in the Minneapolis - St. Paul (Twin Cities) Metro Area, the healthiest and the greenest paths are found for all work trip origin-destinaton (OD) pairs and then aggregated into work trip flows to identify healthier or greener routes. The data, methodology, results and conclusion of this research are shown in sections 2-5 respectively.

# 2 Data

Several sources of data are applied in this study.

The 2011 TomTom speed and road network data was acquired by the research team from the Metropolitan Council, which has licensed the data. The speed data were aggregated and processed based on millions of GPS logging and navigation devices, which were classified based on different time periods: Overnight, Morning Peak Hours (two parts), Mid-Day, Evening Peak Hours (two parts) and Evening. For each period, different speed percentiles from 5th percentile to 95th percentile on each link were measured, in which the 5th percentile speed indicates the fastest 5 percent of speed records (almost the highest speed), while the 95th percentile speed indicates the fastest 95 percent of speed records (almost the lowest speed). This analysis used the 50th percentile (median) speed at morning peak hours (7 am - 9 am ) on each link for the estimation of the shortest travel time path.

The TomTom road network is a GIS shapefile that contains spatial and other information for each link in the Twin Cities. It was used as an input to the project-level of MOVES simulation to estimate the on-road emissions which was then used for concentration estimates based on RLINE dispersion model. In addition, the estimated emission cost and TomTom speed data were joined with the road network to find the healthiest (internal emission cost) path, the greenest (external emission cost) path, and the shortest travel time path respectively.

Surface meteorology data was collected from Minnesota Pollution Control Agency (2013) which describes the hourly surface meteorology for the 5 year period between 2009 and 2013 for Minnesota. It was generated from AERMET and AERMIN models, the meteorological preprocessor for AERMOD (AMS/EPA Regulatory Model) (U.S. Environmental Protection Agency, 2004*b*). As the main input of RLINE model, the meteorology data covers 21 surface stations with attributes of surface friction velocity, the convective velocity scale, the heights of both the convectively-generated and mechanically-generated boundary layer, the Monin-Obhukov length, the surface roughness length, the wind speed and direction at reference height, and that reference height e.g (Snyder and Heist, 2013).

In this study, the concentration estimates were based on the 2013 meteorology data at the Minneapolis - St. Paul International Airport station.

The Longitudinal Employment Household Dynamics (LEHD) Origin-Destination Employment Statistics dataset (LODES7.0) was collected from the United States Census Bureau. It contains the tables of Workplace Area Characteristics (WAC), Residence Area Characteristics (RAC) and Origin and Destination Census blocks for each work trip (US Census Bureau, 2013). LODES data was used to estimate the work trip flows on each link segment with the assumption that each worker in the dataset would select the healthiest path, the greenest path or shortest travel time path, as determined based on current flows.

Minnesota Department of Transportation (MnDOT) roadway condition data includes the pavement quality indicator (PQI), ride quality index (RQI), surface rating (SR), and, most relevant for our analysis, truck percentage ($P$) for highway links in Minnesota from 2000 to 2015. A corresponding shapefile was also provided by MnDOT to locate the data point on the network. Link type source, an important input of MOVES, was established from this data.

An estimate of average annual daily traffic (AADT) for Minnesota (from 2007 to 2014) was collected from the Traffic Volume Program of Minnesota Department of Transportation (MnDOT) (Minnesota Department of Transportation, 2017*a*). This traffic count program estimates AADT for around 33,000 count locations, including trunk highways, county state aid highways (CSAH), county roads (CR) and municipal state aid streets (MSAS). The majority of traffic data are collected by the total short duration count (48 hours) and adjusted by seasonal adjustment factor (and axle correction factor only for trunk highways), based on which the final AADT estimates are determined by AADT Decision Tree and Federal Rounding Conventions. In the Minneapolis - St. Paul Metro area, truck highways are scheduled for traffic counting over a two year period (published in the even years) and the municipalities provide MSAS counts every two or four years based on the municipal traffic counting schedule (Minnesota Department of Transportation, 2016). The seven counties in the Twin Cities update CSAH and CR counts in the odd years.

Minnesota Department of Transportation (2017*b*) provides the several forms of AADT estimates. The GIS shapefile was selected in this study to identify the count locations. The features in the Twin Cities Metro area were selected and joined to the TomTom road network, which was used as an input of MOVES as well.

# 3 Methodology

To overview the methodology detailed below, we apply a project-level of MOVES simulation (Section 3.1) to model the on-road emissions for all the link segments on the road network of the Twin Cities. We then use the RLINE model (Section 3.2) to estimate the on-road and off-road concentrations for each pollutant generated from vehicles. We analyze the internal and external emission costs by measuring the health damage cost of travelers and general population due to exposure (Section 3.3). These three parts give the framework of link-based emission cost analysis. Section 3.4 defines the healthiest and greenest paths mathematically, and Section 3.5 specifies the concept of work trip flow.

## 3.1 MOVES: Pollution Estimation

The Motor Vehicle Emission Simulator (MOVES), developed by United States Environmental Protection Agency (2016), estimates air pollutants, greenhouse gases, and air toxics (Coelho et al., 2014, Lee et al., 2012, Lin et al., 2011, Liu et al., 2013, Mensink and Cosemans, 2008). In contrast with other vehicle emission models such as CMEM (Barth et al., 2000) and VT-Micro (Rakha et al., 2004), MOVES performs quantitative project-level of simulation to estimate the localized emission for different types of pollutants in addition to national and regional level of emission estimation (Lin et al., 2011, United States Environmental Protection Agency, 2015*a*, United States Environmental Protection Agency, 2015*b*).

To identify the healthiest or the greenest paths, we require air pollution estimates for each link segment on the metropolitan road network. We conducted a project level MOVES simulation to estimate the quantity of emitted pollutants and greenhouse gases, including nitrogen oxides ($NO_X$), particulate matter (PM), sulfur dioxide ($SO_2$) and carbon dioxide ($CO_2$).

The inputs to project level simulations, such as meteorology and fuel type, vary across counties. We estimated each county separately and combined their results subsequently for the whole road network. Most of the inputs were set as the defaults specific to time and location, except for the tables of links and link source types, which are described as follows:

- **Links**

  The link table defines the individual roadway link properties: segment length, traffic flow, average speed, and road grade. TomTom data provide segments length, and 50th percentile speed during the morning peak hours (7 am - 9 am ), directly. Traffic flow, vehicles per hour, was extracted from the AADT data by dividing by the AADT to peak period ratio of 6.09, which was computed from the MnDOT's IRIS traffic database for the Twin Cities region (Minnesota Department of Transportation, 2014)). The road grade for all the links were set as 0; future research could improve this with Digital Elevation Model data.

- **Link Source Type**

  Link source type describes the composition of link traffic flow by vehicle type (source type). Observed (i.e. measured) link source type data for each link segment on the Twin Cities road network do not exist.

