

Land-use and socio-economics as determinants of traffic emissions and individual exposure to air pollution

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ABSTRACT

This paper presents a modeling framework developed for the City of Montreal, Canada, and is intended to quantify two indicators that can explain the spatial distribution of traffic-related air pollution at a metropolitan level. The indicators are estimated at the level of the traffic analysis zone (TAZ) and include: (1) the average level of emissions generated per individual, and (2) the level of emissions occurring in a zone as a proxy for air pollution exposure. A regional traffic assignment model is extended with capabilities for emission modeling at an individual trip level while taking into account vehicle (type, age) and trip attributes (road type, speed, volume). We observe that individuals who generate higher emissions from travel tend to reside in areas with lower exposure to traffic emissions while individuals associated with low levels of travel emissions (e.g. travel smaller distances, conduct less trips, use alternative modes) reside in areas with high levels of traffic pollution. A regression analysis of the two indicators against a set of land-use and socio-economic variables shows that generated emissions per individual are positively associated with car ownership and larger vehicles, while being negatively associated with ownership of newer vehicles, and location in dense and walkable neighborhoods with high levels of commercial land-use. Meanwhile, exposure to emissions is positively associated with dense and walkable neighborhoods and negatively associated with car ownership and larger vehicles. These findings indicate major inequities in the generation of and exposure to traffic-related air pollution.

1. INTRODUCTION

The impact of transportation on the global environment is substantial and growing (Chapman, 2007). In Canada specifically there are about 21 million road motor vehicles registered as of 2009, up from 17.5 million in 1999 (Statistics Canada, 2012). At the same time, 82% of Canadian commuters currently drive to work, compared to only 12% who take public transit and 6% who walk or bike (Turcotte, 2011). These unprecedented levels of vehicle mobility have come with unparalleled levels of pollution. The results of this increase are evident in the recent literature, which has shown that exposure to traffic-related air and noise pollution affects various aspects of human health (Brauer, et al., 2008; Gan, et al., 2012; Selander, et al., 2009). It is therefore crucial to develop modeling systems and analysis tools that can evaluate the impacts of various transport policies on urban air quality and identify measures that specifically target polluters and persons at risk.

The objective of this study is to better understand the generation of traffic-related air pollution at a metropolitan scale and identify the regions that are potentially the most affected by these emissions. We propose two measures of traffic emissions that potentially capture inequity in the spatial distribution of emissions: (1) the average level of emissions generated per individual and (2) the level of emissions occurring in a zone as a proxy for air pollution exposure. These indicators are estimated at the traffic analysis zone (TAZ) level by extending a regional traffic assignment model with capabilities for individual trip emission modeling while taking into account vehicle (type, age) and trip attributes (road type, speed, volume). We examine the spatial distribution of emissions as well as capture the determinants of emissions generated and exposed to through a multivariate regression analysis of the two indicators against a set of land-use and socio-economic variables.

2. CONTEXT

The linkage between transportation modeling and detailed environmental modeling is a research area that has grown rapidly in the past few years in light of the importance of extending the capabilities of transportation models with environmental simulation. These studies have found considerable evidence that long-term exposure to local traffic-related air and noise pollution is potentially dangerous to various aspects of human health including birth outcomes (Brauer, et al., 2008), children's health (Kim, et al., 2004; Zmirou, et al., 2004; and Kramer, et al., 2000) and respiratory and cardiovascular diseases, including lung cancer (Gan, et al., 2012; Selander, et al., 2009; Chen, et al., 2008; Babisch, et al., 2005; Hoek, et al., 2002; and Kunzli, et al., 2000).

Simultaneously, the transportation research field has also moved toward analytical frameworks that provide a comprehensive analysis of vehicle emissions. Several activity-based and agent-based traffic assignment models have been used to calculate refined emission estimates at a person and trip level taking into account vehicle (vehicle type, model year, fuel) and trip characteristics (drive-cycle, link type and link grade) (Anderson et al., 1996). Building on those advancements, a number of studies have also included an analysis of atmospheric dispersion based on link emissions (Int Panis et al., 2011; Hatzopoulou et al., 2010; Hulsman et al., 2009). Several efforts were even successful at estimating the effects of cold and hot starts as well as soak emissions (Hao et al., 2010).

Using significantly more aggregate travel and emission modeling tools, a number of studies have calculated individual and household emissions (from transport only) at a metropolitan level and analyzed the relationship between emissions and a host of socio-economic, land-use and transport supply variables. In one of the earliest studies conducted in California, Khan (1998) found that richer households might have higher vehicle emissions because they drive more often and own more vehicles. Poorer households were likely to have higher emissions as well because of their older, higher polluting vehicles. Frank et al. (2000) explored the relationship between land use patterns and household vehicle emissions in the Puget Sound region and found that household density, work tract employment density, and street connectivity (block density) were inversely related to household vehicle emissions, while commute trip distance had a positive influence. More recently, Brand and Preston (2010) estimated CO₂ emissions at the individual level for the Oxfordshire region in the United Kingdom. They found a significant relationship between individual CO₂ emissions and age, gender and car ownership. Income, household location, working status and accessibility were not found to be significant. In another study with a similar methodology focusing on the Seoul metropolis area, Ko et al. (2011) found that household location and income were significant in relation to individual CO₂ emissions, along with age and car ownership. Barla et al. (2011) observed similar effects in Quebec City.

In this paper, we exploit the recent advances in travel and emission modeling by developing a framework that estimates emissions at a relatively fine level of detail. In addition, we not only estimate emissions generated on an individual and household level but also estimate those occurring in different zones as a proxy for air quality. Our analysis extends the existing literature by setting the stage for health and equity analysis of transportation systems.

3. STUDY AREA

Our study area includes the Montreal metropolitan region, which covers an area of approximately 7,000 km² and has a population of about 3.8 million (Statistics Canada, 2011). The region is dominated by the island of Montreal, with approximately 47% of the region's population and 71% of the region's 1.4 million employment opportunities (AMT, 2010). The rest of the region consists of two sub-regions north of Montreal: Laval and the twenty municipalities of the North Shore, and another two sub-regions south of the island: Longueuil and the twenty five South Shore municipalities. Figure 1 provides the population distribution in terms of density across the Montreal metropolitan region with all the major sub-regions identified. Further, the figure identifies the central business district (CBD) in a red box.