  MnDOT roadway condition database provides the truck percentage ($P$) on highway link segments in the Twin Cities, for single unit trucks, buses, and combination trucks. Based on the average statewide vehicle classification in Minnesota, the fractions of buses, single unit truck and combination trucks are 0.207, 0.505 and 0.288 respectively (Wilde and Stahl, 2010). Combining the vehicle source type defined in MOVES, Table 1 shows the setting of the vehicle type fraction for different types of trucks on highway links by assuming each sub-category shares the same fraction. While among passenger vehicles, the fractions of cars, trucks and motorcycles are

0.698, 0.292 and 0.001 respectively (Traffic Forecasts and Analysis Section, MnDOT office of Transportation Data and Analysis, 2012).

Truck percentage data on other link segments are not available in the Twin Cities. Wilde and Stahl (2010) proposed to categorize vehicle classifications by average daily traffic ranges. Hence, we estimate a linear regression of truck percentage on the same AADT ranges using the samples of highway links. The results are shown in Table 2. The fraction setting of MOVES-used type then follows the rules shown in Table 1 based on the estimated $P$.

Table 1: Vehicle Type Fraction Setting for Highway Link Segments

| MnDOT use type | Avg Percentage | MOVES use type | Value |
|---|---|---|---|
| Autos, pickups | 1-P | 21.Passenger Cars | 0.698*(1-P) |
| | | 31.Passenger Truck | 0.292*(1-P) |
| | | 11.Motorcycle | 0.010*(1-P) |
| Buses, Trucks w/ Trailers | 0.207*P | 41. Intercity Bus | 0.207*P/3 |
| | | 42. Transit Bus | 0.207*P/3 |
| | | 43. School Bus | 0.207*P/3 |
| Single Unit Truck (SU) | 0.505*P | 51. Refuse Truck | 0.505*P/3 |
| | | 52. Single-Unit Short-Haul Truck | 0.505*P/3 |
| | | 53. Single-Unit Long-Haul Truck | 0.505*P/3 |
| Combination Truck (TST) | 0.288*P | 61. Combination Short-Haul Truck | 0.288*P/2 |
| | | 62. Combination Long-Haul Truck | 0.288*P/2 |

Table 2: Truck Percentage Estimation Based on AADT Range

| Variables | | Estimate | Std. Error | Significance |
|---|---|---|---|---|
| Intercept | | 10.4168 | 0.251 | *** |
| AADT Range | 400-1499 | 0.928 | 0.2677 | *** |
| | 1500–7000 | -1.1968 | 0.261 | *** |
| | >7000 | -2.4428 | 0.2618 | *** |
| $R^2$ | | 0.049 | | |

Note: *** $p < 0.01$

## 3.2 RLINE Dispersion Model

For city-wide estimates, with sufficient information on source emissions and meteorology, dispersion models are well suited to modeling short-term concentration (Gulliver and Briggs, 2011).

Many dispersion models have been proposed in previous studies. The Environmental Protection Agency's (EPA) Regulatory Model (AERMOD) is a steady-state plume model for multiple sources including point, area and volume sources (Cimorelli et al., 2005, U.S. Environmental Protection Agency, 2004*a*). It has the ability to characterize the planetary boundary layer through both surface and mixed layer scaling in air dispersion modeling. AERMOD is more frequently used for stationary sources including industries (Zhai et al., 2016). To simulate line-type source, such as on-road vehicles, AERMOD represents the line source as an elongated area source or a series of volume sources (Heist et al., 2013).

RLINE is a research dispersion modeling tool developed by the EPA based on a steady-state Gaussian dispersion model with new formulations for horizontal and vertical plume spread (Snyder and Heist, 2013, Snyder et al., 2013, Venkatram et al., 2013). It simulates line source emissions specifically by integrating emissions of point sources numerically and applies the surface meteorology data provided by AERMET and AERMIN models, the meteorological preprocessor for AERMOD. RLINE is suitable for flat roadways without surrounding complexities. In this study, we elected to use RLINE to estimate the concentrations both on-road and off-road.

- Emission Source Input

  Emission source input identifies the line-type emission sources, including the coordinates of each link (starting and ending points), initial vertical dispersion, number of lanes, emission rate and roadway configurations, in which project-level of MOVES simulation provides the emission rate for road links.

  In RLINE, each of the 48,000 links on the road network represents a line-type emission source, which generates a certain amount of pollution.

- Receptor Input

  Receptor input specifies the locations of concentration receptors.

  For internal emission cost analysis, on-road concentrations determine emission exposure for on-road drivers. Hence, we selected the center point of each of the 48,000 links on the Twin Cities network as a receptor.

  For external emission cost analysis, vehicle emissions affect the health of general population. The centroid of each of the 54,000 census blocks in the Twin Cities was selected as a receptor to represent the off-road concentrations.

## 3.3 Emission Cost Analysis

As a key cost component of travel, on-road emission is typically considered an external cost of transport, due to damages to human health, vegetation, materials, aquatic ecosystems, visibility, climate change, e.g. (Maibach et al., 2008, Mayeres et al., 1996). The estimates of external costs depend on different pollutants (Koomey, 1990, Matthews et al., 2001). Small and Kazimi (1995) measures the health damage costs of VOC, $NO_x$, $SO_x$ and PM10 emissions from motor vehicles based on the raised mortality and morbidity. National Highway Traffic Safety Administration (2010) estimated the unit emission cost referring to the values of reductions in health damage costs per ton of emission of each pollutant that is avoided. These values represent the savings due to lower concentrations when emissions of each pollutant that contributes to PM2.5 concentrations are reduced.

In this study, we are concerned more about the unit intake-emission cost which describes the health damage cost per unit of emission intake specific to pollutants. Intake fraction, the fraction of emissions that are inhaled by exposed people, relates emission to inhalation (Bennett et al., 2002, Evans et al., 2002). Assuming exposure efficiency is constant across exposed individuals, the unit intake-emission cost is represented as,

$$u_{I,p} = \frac{u_{E,p}}{F_I} \tag{1}$$

Where:
$u_{E,p}$ = unit emission cost of pollutant $p$;
$F_I$ = intake fraction.

Marshall et al. (2005) estimated the intake fraction for nonreactive gaseous vehicle emissions in US urban areas, and gives the range of intake fraction of between 7 and 21 per million. Evans et al. (2002) measured the intake fraction for primary vehicle PM2.5 which is between 3 and 18 per million for urban locations and between 1 and 18 per million for rural locations based on a stratified random sample of 40 highway segments. Hence, a 10 per million intake fraction was set in this study, based on which Table 3 shows the unit intake damage cost with reference to the unit emission cost estimated by National Highway Traffic Safety Administration (2010).

Table 3: Unit Intake-Emission Cost

| | Unit Intake-Emission Cost (\$/g) |
|---|---|
| $PM$ | 30,650 |
| $SO_2$ | 3,960 |
| $NO_X$ | 670 |

Note: PM refers to PM2.5 and PM10.

### 3.3.1 Internal Emission Cost

The internal emission cost of auto travelers was defined as the health damage cost due to air pollution intake during commute (home to work) travel, which highly depends on the on-road concentration of pollutants, travelers' breathing rate, exposure time, and unit damage cost of pollutants (Hassanien et al., 2009). Considering the continuous changes of pollution concentration due to dispersion, the internal emission cost is written as:

$$E_{C,I,i} = \sum_p u_{I,p} * \int_0^{T_i} B_r * C_{p,i}(t)\,dt \tag{2}$$

Where:
$E_{C,I,i}$ = internal emission cost of link $i$,
$u_{I,p}$ = unit intake-emission cost of pollutant $p$,
$C_{p,i}(t)$ = concentrations of pollutant $p$ of link $i$, which varies with time,
$T_i$ = exposure time on link $i$,
$B_r$ = breathing rate.