The spatial economy of the Montreal region is anchored by the CBD; 59% of the region's employment opportunities are within 10 km of downtown, while the remaining job distribution follows a concentric distance-decay curve (Shearmur and Coffey, 2002). The other major employment centre in the region is found near Montreal's main airport in Ville-Saint-Laurent/Dorval, located 10-15 km west of downtown. The imbalance between jobs and residents previously mentioned for the island of Montreal is especially large for the CBD and surrounding central areas. In the central areas there are 24 workers for every 10 residents, an employment surplus that is being fed by Laval, Longueuil, and other municipalities on the North and South shores (Shearmur and Motte, 2009). Meanwhile, the island of Montreal is connected to the other sub-regions through a system of bridges. Five bridges connect the island to the north (with a recent addition of a sixth bridge in 2011) and five to the south, while two bridges at either end of

the island connect the peripheral eastern and western edges. With the very high proportion of off-island and on-island commuters, bridges linking the island to the rest of the region have become the salient element of the road network. At the same time, most of the residential growth is occurring in the periphery zones of the region particularly in the north and south shore municipalities (AMT, 2010). Overall, there are over two million vehicles registered in the region, resulting in a regional household vehicle ownership rate of about 1.2 vehicles (AMT, 2010).

4. METHODOLOGY

Our research methodology is divided into three main steps: (1) transportation modeling, (2) emission modeling, and (3) statistical analysis.

4.1. Transportation Modeling

A regional traffic assignment model was developed for the Montreal metropolitan area. The model takes as input the 2008 Origin-Destination (OD) trip data for the Montreal region provided by the Agence Métropolitaine de Transport (AMT) and assigns it on the network using a stochastic assignment in the VISUM platform (PTV Vision, 2009). The regional network consists of 127,217 road links and 90,467 nodes associated with 1,552 TAZs. It also contains various road characteristics such as the type, length, speed limit, capacity, and number of lanes.

Only the driving trips were extracted from the OD survey for the purpose of this study and segmented into 24 1-hour origin-destination matrices based on trip departure times. The OD matrices were generated at the traffic analysis zone (TAZ) level. For the purpose of this exercise, only morning (6-8am) and afternoon (4-6pm) peak periods were simulated. The simulated traffic was assigned to the network employing the stochastic user equilibrium approach (SUE) in VISUM. The SUE approach allows for route choice distribution based on perceived travel times thus incorporating realistic route choice behavior compared to the traditional deterministic user equilibrium approach (PTV Vision, 2009). The validation exercise comparing link volumes based on the SUE outputs with observed link volume data provided satisfactory results (correlation = 0.62 – 0.86 based on 160 data collection points comparing 24-hour flows). Output from the traffic assignment simulations consisted of an array that contained a detailed description of all paths connecting pairs of origin-destination zones in the 6-8 am and 4-6 pm periods. This “path array” contains approximately 1,000,000 paths per hour for which the following characteristics are listed: links along the path, traffic volumes per link, average speed per link, and link type.

4.2. Emission Modeling

Linked with the regional traffic assignment model, an emission post-processor was developed that incorporated four main data sources as inputs while outputting an individual emission level for each individual trip. The post-processor goes through the list of individuals in the OD survey and assigns a vehicle for each individual driver based on vehicle ownership data obtained from the Societe de l'Assurance Automobile du Quebec (SAAQ). It then randomly selects a path for each trip based on the path array. For each link along the path, based on the link type, average speed, and vehicle type/age, it attaches an emission factor (EF) in g/veh.km, and finally, multiplies the EF by the length of the link. After generating an emission per individual trip, total emissions per person are aggregated and assigned to the TAZ where the individual resides. We

also calculate total emissions occurring on the network in each TAZ. Figure 2 presents the design and operation of the post-processor.

Four main databases are used to calculate individual trip emissions, these include: 1) the OD trip table, 2) the vehicle ownership database, 3) the paths array, and 4) the EF look-up table.

1) The Origin-Destination survey data contains information on 319,915 trips conducted in the Montreal metropolitan region; each trip is associated with a set of attributes including origin, destination, departure time, travel mode, and attributes of the individual performing the trip including residential location. In addition, every trip is associated with a weight or “expansion factor” which allows us to scale the sample up to the total population. This survey is conducted every five years and is the primary source in Montreal of information on travel habits. The most recent survey was conducted in 2008 and the results were released in 2010. Participants in the survey were identified through a random sample of the Montreal population using telephone listings; the sample is validated against census data using a wide range of variables (age, gender, employment status, home location, work location, etc.). In 2008, 66,100 households (representing 4% of the population) were interviewed including 156,700 individuals. Telephone interviews took place in autumn, a time period when most urban travel habits are stable. The survey included individual and household-level socio-demographic information as well as a diary of each trip (i.e., trip origin, destination, purpose, mode of transportation).

2) The SAAQ database includes vehicle ownership information for the Montreal region at the level of the Forward Sorting Area (FSA), indicated by the first three characters of the postal code. Within each FSA, the total number of vehicles by type (e.g. passenger car, sports utility vehicle, minivan, small truck, large truck) and model year (1981-2011) is provided. The SAAQ data contains 12 vehicle designations. These designations were collapsed into two groups, one for passenger cars and one for passenger trucks (which includes SUVs, minivans, and pick-up trucks). While it is possible that the 12 vehicle designations have different emission profiles, it is important to recognize that vehicle emissions on roadways are not only dependent on vehicle types and models but also influenced by fuel and engine technology, engine displacement, model year group, and regulatory class (USEPA, 2010). In fact the emission differences between different passenger cars of the same model year (and regulatory class) undergoing the same drive-cycle are smaller than emission differences for the same car undergoing different driving patterns. In real-road conditions, the differences due to vehicle make within the same category (passenger truck or passenger car) can be neglected. For this reason the USEPA’s model MOVES 2010 has aggregated passenger vehicles into two broad categories: (1) passenger car (i.e. all sedans, coupes, and station wagons manufactured primarily for the purpose of carrying passengers) and (2) passenger trucks (which includes SUVs, minivans, and pick-up trucks) coming from a larger vehicle classification which was included in the older MOBILE6 series. The distribution of the fleet was computed for each FSA, based on the two vehicle types and thirty model years provided. After linking the home TAZ and the home FSA of the driver, a random vehicle (type and model year) is assigned to each individual based on the vehicle fleet distribution of the home FSA.

3) The path array output from the regional traffic model contains information on each path between every active OD pair. Every path in the array has information on the volume of vehicles for that path as well as the type, length, speed, and volume of each link along the path. A path

was allocated to each driver based on their origin and destination TAZs. In the case of multiple paths for one OD pair, a path was randomly allocated based on the volume proportion between the multiple paths.

4) Vehicle emission factors were generated using MOVES. All default input distributions within MOVES were replaced with Montreal-specific data reflecting the vehicle fleet, fuel composition, and ambient conditions. Using specifically the vehicle age distribution by type obtained from the SAAQ database, we generated fleet-wide EFs. These EFs (in g/veh.km) vary by vehicle type (passenger car and passenger truck), age (30 model years), fuel (gasoline), average speed (15 speed bins ranging from 2.5mph to >65mph), and facility type (uninterrupted, interrupted). The latter is based on MOVES' differentiation between two different driving behaviors based on two different types of road facilities. Uninterrupted facilities are roadways that have controlled access points with no signal control (i.e. expressways), resulting in more free-flowing traffic. Interrupted facilities, on the other hand, are roadways with intersections, signal lights, or stop-signs, resulting in more stop-and-go driving. Emissions are computed for Nitrogen Oxides (NO_x), Carbon Monoxide, and greenhouse gases (as $\text{CO}_{2\text{-eq}}$). This leads to a large multi-dimensional look-up table with 5,400 EFs. Following the generation of the look-up table, trip emissions (in grams) are calculated by matching the corresponding EF (g/veh.km) with each link along the trip taking into account vehicle characteristics and multiplying by the length of the link (km). Further, emissions for each path are multiplied by the trip expansion factor and then assigned to the TAZ of the driver's home location, as well as allocated onto the TAZs of every link on the driver's path. In our analysis, we restrict ourselves to examining the NO_x related emissions as they have the highest co-locational association with other traffic-related pollutants (Beckerman et al., 2008; Wheeler et al., 2008).

The emission post-processor estimates two indicators of traffic-related emissions: 1) an average level of emissions generated per person for each TAZ calculated by dividing the total emissions generated by residents of the TAZ with the TAZ's population. This measure is an indicator of the "polluting power" of the TAZ; and 2) an average level of emissions occurring in a TAZ calculated by dividing the total emissions allocated to that TAZ by its area (in km^2). This measure relates to the amount of pollution experienced by a TAZ; in this study we use it as a proxy for air pollution exposure in the absence of an air pollution dispersion model.

4.3. Statistical Analysis

In order to capture the strengths of associations between vehicle emissions and land-use and socio-economic attributes, a regression analysis was performed on the two TAZ-level indicators: 1) average emissions generated per individual, 2) emissions exposed to per km^2 . Multivariate regressions were run on the logarithm of the two indicators as both distributions are lognormal. In this respect, an extensive database of variables potentially affecting emissions was computed at the TAZ level for the Montreal metropolitan region. The database includes a range of socio-economic, land-use and transportation related variables (e.g. population, residential density, highway length, etc.). Factor analysis is then employed in order to structure the large dataset into a number of factors for use in the linear regression. The individual variables were first classified into two categories: (1) variables affecting travel demand (e.g. car ownership, average income, vehicle age, etc.), and (2) variables affecting transport supply (e.g. network density, bus stop density, walkability, etc.).

The results of the factor analysis are shown in Table 1. Based on the six demand variables, three factors were derived. The first factor (i.e. high income, newer vehicles) represents the effect of household income and vehicle age. A zone that exhibits a high value for this factor can include more households with high income and newer vehicles. The second and third factors represent high vehicle ownership and larger vehicles (second factor) and older vehicles (third factor). Cumulatively, the three factors account for 81.5% of the variability in the six demand-based variables. Based on the supply variables three factors were derived to capture the effects of zones that are: (1) dense, walkable and have transit oriented development (TOD), (2) commercial, and (3) government and institutional.

5. RESULTS AND DISCUSSION

5.1. Spatial Distribution of Emissions

The average emitted NO_x per person (am and pm peak periods only) across the 1,552 TAZs in the region ranges from 0.0 to 17.5 grams. The spatial distribution of results across the region is shown in Figure 3. As expected, the high emitting individuals tend to reside on the periphery of the region, which is furthest from the central business district (CBD). Concurrently, the majority of low emitting individuals live centrally, on the island, much closer to the CBD. Overall, these results clearly confirm the intuitive hypothesis that high polluting individuals reside away from the downtown in suburban areas. When we overlay the map of emissions occurring on the network onto Figure 3, it is evident that most of the emissions occur in areas where the lowest polluting individuals reside (Figure 4). This is confirmed when plotting the emissions occurring within a TAZ. Indeed, it is clear that there is much higher pollution along the main highway corridors and in the areas closer to downtown. In addition, emissions are very low for all of the zones on the region's periphery. The spatial distribution of NO_x emissions per km^2 is presented in Figure 5.

While it is hard to validate link-level NO_x emissions at a regional level, we compared our link-based emissions and TAZ-based emissions with NO_2 ambient air quality levels previously mapped for Montreal based on a land-use regression analysis. The resulting model features raster-based NO_2 levels across the Island of Montreal (Crouse et al., 2009). The resulting overlay between link-level NO_x emissions and NO_2 levels is presented in Figure 6. Based on the number of raster cells falling in each TAZ, we calculate the average NO_2 level (in ppb) per TAZ and correlate this level with the level of NO_x emissions occurring in the same TAZ per km^2 (based on Figure 5). The Spearman's rank correlation coefficient between the two datasets was found to be 0.424 (significant at the 1% level). While the aggregation to the level of the TAZ is expected to introduce disparity in the two datasets (therefore reducing the correlation coefficient), a visual inspection of Figure 6 clearly indicates that our highest simulated NO_x emissions do correspond to the areas with the highest NO_2 levels in Montreal.