For a specific link segment, the on-road concentrations estimated by RLINE dispersion model provide $C_{p,i}(t)$, and the exposure time travel speed and segment length determine $T_i$.

### 3.3.2 External Emission Cost

The external emission cost of auto travelers is the health damage cost from emitted pollutants imposed on others (non-drivers) (We also considered the costs of greenhouse gas ($CO_2$) in the external emission cost). The off-road concentrations and affected population are the determinants for the external cost. The external emission cost is written as:

$$E_{C,E,i} = \left( \left( \sum_p \sum_k u_{I,p} * P_{D,k} * \int_0^T B_r * C_{p,i,k}(t)\,dt \right) + (Q_{i,CO_2} * u_{CO_2}) \right) * V_i^{-1} \tag{3}$$

Where:
$E_{C,E,i}$= external emission cost of link $i$,
$P_{D,k}$= daytime population of block $k$,
$C_{p,i,k}(t)$= off-road concentration of block $k$ contributed by emissions from link $i$,
$Q_{i,CO_2}$= quantity of $CO_2$ generated on link $i$,
$u_{CO_2}$=unit emission cost of $CO_2$, \$22/ton (2010 US dollar),
$V_i$= traffic flow on link $i$,

Daytime population was defined as "the number of people who are present in an area during normal business hours, including workers" (United States Census Bureau, 2015). United States Census Bureau (2013) estimated the commuter-adjusted daytime population based on the 2006-2010 5-year American Community Survey (ACS) at the level of county subdivisions for Minnesota. The percentage daytime population change for each county subdivision was applied for all the contained blocks. Future research could improve this estimate.

## 3.4 Healthiest Path vs. Greenest Path

The route with the lowest on-road pollution intake defines the *healthiest* path. A complement to this, the route with the lowest external emission cost considering the health damage costs borne by others due to pollutants from motor vehicles defines the *greenest* path. Both the healthiest path and the greenest path give new rules of traffic route assignment to minimize the costs of either pollution-intake or emissions from the perspective of travelers.

For a given origin-destination (OD) pair, the general mathematical expression of the healthiest path is written as:

$$E_{C,I,R_{OD,k}} = \sum_{i \in R_{OD,k}} E_{C,I,i} \tag{4}$$

$$E_{C,R_{OD,H}} = min(E_{C,I,R_{OD,k}}) \tag{5}$$

Where:
$R_{OD,k}$ = $k^{th}$ path between origin $O$ and destination $D$;
$E_{C,I,R_{OD,k}}$ = internal emission cost of the $k^{th}$ path traveling between $O$ and $D$;
$E_{C,R_{OD,H}}$ = internal emission cost along with the healthiest path between $O$ and $D$, in which $R_{OD,H}$ refers to the healthiest path

Similarly, the greenest path, which aims to minimize the external emission cost is given as:

$$E_{C,E,R_{OD,k}} = \sum_{i \in R_{OD,k}} E_{C,E,i} \tag{6}$$

$$E_{C,R_{OD,G}} = min(E_{C,E,R_{OD,k}}) \tag{7}$$

Where:
$E_{C,E,R_{OD,k}}$ = external emission cost of the $k^{th}$ path traveling between $O$ and $D$;
$E_{C,R_{OD,G}}$ = external emission cost along with the greenest path between $O$ and $D$, in which $R_{OD,G}$ refers to the greenest path.

## 3.5 Work Trip Flow

Work trip flow is defined as the times a link that is used by the shortest paths among work trips. This concept derives from the definition of betweenness (Freeman, 1977), a network structure measure explaining the contribution of network elements to the whole network (Xie and Levinson, 2007). It is expressed as:

$$q_i = \sum_{v=1}^{V} f(R_{OD}, i) \tag{8}$$

$$f(R_{OD}) = \begin{cases} 1 & if\ R_{OD}\ pass\ through\ link\ i \\ 0 & Others \end{cases} \tag{9}$$

Where:
$q_i$= work trip flow on link $i$,
$V$= total number of work trips.

In this study, the healthiest and the greenest paths have been considered as the shortest paths to measure work trip flows in the realm of emission. The patterns of their spatial distributions indicate the healthier or greener roads. For comparison, work trips flows of using the shortest travel time path have been measured as well.

The OD table of LEHD was applied to work trip flows measurement.

# 4 Results

## 4.1 RLINE Dispersion Model Estimates

On-road and off-road concentrations of PM, $SO_2$, and $NO_X$ estimated by RLINE model for the Minneapolis-St.Paul Metropolitan area are shown in Figures 2 and 3. The on-road concentrations determine the emission intake of travelers along their commute trips, while the off-road ones affect the health of the general population.

The average on-road concentrations in the Twin Cities area are PM: 1.916$\mu g/m^3$, $SO_2$: 0.743$\mu g/m^3$, $NO_X$: 27.197$\mu g/m^3$.

Specifically, Figure 2 shows that all pollutants have higher on-road concentrations in urban areas (PM: 2.216$\mu g/m^3$, $SO_2$: 0.845$\mu g/m^3$, $NO_X$: 33.471$\mu g/m^3$ ) than rural areas (PM: 0.955$\mu g/m^3$, $SO_2$: 0.416$\mu g/m^3$, $NO_X$: 7.143$\mu g/m^3$) (Figure 1 illustrates the geographical boundary of the urban area). Downtown Minneapolis and downtown St.Paul have the highest on-road concentrations overall (PM: 3.099$\mu g/m^3$, $SO_2$: 1.656$\mu g/m^3$, $NO_X$: 48.755$\mu g/m^3$) because downtown roads serve more traffic in the morning peak hours.

In addition, the on-road concentration maps clearly reflect the shape of the highway network in the Twin Cities. The concentrations on urban highways, I-35W, I-35E, I-394, e.g., are relatively higher as well due to higher traffic flows. The average concentrations of urban highways for different pollutants are PM: 3.064$\mu g/m^3$, $SO_2$: 1.059$\mu g/m^3$, $NO_X$: 67.500$\mu g/m^3$.

The average off-road concentrations in the Twin Cities area are PM: 1.178$\mu g/m^3$, $SO_2$: 0.455$\mu g/m^3$, $NO_X$: 17.231$\mu g/m^3$, which are lower than the on-road ones since the off-road receptors are farther from the emission sources. However, Figure 3 shows the similar patterns as Figure 2 that urban areas, especially in the core cities, have higher concentrations than rural areas and near-road blocks are affected by on-road emissions the most in which the concentrations are relatively higher, especially for those near the highways. Such a consistency is expected since both on-road and off-road concentrations we are concerned with here are determined by vehicle emissions, and decrease with distance increases from the emission sources to the receptors.

Notably, there are some blocks showing unexpected on-road or off-road concentrations estimates, like the strange red dot on Figure 3b. We investigated all the input files of RLINE dispersion model and identified the problems.