5.2. Statistical Analysis

In order to better understand the underlying factors associated with the generation and exposure to emissions, the two indicators of emissions were regressed against the set of factors derived from socio-economic, land-use and transport supply variables at the TAZ level. A summary of the regression results is presented in Table 2.

We observe that the emitted NO_x per person per TAZ are positively associated with high car ownership and larger vehicles and negatively associated with dense, walkable, TOD zones. Commercial zones also tend to decrease the average individual emissions since zones with higher amounts of commercial land-use tend to be located in areas with higher accessibility, thus reducing trip length. In addition, zones with high income and newer vehicles tend to decrease individual level emissions. This is likely because newer vehicles have lower emission factors. It is important to distinguish this factor from 'high car ownership and larger vehicles'. This factor (high income, newer vehicles) seems to represent high-income urban dwellers who are not necessarily high emitters. This is an interesting finding, since it indicates that income influences emissions generation only when it is connected to higher car ownership. The final factor with negative association is 'older vehicles'. The negative sign is counter-intuitive since older vehicles tend to have significantly higher emission factors (Figure 7). This finding is however confirmed by examining the level of car ownership of owners of older vehicles. Indeed, a cross tabulation of car ownership and average vehicle age (Table 3) confirms that the factor 'older vehicles' also includes low vehicle ownership. In fact, there is clear evidence indicating that a lower vehicle ownership leads to lower vehicle mileage (NHTS, 2009). We can then conclude that households with older vehicles tend to make fewer trips therefore offsetting the higher emissions of their vehicles.

The multivariate regression model for NO_x emissions occurring per km^2 (used as a proxy for air pollution exposure) had four significant factors. Zones that were dense, walkable, and accessible by transit or had more commercial land-use were positively associated with air pollution exposure. Meanwhile, zones with high car ownership and larger vehicles or ones with older vehicles were negatively correlated with exposed to NO_x per km^2 . This is likely because zones with higher car ownership and larger vehicles are located further away from the downtown and do not attract as much traffic.

The regression analysis points towards asymmetry in the roles of the factors influencing emissions generated and exposed to. To further explore this asymmetry, we conducted a two-step cluster analysis based on the two indicators. The cluster analysis divided the 1,552 zones into four clusters: 1) low emitter, high exposure; 2) low emitter, moderate exposure; (3) high emitter, moderate exposure; and (4) high emitter, low exposure. Based on the spatial distribution of the clusters (Figure 8), it is evident that the lowest emitting zones (highlighted in white and the lightest shade of grey) are also the ones that are exposed to the highest emissions. They are mostly located in central areas and in the CBD. In contrast, high emitting zones (dark grey) are also exposed to low amounts of pollution and located outside of the urban core. This analysis points towards spatial and socio-economic disparities in air pollution generation and exposure.

It is interesting to situate these results within the context of the region's spatial economy. As has been mentioned, the central areas of Montreal have a large disparity in jobs vs. residents, matched on the opposite side of the spectrum by areas such as Laval or Longueuil, which only have between 6-7 jobs for every 10 residents. It has also been shown that the CBD is the only employment centre attracting labour from across the entire region, in contrast to smaller suburban centres that tend to have local labour catchments (Shearmur and Motte, 2009). The central areas of Montreal therefore rely on the suburbs for labour. At the same time, a form of income redistribution is occurring wherein income, often high income, is made through

employment in the CBD and is then transferred back to the suburbs where the high-income earners typically live (Shearmur and Motte, 2009). This income redistribution is mirrored by the results of our study which show an opposite redistribution of traffic's negative externalities from suburbs to central areas downtown. Downtown residents are therefore faced with a net loss of wealth along with a net gain in pollution, the majority of which they are not responsible for. While the paper does not directly establish a link between air pollution exposure and socio-economic disadvantage; the spatial distribution of traffic emissions within the region established here, points towards significant concerns from an environmental justice perspective.

6. CONCLUSION AND DIRECTIONS FOR FUTURE RESEARCH

In this study, we have estimated two key indicators of emissions through the development of a multi-model framework involving a regional traffic assignment model, a vehicle emissions model, and an emission post-processor. The two indicators are 1) the average level of NO_x emissions generated per individual in a TAZ, and (2) the average level of NO_x occurring in a TAZ per km^2 . Our findings indicate significant spatial disparity between the areas that generate or are responsible for high levels of individual emissions and areas that experience high emissions. Both measures were a function of socioeconomic and built environment characteristics. We observe that the factors which positively influence the emissions generated are also the ones which negatively influence the emissions occurring in a zone therefore pointing towards equity issues in the generation and distribution of traffic-related emissions.

These findings are of relevance to policy evaluation at the Metropolitan level. When cities are faced with challenges such as reducing traffic emissions by 2030 to a certain percentage less than 1990 levels; a main question arises: Are these the emissions generated within the city or emissions generated by individuals residing in the city? In areas where most of the traffic emissions are generated by residents living outside the city, policy development becomes a challenging task. The modeling framework that we propose provides a way to quantify the responsibility for emissions generated and the impact of every individual's emissions on the region. It will be used to simulate regional-level transport policies and their effects on the spatial distributions of emissions and on equity in emissions generated and exposed to.

The developed modeling framework is associated with a range of limitations. In our emission modeling exercise, we focus our attention on private vehicle emissions. We are currently introducing transit emissions but we have not yet considered emissions generated by commercial traffic (freight and delivery trucks). The task of obtaining data on commercial traffic is far from trivial. In terms of traffic assignment, we employed the Stochastic User Equilibrium algorithm. We do intend to explore more advanced assignment procedures including Dynamic Traffic Assignment for generating inputs to the emission post-processor. Moreover, our current implementation of vehicle allocation is based on the vehicle type/age distribution of the residential zone of the trip-maker while not explicitly accounting for factors related to household vehicle use and potential trip chaining. In future research attempts, a vehicle allocation model based on data related to the use of specific vehicles for specific trips and by specific individuals will be developed. The nearest future extensions for this model include: linkage with dispersion models, estimation of population exposure, quantification of equity, and the evaluation of policy scenarios.