At first, the accuracy of the speed estimation of TomTom speed data is not guaranteed. TomTom speed data, as described, were aggregated and processed based on GPS data, which is difficult to accurately estimate travel speed for specific links with low penetration rate, low polling frequency and limited types of probe vehicles (Jenelius and Koutsopoulos, 2013, Liu et al., 2016, 2009). In this speed dataset, 60 (out of 48,000) links have a travel speed lower than 5 km/h, for which their upstream or downstream link segments have a much higher travel speed. At second, run options we selected in RLINE model generates potential errors of the estimates. Considering the number of emission sources (48,000) and receptors (48,000 for on-road estimates, 54,000 for off-road estimates), we used the analytical rather than numerical solution to reduce the run time, at the cost of accuracy. In addition, we randomly selected two days of meteorology records to run the estimation and gave the average. An annual average should mitigate the noise.

The strange red dot on Figure 3b is caused by the noise in RLINE estimation since, as Figure 4 shows, there is no unexpected higher $SO_2$ emission rate on the roads near that block.

Figure 4 also shows the emission rate of other pollutants generated from MOVES simulation.

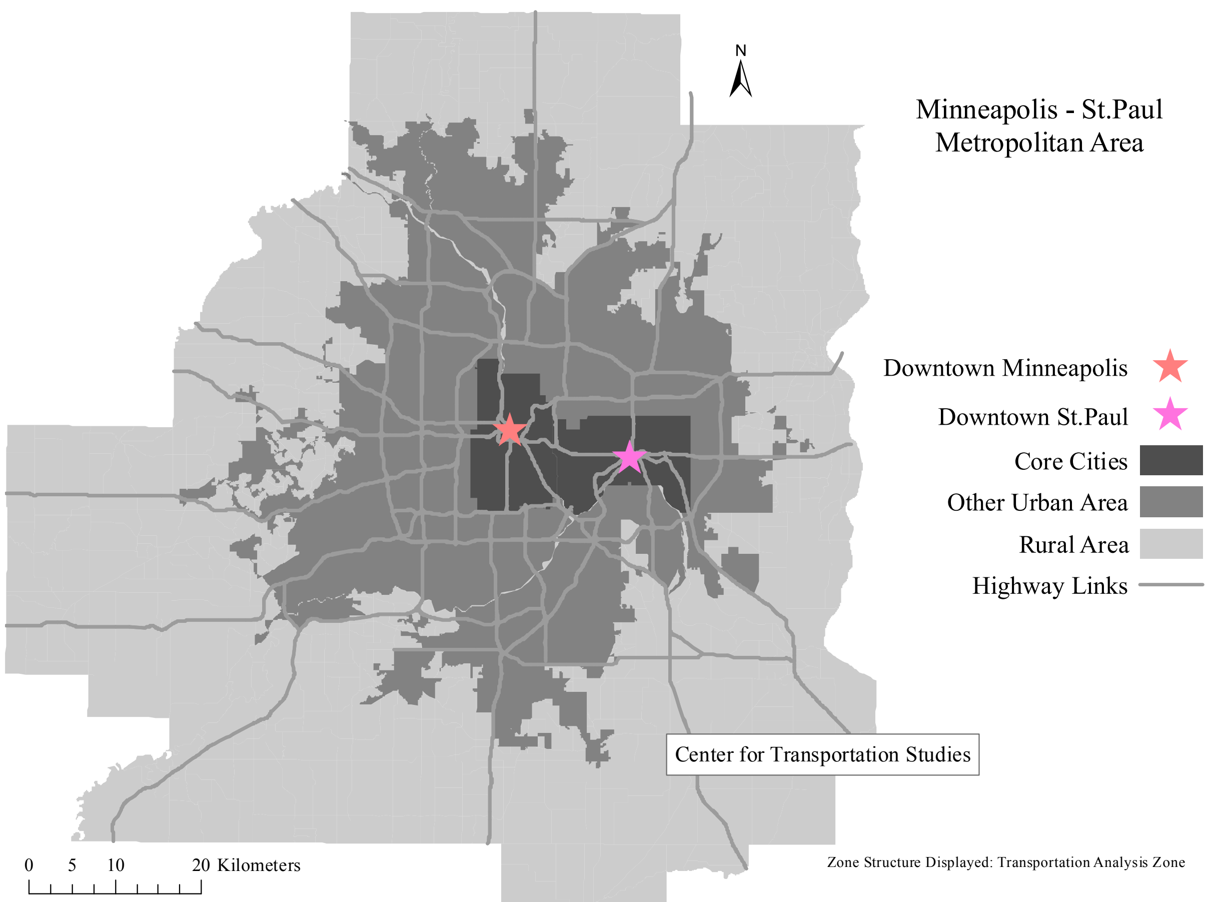
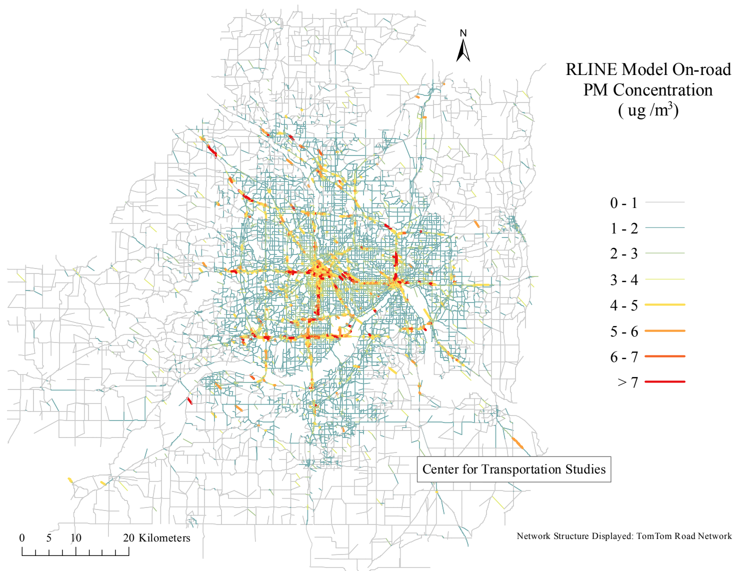
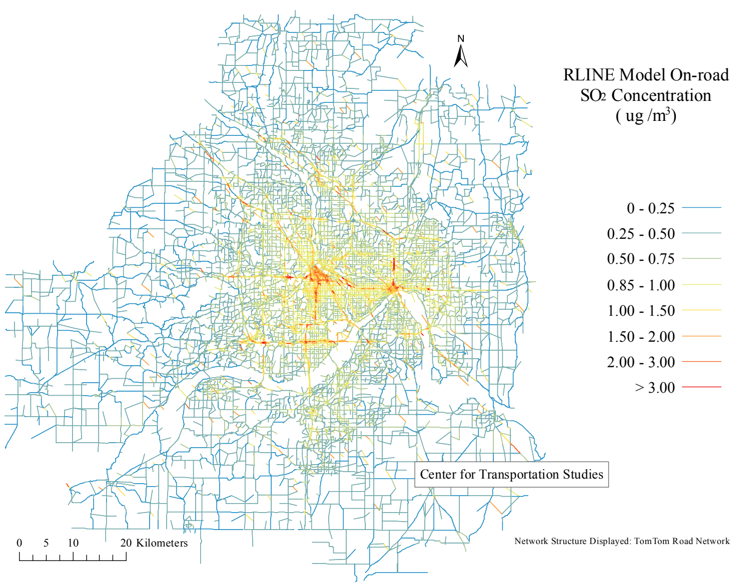