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ABSTRACT

This paper presents a modeling framework developed for the City of Montreal, Canada, and is intended to quantify two indicators that can explain the spatial distribution of traffic-related air pollution at a metropolitan level. The indicators are estimated at the level of the traffic analysis zone (TAZ) and include: (1) the average level of emissions generated per individual, and (2) the level of emissions occurring in a zone as a proxy for air pollution exposure. A regional traffic assignment model is extended with capabilities for emission modeling at an individual trip level while taking into account vehicle (type, age) and trip attributes (road type, speed, volume). We observe that individuals who generate higher emissions from travel tend to reside in areas with lower exposure to traffic emissions while individuals associated with low levels of travel emissions (e.g. travel smaller distances, conduct less trips, use alternative modes) reside in areas with high levels of traffic pollution. A regression analysis of the two indicators against a set of land-use and socio-economic variables shows that generated emissions per individual are positively associated with car ownership and larger vehicles, while being negatively associated with ownership of newer vehicles, and location in dense and walkable neighborhoods with high levels of commercial land-use. Meanwhile, exposure to emissions is positively associated with dense and walkable neighborhoods and negatively associated with car ownership and larger vehicles. These findings indicate major inequities in the generation of and exposure to traffic-related air pollution.

1. INTRODUCTION

The impact of transportation on the global environment is substantial and growing (Chapman, 2007). In Canada specifically there are about 21 million road motor vehicles registered as of 2009, up from 17.5 million in 1999 (Statistics Canada, 2012). At the same time, 82% of Canadian commuters currently drive to work, compared to only 12% who take public transit and 6% who walk or bike (Turcotte, 2011). These unprecedented levels of vehicle mobility have come with unparalleled levels of pollution. The results of this increase are evident in the recent literature, which has shown that exposure to traffic-related air and noise pollution affects various aspects of human health (Brauer, et al., 2008; Gan, et al., 2012; Selander, et al., 2009). It is therefore crucial to develop modeling systems and analysis tools that can evaluate the impacts of various transport policies on urban air quality and identify measures that specifically target polluters and persons at risk.

The objective of this study is to better understand the generation of traffic-related air pollution at a metropolitan scale and identify the regions that are potentially the most affected by these emissions. We propose two measures of traffic emissions that potentially capture inequity in the spatial distribution of emissions: (1) the average level of emissions generated per individual and (2) the level of emissions occurring in a zone as a proxy for air pollution exposure. These indicators are estimated at the traffic analysis zone (TAZ) level by extending a regional traffic assignment model with capabilities for individual trip emission modeling while taking into account vehicle (type, age) and trip attributes (road type, speed, volume). We examine the spatial distribution of emissions as well as capture the determinants of emissions generated and exposed to through a multivariate regression analysis of the two indicators against a set of land-use and socio-economic variables.

2. CONTEXT

The linkage between transportation modeling and detailed environmental modeling is a research area that has grown rapidly in the past few years in light of the importance of extending the capabilities of transportation models with environmental simulation. These studies have found considerable evidence that long-term exposure to local traffic-related air and noise pollution is potentially dangerous to various aspects of human health including birth outcomes (Brauer, et al., 2008), children's health (Kim, et al., 2004; Zmirou, et al., 2004; and Kramer, et al., 2000) and respiratory and cardiovascular diseases, including lung cancer (Gan, et al., 2012; Selander, et al., 2009; Chen, et al., 2008; Babisch, et al., 2005; Hoek, et al., 2002; and Kunzli, et al., 2000).

Simultaneously, the transportation research field has also moved toward analytical frameworks that provide a comprehensive analysis of vehicle emissions. Several activity-based and agent-based traffic assignment models have been used to calculate refined emission estimates at a person and trip level taking into account vehicle (vehicle type, model year, fuel) and trip characteristics (drive-cycle, link type and link grade) (Anderson et al., 1996). Building on those advancements, a number of studies have also included an analysis of atmospheric dispersion based on link emissions (Int Panis et al., 2011; Hatzopoulou et al., 2010; Hulsman et al., 2009). Several efforts were even successful at estimating the effects of cold and hot starts as well as soak emissions (Hao et al., 2010).

Using significantly more aggregate travel and emission modeling tools, a number of studies have calculated individual and household emissions (from transport only) at a metropolitan level and analyzed the relationship between emissions and a host of socio-economic, land-use and transport supply variables. In one of the earliest studies conducted in California, Khan (1998) found that richer households might have higher vehicle emissions because they drive more often and own more vehicles. Poorer households were likely to have higher emissions as well because of their older, higher polluting vehicles. Frank et al. (2000) explored the relationship between land use patterns and household vehicle emissions in the Puget Sound region and found that household density, work tract employment density, and street connectivity (block density) were inversely related to household vehicle emissions, while commute trip distance had a positive influence. More recently, Brand and Preston (2010) estimated CO₂ emissions at the individual level for the Oxfordshire region in the United Kingdom. They found a significant relationship between individual CO₂ emissions and age, gender and car ownership. Income, household location, working status and accessibility were not found to be significant. In another study with a similar methodology focusing on the Seoul metropolis area, Ko et al. (2011) found that household location and income were significant in relation to individual CO₂ emissions, along with age and car ownership. Barla et al. (2011) observed similar effects in Quebec City.

In this paper, we exploit the recent advances in travel and emission modeling by developing a framework that estimates emissions at a relatively fine level of detail. In addition, we not only estimate emissions generated on an individual and household level but also estimate those occurring in different zones as a proxy for air quality. Our analysis extends the existing literature by setting the stage for health and equity analysis of transportation systems.

3. STUDY AREA

Our study area includes the Montreal metropolitan region, which covers an area of approximately 7,000 km² and has a population of about 3.8 million (Statistics Canada, 2011). The region is dominated by the island of Montreal, with approximately 47% of the region's population and 71% of the region's 1.4 million employment opportunities (AMT, 2010). The rest of the region consists of two sub-regions north of Montreal: Laval and the twenty municipalities of the North Shore, and another two sub-regions south of the island: Longueuil and the twenty five South Shore municipalities. Figure 1 provides the population distribution in terms of density across the Montreal metropolitan region with all the major sub-regions identified. Further, the figure identifies the central business district (CBD) in a red box.