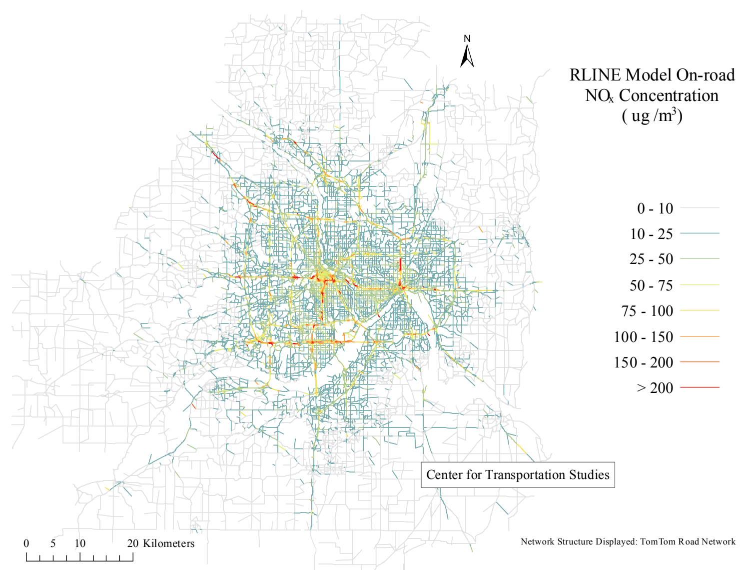

Figure 1: The Geographical Boundary of the Twin Cities




(a) PM

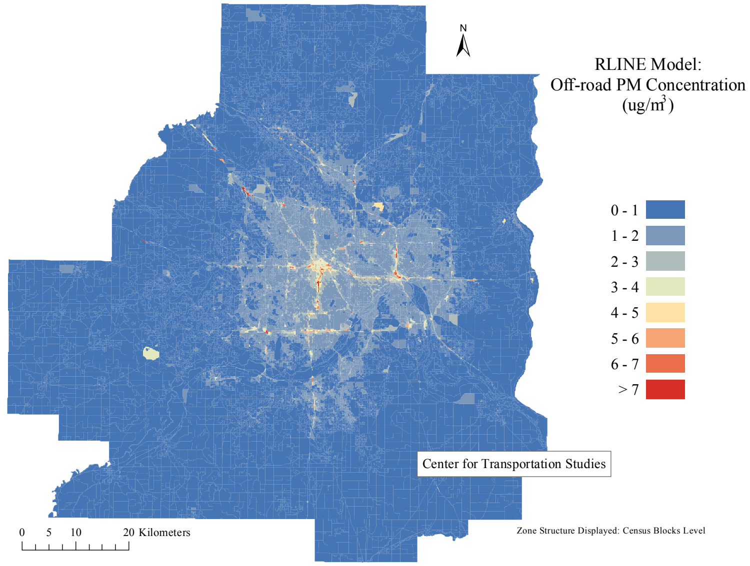



(b) $SO_2$

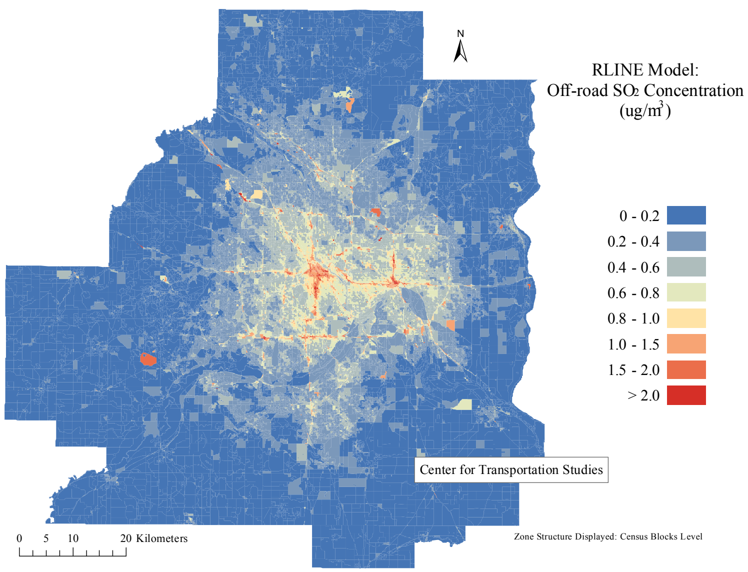



(c) $NO_X$

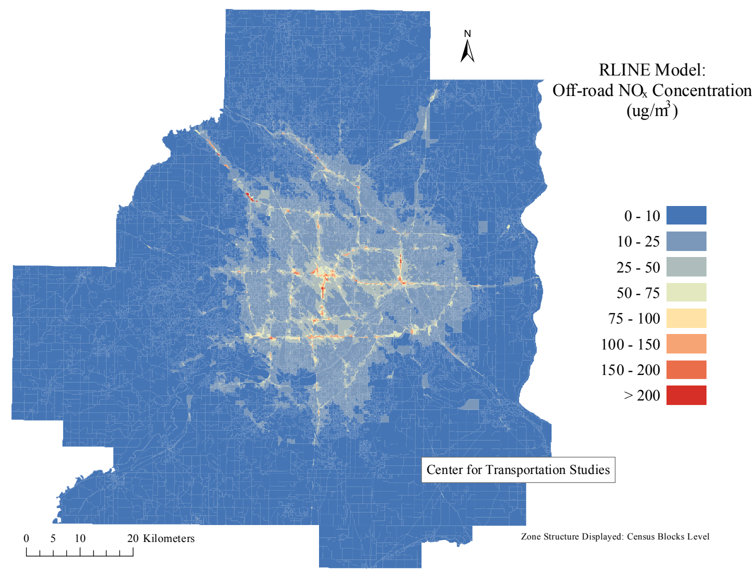
Figure 2: On-road Pollution Concentration from Motor Vehicle Emissions