The spatial economy of the Montreal region is anchored by the CBD; 59% of the region's employment opportunities are within 10 km of downtown, while the remaining job distribution follows a concentric distance-decay curve (Shearmur and Coffey, 2002). The other major employment centre in the region is found near Montreal's main airport in Ville-Saint-Laurent/Dorval, located 10-15 km west of downtown. The imbalance between jobs and residents previously mentioned for the island of Montreal is especially large for the CBD and surrounding central areas. In the central areas there are 24 workers for every 10 residents, an employment surplus that is being fed by Laval, Longueuil, and other municipalities on the North and South shores (Shearmur and Motte, 2009). Meanwhile, the island of Montreal is connected to the other sub-regions through a system of bridges. Five bridges connect the island to the north (with a recent addition of a sixth bridge in 2011) and five to the south, while two bridges at either end of

the island connect the peripheral eastern and western edges. With the very high proportion of off-island and on-island commuters, bridges linking the island to the rest of the region have become the salient element of the road network. At the same time, most of the residential growth is occurring in the periphery zones of the region particularly in the north and south shore municipalities (AMT, 2010). Overall, there are over two million vehicles registered in the region, resulting in a regional household vehicle ownership rate of about 1.2 vehicles (AMT, 2010).

4. METHODOLOGY

Our research methodology is divided into three main steps: (1) transportation modeling, (2) emission modeling, and (3) statistical analysis.

4.1. Transportation Modeling

A regional traffic assignment model was developed for the Montreal metropolitan area. The model takes as input the 2008 Origin-Destination (OD) trip data for the Montreal region provided by the Agence Métropolitaine de Transport (AMT) and assigns it on the network using a stochastic assignment in the VISUM platform (PTV Vision, 2009). The regional network consists of 127,217 road links and 90,467 nodes associated with 1,552 TAZs. It also contains various road characteristics such as the type, length, speed limit, capacity, and number of lanes.

Only the driving trips were extracted from the OD survey for the purpose of this study and segmented into 24 1-hour origin-destination matrices based on trip departure times. The OD matrices were generated at the traffic analysis zone (TAZ) level. For the purpose of this exercise, only morning (6-8am) and afternoon (4-6pm) peak periods were simulated. The simulated traffic was assigned to the network employing the stochastic user equilibrium approach (SUE) in VISUM. The SUE approach allows for route choice distribution based on perceived travel times thus incorporating realistic route choice behavior compared to the traditional deterministic user equilibrium approach (PTV Vision, 2009). The validation exercise comparing link volumes based on the SUE outputs with observed link volume data provided satisfactory results (correlation = 0.62 – 0.86 based on 160 data collection points comparing 24-hour flows). Output from the traffic assignment simulations consisted of an array that contained a detailed description of all paths connecting pairs of origin-destination zones in the 6-8 am and 4-6 pm periods. This “path array” contains approximately 1,000,000 paths per hour for which the following characteristics are listed: links along the path, traffic volumes per link, average speed per link, and link type.

4.2. Emission Modeling

Linked with the regional traffic assignment model, an emission post-processor was developed that incorporated four main data sources as inputs while outputting an individual emission level for each individual trip. The post-processor goes through the list of individuals in the OD survey and assigns a vehicle for each individual driver based on vehicle ownership data obtained from the Societe de l'Assurance Automobile du Quebec (SAAQ). It then randomly selects a path for each trip based on the path array. For each link along the path, based on the link type, average speed, and vehicle type/age, it attaches an emission factor (EF) in g/veh.km, and finally, multiplies the EF by the length of the link. After generating an emission per individual trip, total emissions per person are aggregated and assigned to the TAZ where the individual resides. We

also calculate total emissions occurring on the network in each TAZ. Figure 2 presents the design and operation of the post-processor.

Four main databases are used to calculate individual trip emissions, these include: 1) the OD trip table, 2) the vehicle ownership database, 3) the paths array, and 4) the EF look-up table.

1) The Origin-Destination survey data contains information on 319,915 trips conducted in the Montreal metropolitan region; each trip is associated with a set of attributes including origin, destination, departure time, travel mode, and attributes of the individual performing the trip including residential location. In addition, every trip is associated with a weight or “expansion factor” which allows us to scale the sample up to the total population. This survey is conducted every five years and is the primary source in Montreal of information on travel habits. The most recent survey was conducted in 2008 and the results were released in 2010. Participants in the survey were identified through a random sample of the Montreal population using telephone listings; the sample is validated against census data using a wide range of variables (age, gender, employment status, home location, work location, etc.). In 2008, 66,100 households (representing 4% of the population) were interviewed including 156,700 individuals. Telephone interviews took place in autumn, a time period when most urban travel habits are stable. The survey included individual and household-level socio-demographic information as well as a diary of each trip (i.e., trip origin, destination, purpose, mode of transportation).

2) The SAAQ database includes vehicle ownership information for the Montreal region at the level of the Forward Sorting Area (FSA), indicated by the first three characters of the postal code. Within each FSA, the total number of vehicles by type (e.g. passenger car, sports utility vehicle, minivan, small truck, large truck) and model year (1981-2011) is provided. The SAAQ data contains 12 vehicle designations. These designations were collapsed into two groups, one for passenger cars and one for passenger trucks (which includes SUVs, minivans, and pick-up trucks). While it is possible that the 12 vehicle designations have different emission profiles, it is important to recognize that vehicle emissions on roadways are not only dependent on vehicle types and models but also influenced by fuel and engine technology, engine displacement, model year group, and regulatory class (USEPA, 2010). In fact the emission differences between different passenger cars of the same model year (and regulatory class) undergoing the same drive-cycle are smaller than emission differences for the same car undergoing different driving patterns. In real-road conditions, the differences due to vehicle make within the same category (passenger truck or passenger car) can be neglected. For this reason the USEPA’s model MOVES 2010 has aggregated passenger vehicles into two broad categories: (1) passenger car (i.e. all sedans, coupes, and station wagons manufactured primarily for the purpose of carrying passengers) and (2) passenger trucks (which includes SUVs, minivans, and pick-up trucks) coming from a larger vehicle classification which was included in the older MOBILE6 series. The distribution of the fleet was computed for each FSA, based on the two vehicle types and thirty model years provided. After linking the home TAZ and the home FSA of the driver, a random vehicle (type and model year) is assigned to each individual based on the vehicle fleet distribution of the home FSA.

3) The path array output from the regional traffic model contains information on each path between every active OD pair. Every path in the array has information on the volume of vehicles for that path as well as the type, length, speed, and volume of each link along the path. A path

was allocated to each driver based on their origin and destination TAZs. In the case of multiple paths for one OD pair, a path was randomly allocated based on the volume proportion between the multiple paths.

4) Vehicle emission factors were generated using MOVES. All default input distributions within MOVES were replaced with Montreal-specific data reflecting the vehicle fleet, fuel composition, and ambient conditions. Using specifically the vehicle age distribution by type obtained from the SAAQ database, we generated fleet-wide EFs. These EFs (in g/veh.km) vary by vehicle type (passenger car and passenger truck), age (30 model years), fuel (gasoline), average speed (15 speed bins ranging from 2.5mph to >65mph), and facility type (uninterrupted, interrupted). The latter is based on MOVES' differentiation between two different driving behaviors based on two different types of road facilities. Uninterrupted facilities are roadways that have controlled access points with no signal control (i.e. expressways), resulting in more free-flowing traffic. Interrupted facilities, on the other hand, are roadways with intersections, signal lights, or stop-signs, resulting in more stop-and-go driving. Emissions are computed for Nitrogen Oxides (NO_x), Carbon Monoxide, and greenhouse gases (as CO_{2-eq}). This leads to a large multi-dimensional look-up table with 5,400 EFs. Following the generation of the look-up table, trip emissions (in grams) are calculated by matching the corresponding EF (g/veh.km) with each link along the trip taking into account vehicle characteristics and multiplying by the length of the link (km). Further, emissions for each path are multiplied by the trip expansion factor and then assigned to the TAZ of the driver's home location, as well as allocated onto the TAZs of every link on the driver's path. In our analysis, we restrict ourselves to examining the NO_x related emissions as they have the highest co-locational association with other traffic-related pollutants (Beckerman et al., 2008; Wheeler et al., 2008).

The emission post-processor estimates two indicators of traffic-related emissions: 1) an average level of emissions generated per person for each TAZ calculated by dividing the total emissions generated by residents of the TAZ with the TAZ's population. This measure is an indicator of the "polluting power" of the TAZ; and 2) an average level of emissions occurring in a TAZ calculated by dividing the total emissions allocated to that TAZ by its area (in km²). This measure relates to the amount of pollution experienced by a TAZ; in this study we use it as a proxy for air pollution exposure in the absence of an air pollution dispersion model.

4.3. Statistical Analysis

In order to capture the strengths of associations between vehicle emissions and land-use and socio-economic attributes, a regression analysis was performed on the two TAZ-level indicators: 1) average emissions generated per individual, 2) emissions exposed to per km². Multivariate regressions were run on the logarithm of the two indicators as both distributions are lognormal. In this respect, an extensive database of variables potentially affecting emissions was computed at the TAZ level for the Montreal metropolitan region. The database includes a range of socio-economic, land-use and transportation related variables (e.g. population, residential density, highway length, etc.). Factor analysis is then employed in order to structure the large dataset into a number of factors for use in the linear regression. The individual variables were first classified into two categories: (1) variables affecting travel demand (e.g. car ownership, average income, vehicle age, etc.), and (2) variables affecting transport supply (e.g. network density, bus stop density, walkability, etc.).

The results of the factor analysis are shown in Table 1. Based on the six demand variables, three factors were derived. The first factor (i.e. high income, newer vehicles) represents the effect of household income and vehicle age. A zone that exhibits a high value for this factor can include more households with high income and newer vehicles. The second and third factors represent high vehicle ownership and larger vehicles (second factor) and older vehicles (third factor). Cumulatively, the three factors account for 81.5% of the variability in the six demand-based variables. Based on the supply variables three factors were derived to capture the effects of zones that are: (1) dense, walkable and have transit oriented development (TOD), (2) commercial, and (3) government and institutional.

5. RESULTS AND DISCUSSION

5.1. Spatial Distribution of Emissions

The average emitted NO_x per person (am and pm peak periods only) across the 1,552 TAZs in the region ranges from 0.0 to 17.5 grams. The spatial distribution of results across the region is shown in Figure 3. As expected, the high emitting individuals tend to reside on the periphery of the region, which is furthest from the central business district (CBD). Concurrently, the majority of low emitting individuals live centrally, on the island, much closer to the CBD. Overall, these results clearly confirm the intuitive hypothesis that high polluting individuals reside away from the downtown in suburban areas. When we overlay the map of emissions occurring on the network onto Figure 3, it is evident that most of the emissions occur in areas where the lowest polluting individuals reside (Figure 4). This is confirmed when plotting the emissions occurring within a TAZ. Indeed, it is clear that there is much higher pollution along the main highway corridors and in the areas closer to downtown. In addition, emissions are very low for all of the zones on the region's periphery. The spatial distribution of NO_x emissions per km^2 is presented in Figure 5.

While it is hard to validate link-level NO_x emissions at a regional level, we compared our link-based emissions and TAZ-based emissions with NO_2 ambient air quality levels previously mapped for Montreal based on a land-use regression analysis. The resulting model features raster-based NO_2 levels across the Island of Montreal (Crouse et al., 2009). The resulting overlay between link-level NO_x emissions and NO_2 levels is presented in Figure 6. Based on the number of raster cells falling in each TAZ, we calculate the average NO_2 level (in ppb) per TAZ and correlate this level with the level of NO_x emissions occurring in the same TAZ per km^2 (based on Figure 5). The Spearman's rank correlation coefficient between the two datasets was found to be 0.424 (significant at the 1% level). While the aggregation to the level of the TAZ is expected to introduce disparity in the two datasets (therefore reducing the correlation coefficient), a visual inspection of Figure 6 clearly indicates that our highest simulated NO_x emissions do correspond to the areas with the highest NO_2 levels in Montreal.