(a) PM

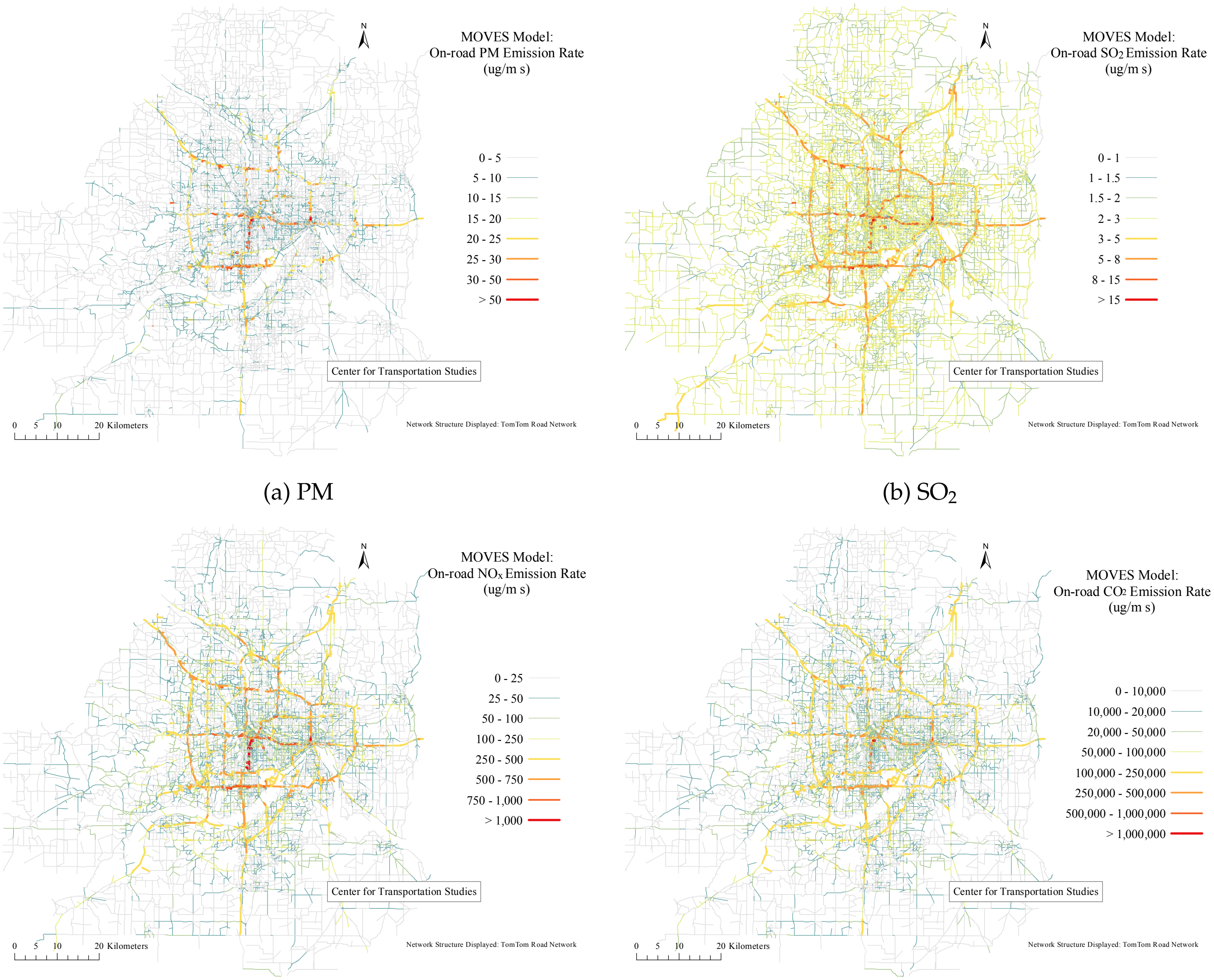



(b) $SO_2$




(c) $NO_X$

Figure 3: Off-road Pollution Concentration from Motor Vehicle Emissions




(a) PM

(b) $SO_2$

(c) $NO_X$

(d) $CO_2$

Figure 4: Estimates of Emission Rate ($\mu g/m\ s$) from MOVES Simulation

## 4.2 Internal vs. External Emission Cost Analysis

The link-based internal and external emission costs were estimated for the road network based on the on-road and off-road concentrations.

The estimates show that the mean value of internal emission costs for all link segments is approximately \$0.0009/km, and most links (92%) have an internal emission cost less than \$0.002/km. As expected, comparing locations, driving in downtown (\$0.0017/km) results in intake of more internal emission cost than other urban (\$0.0008/km) and rural areas (\$0.0003/km) due to higher concentrations. However, the average internal emission cost of highways (\$0.00085/km) are slightly lower than other roads (\$ 0.00090 /km), which is explained by faster highways decreasing drivers' exposure time.

The link-based external emission cost is much higher than the internal one that the average is around \$0.0192/km which indicates that the emission costs travelers impose on others are greater than those borne by themselves. It is expected as the external unit costs include damage to non-travelers, while the internal costs here exclude pollution costs from non-transport sources. Similarly, for different locations, using downtown roadways generates more external emission cost (\$0.0298/km) than other urban (\$0.0184/km) and rural areas (\$0.0114/km).

Daytime population density is much higher in the downtown area as Figure 5 shows which indicates that more people are affected by on-road emissions in downtown. In addition, downtown roadways serve more traffic during morning peak hours which results in more serious congestion. Stop-and-go traffic conditions lower vehicle fuel efficiency (U.S. Environmental Protecting Agency, 2017) which generates more on-road emissions per vehicle. In addition, driving on highways generates less external emission cost (\$0.0110/km) than other roads (\$0.0198/km) which is mainly because of stop-and-go traffic on other roads.

Figure 6 gives the distribution patterns of the link-based internal and external emission cost estimates on the Twin Cities' road network, which is consistent with our discussions above.

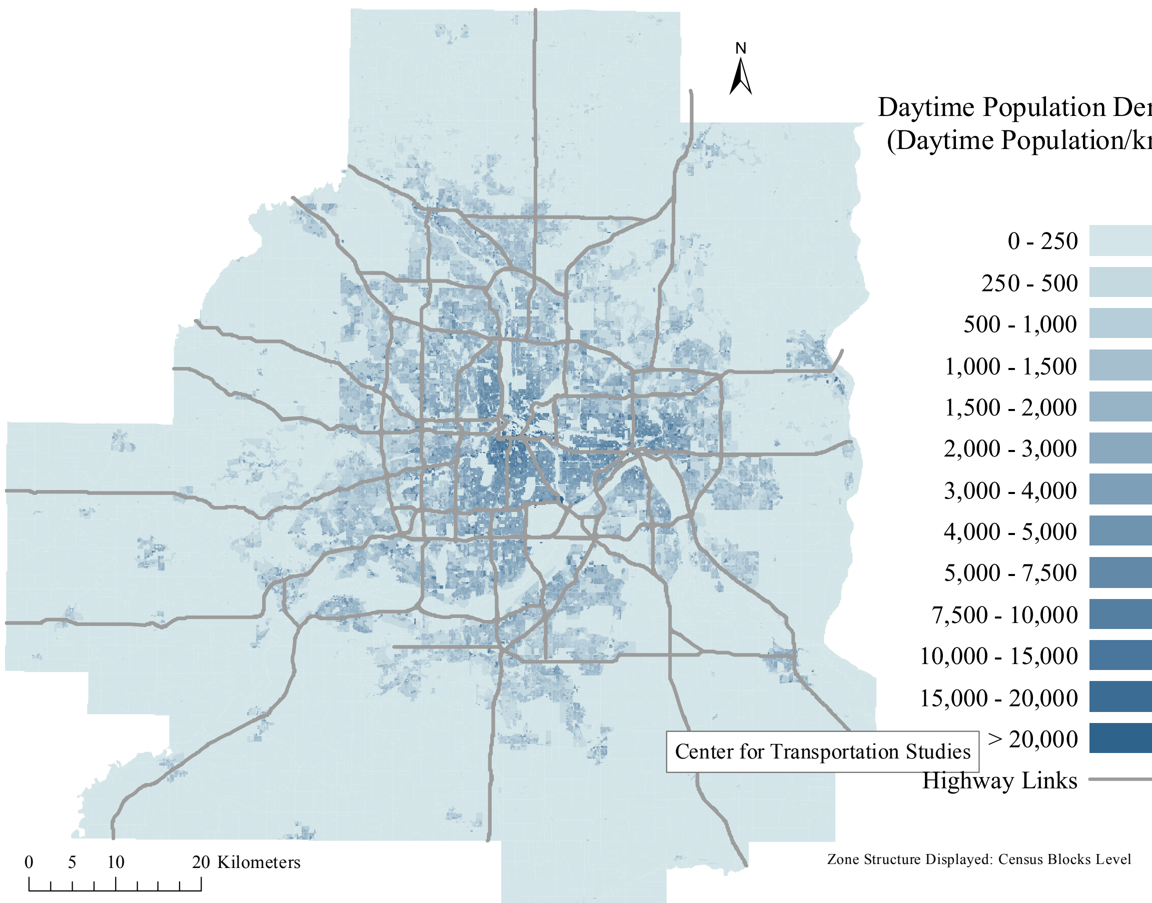
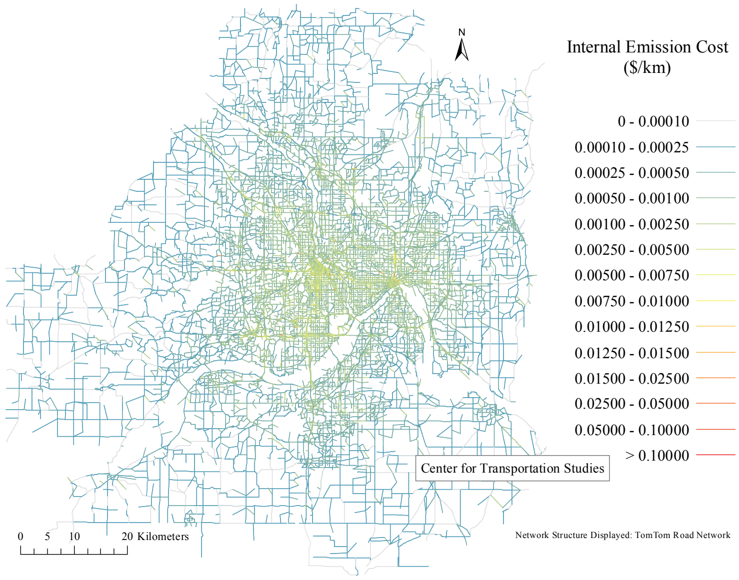
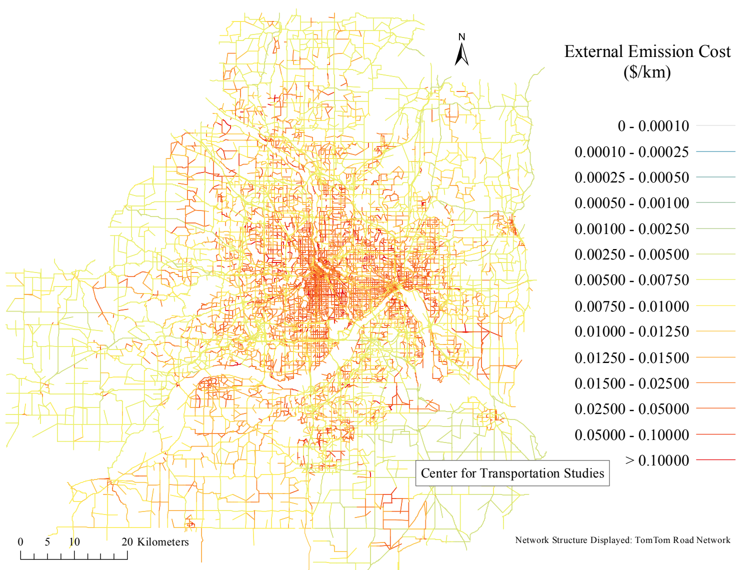



Figure 5: Daytime Population Density of the Twin Cities




(a) Internal Emission Cost




(b) External Emission Cost

Figure 6: On-road Emission Cost

### 4.3 Work Trip Flow

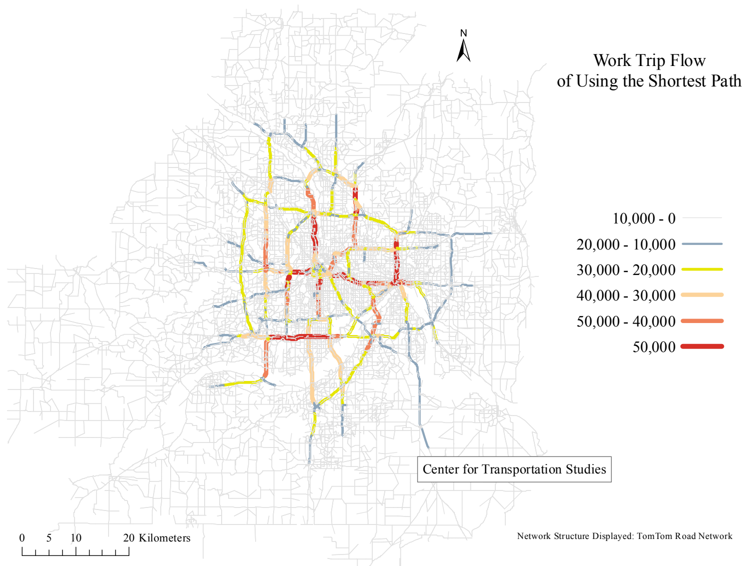
Figure 7 shows the work trip flow estimates for the healthiest path and the greenest path comparing with that of using the traditional shortest travel time path, based on current traffic levels, i.e. assuming other traffic does not reroute.

As the baseline, the work trip flow in the Twin Cities allocated to the shortest travel time path (Figure 7a) reflects that highways serve more work trips than others roads, as travelers optimize travel times on routes with higher speeds. Its spatial distribution clearly gives the shape of the highway network.

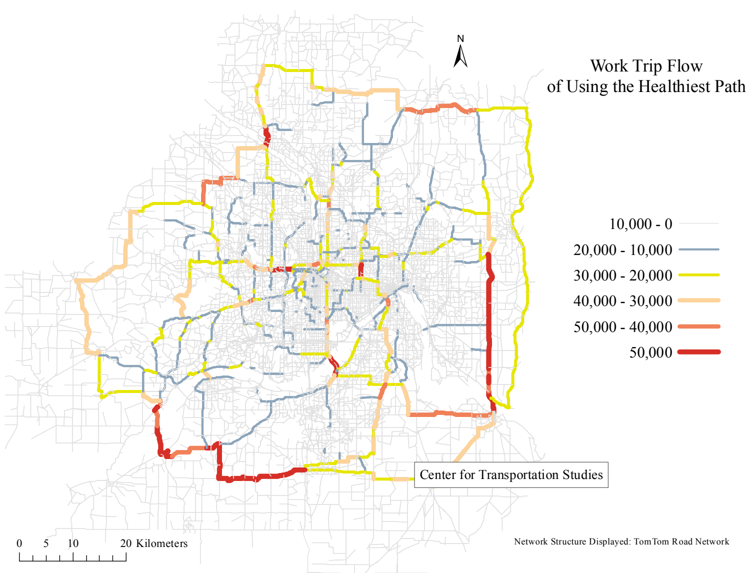
To minimize the intake emission cost, however, the hypothetical personally healthiest travel path detours to exurban areas where the on-road concentrations are lower. As Figure 7b shows, a complete circle on the exurban area of the Twin Cities is generated which identifies the less polluted roads (trading off lower pollution levels for longer exposure times). In addition, several major healthier paths are also identified which connect downtown Minneapolis with the exurban area.

For Figure 7c, it is shown that, basically, the work trip flow on the hypothetical greenest path has largely the same distribution patterns as baseline shortest path estimates. Slight differences exist, as shown when the colors on the maps shift. For instance, more work trips reassign from I-94 and I-35W to MN-100 if travelers elected to use the greenest path rather than the shortest one.

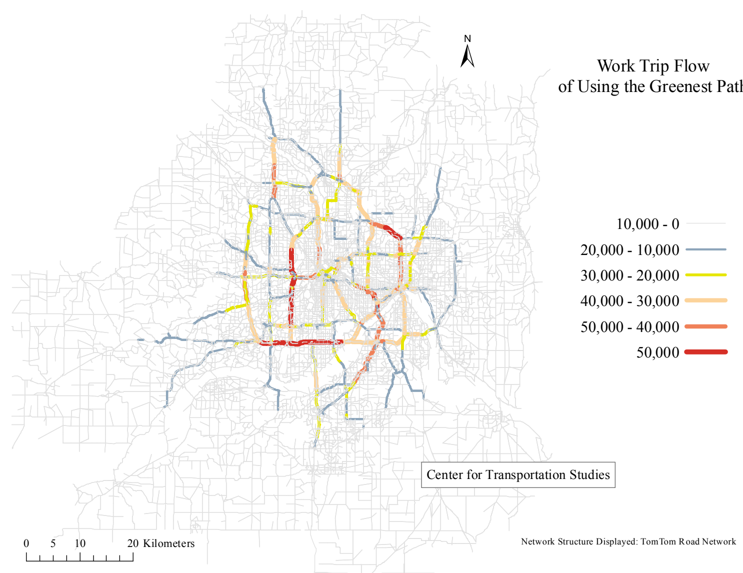
Highways are both greener and shorter. The job-weighted average time increase of using the greenest path is 2.64 min with an average external emission cost saving of \$0.076. The healthiest path, however, generates more detours which increases the average travel time by 18.48 min with savings of \$0.010 of internal emission cost.




(a) The Shortest Path




(b) The Healthiest Path




(c) The Greenest Path

Figure 7: Work Trip Flow of Using Different Types of Paths

# 5 Conclusion

This study analyzed the internal and external emission cost from roads in the Minneapolis - St. Paul metropolitan area based on EPA MOVES and RLINE dispersion model, and evaluated the work trip flows based on the healthiest and greenest paths.

Generally, on-road emissions are categorized as an external cost expressing the health damage from emitted pollutants imposed on others. However, as active agents in transportation system, travelers also bear health damage costs due to pollution intake, which logically should be considered as an internal cost of travel.

The healthiest and greenest paths were proposed to estimate the minimum pollution exposure and emission costs during traveling. The link costs associated with the greenest and healthiest paths are valuable data as inputs to a full cost accounting of the cost of travel, and could subsequently be used in planning and economic analyses.

Urban highways have higher on-road concentrations due to higher traffic flows, which means the blocks closer to highways have higher off-road concentrations, as expected. However, pollution intake on highways is slightly lower than other roads on average since using highways decreases the exposure time for travelers. In addition, the model implies driving on highways generates less external emission costs which is mainly because the stop-and-go traffic on other roads. More importantly, comparing with the internal and external versions of costs, the emission cost travelers impose on others (external) is much greater than that borne by themselves (internal).

The work trip flows on the greenest path have similar patterns to the shortest path. In contrast, using the healthiest path generates more detours onto exurban roadways.

Given actual values of time (typically on the order of $0.25/minute), it is highly unlikely many travelers would be persuaded to shift routes based on such small pollution or health savings suggested by the greenest and healthiest paths compared with the shortest path. However, external costs should still be internalized.

From a policy perspective, road pricing presents a family of potential mechanisms to encourage use of socially optimal routes. Present implementations of road pricing are quite crude compared to what is technically feasible. Currently, prices are fixed by area (there is a fixed charge to drive into central London, Singapore, or Stockholm for the day), or by link (e.g. most highway or bridge tolls) or for a given on ramp - off ramp pair (e.g. the New Jersey Turnpike). There are off-peak discounts on many priced roads. Further, a few facilities vary by time-of-day (e.g. SR 91 in southern California) or dynamically (e.g. the High Occupancy/Toll lanes on I-394 in Minneapolis). However the technology exists to geolocate individual vehicles and charge tolls varying by time of day, and by the specific route chosen to connect the origin and destination, and thus by the level of pollution produced or inadvertently consumed.

It is noteworthy that, in this study, we measured the external emission cost based on the daytime population, which, however, does not identify the part of costs borne by drivers before they arrive at their workplaces. In a strict accounting sense, the external emission cost should consider the emission-intake of off-road daytime population based on the off-road concentrations and the emission-intake of on-road drivers based on on-road concentrations, and travelers need to be subtracted from daytime population for the part of the day when they are in motion. This, at first, requires more detail about the daytime population changes, like a dynamic trip table showing the number of persons driving into and out of each block at each specific time, which is not available in a measured form anywhere, and in modeled form in some metropolitan areas. On average, the external emission cost generated from a driver and borne by other drivers should approximate the internal emission cost that the driver should pay. Comparing with the daytime-population-based external emission cost, the driver-based external emission cost is small relative to that for the daytime population, so it was neglected in this study.

Further studies may focus on the identification of driver-based external emission cost, error mitigations of concentration estimates and adjustment factors of travelers' exposure efficiency. These would help to improve the emission cost analysis.

Concentration estimates are the determinant inputs for emission cost analysis. As described, the accuracy of speed data and the analytical solution of RLINE dispersion model results in unreasonable concentration outputs for specific links and blocks. The final estimates of internal and external emission cost are then affected, which brings additional errors.

In addition, the estimated emission cost is a population-weighted average on the basis of a population-weighted breathing rate and a population-weighted intake fraction. The exposure efficiency of individual on-road travelers, differs from the average intake fraction. Individuals may have different emission costs depending on factors like age and income. For instance, children and the elderly may have a higher internal emission cost than the average, and even higher than the external cost. Future research should consider those factors for an individual-based emission cost analysis.

A full cost analysis of other key cost components of travel, time, safety, money, e.g. for both internal and external versions should be considered in future studies as well. Finally, the greenest and healthiest paths assumed today's flows and travel speeds as inputs. While observed networks are not strictly speaking in equilibrium, and travelers are not necessarily taking the shortest (travel time) path, these networks are probably closer to equilibrium than these hypothetical alternatives. When combined with other external and internal costs beyond pollution, and priced appropriately, it should be possible to find a full cost equilibrium routing incorporating traditional travel time, as well as pollution as discussed here, and crash and other costs.

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