5.2. Statistical Analysis

In order to better understand the underlying factors associated with the generation and exposure to emissions, the two indicators of emissions were regressed against the set of factors derived from socio-economic, land-use and transport supply variables at the TAZ level. A summary of the regression results is presented in Table 2.

We observe that the emitted NO_x per person per TAZ are positively associated with high car ownership and larger vehicles and negatively associated with dense, walkable, TOD zones. Commercial zones also tend to decrease the average individual emissions since zones with higher amounts of commercial land-use tend to be located in areas with higher accessibility, thus reducing trip length. In addition, zones with high income and newer vehicles tend to decrease individual level emissions. This is likely because newer vehicles have lower emission factors. It is important to distinguish this factor from ‘high car ownership and larger vehicles’. This factor (high income, newer vehicles) seems to represent high-income urban dwellers who are not necessarily high emitters. This is an interesting finding, since it indicates that income influences emissions generation only when it is connected to higher car ownership. The final factor with negative association is ‘older vehicles’. The negative sign is counter-intuitive since older vehicles tend to have significantly higher emission factors (Figure 7). This finding is however confirmed by examining the level of car ownership of owners of older vehicles. Indeed, a cross tabulation of car ownership and average vehicle age (Table 3) confirms that the factor ‘older vehicles’ also includes low vehicle ownership. In fact, there is clear evidence indicating that a lower vehicle ownership leads to lower vehicle mileage (NHTS, 2009). We can then conclude that households with older vehicles tend to make fewer trips therefore offsetting the higher emissions of their vehicles.

The multivariate regression model for NO_x emissions occurring per km^2 (used as a proxy for air pollution exposure) had four significant factors. Zones that were dense, walkable, and accessible by transit or had more commercial land-use were positively associated with air pollution exposure. Meanwhile, zones with high car ownership and larger vehicles or ones with older vehicles were negatively correlated with exposed to NO_x per km^2 . This is likely because zones with higher car ownership and larger vehicles are located further away from the downtown and do not attract as much traffic.

The regression analysis points towards asymmetry in the roles of the factors influencing emissions generated and exposed to. To further explore this asymmetry, we conducted a two-step cluster analysis based on the two indicators. The cluster analysis divided the 1,552 zones into four clusters: 1) low emitter, high exposure; 2) low emitter, moderate exposure; (3) high emitter, moderate exposure; and (4) high emitter, low exposure. Based on the spatial distribution of the clusters (Figure 8), it is evident that the lowest emitting zones (highlighted in white and the lightest shade of grey) are also the ones that are exposed to the highest emissions. They are mostly located in central areas and in the CBD. In contrast, high emitting zones (dark grey) are also exposed to low amounts of pollution and located outside of the urban core. This analysis points towards spatial and socio-economic disparities in air pollution generation and exposure.

It is interesting to situate these results within the context of the region’s spatial economy. As has been mentioned, the central areas of Montreal have a large disparity in jobs vs. residents, matched on the opposite side of the spectrum by areas such as Laval or Longueuil, which only have between 6-7 jobs for every 10 residents. It has also been shown that the CBD is the only employment centre attracting labour from across the entire region, in contrast to smaller suburban centres that tend to have local labour catchments (Shearmur and Motte, 2009). The central areas of Montreal therefore rely on the suburbs for labour. At the same time, a form of income redistribution is occurring wherein income, often high income, is made through

employment in the CBD and is then transferred back to the suburbs where the high-income earners typically live (Shearmur and Motte, 2009). This income redistribution is mirrored by the results of our study which show an opposite redistribution of traffic's negative externalities from suburbs to central areas downtown. Downtown residents are therefore faced with a net loss of wealth along with a net gain in pollution, the majority of which they are not responsible for. While the paper does not directly establish a link between air pollution exposure and socio-economic disadvantage; the spatial distribution of traffic emissions within the region established here, points towards significant concerns from an environmental justice perspective.

6. CONCLUSION AND DIRECTIONS FOR FUTURE RESEARCH

In this study, we have estimated two key indicators of emissions through the development of a multi-model framework involving a regional traffic assignment model, a vehicle emissions model, and an emission post-processor. The two indicators are 1) the average level of NO_x emissions generated per individual in a TAZ, and (2) the average level of NO_x occurring in a TAZ per km^2 . Our findings indicate significant spatial disparity between the areas that generate or are responsible for high levels of individual emissions and areas that experience high emissions. Both measures were a function of socioeconomic and built environment characteristics. We observe that the factors which positively influence the emissions generated are also the ones which negatively influence the emissions occurring in a zone therefore pointing towards equity issues in the generation and distribution of traffic-related emissions.

These findings are of relevance to policy evaluation at the Metropolitan level. When cities are faced with challenges such as reducing traffic emissions by 2030 to a certain percentage less than 1990 levels; a main question arises: Are these the emissions generated within the city or emissions generated by individuals residing in the city? In areas where most of the traffic emissions are generated by residents living outside the city, policy development becomes a challenging task. The modeling framework that we propose provides a way to quantify the responsibility for emissions generated and the impact of every individual's emissions on the region. It will be used to simulate regional-level transport policies and their effects on the spatial distributions of emissions and on equity in emissions generated and exposed to.

The developed modeling framework is associated with a range of limitations. In our emission modeling exercise, we focus our attention on private vehicle emissions. We are currently introducing transit emissions but we have not yet considered emissions generated by commercial traffic (freight and delivery trucks). The task of obtaining data on commercial traffic is far from trivial. In terms of traffic assignment, we employed the Stochastic User Equilibrium algorithm. We do intend to explore more advanced assignment procedures including Dynamic Traffic Assignment for generating inputs to the emission post-processor. Moreover, our current implementation of vehicle allocation is based on the vehicle type/age distribution of the residential zone of the trip-maker while not explicitly accounting for factors related to household vehicle use and potential trip chaining. In future research attempts, a vehicle allocation model based on data related to the use of specific vehicles for specific trips and by specific individuals will be developed. The nearest future extensions for this model include: linkage with dispersion models, estimation of population exposure, quantification of equity, and the evaluation of policy scenarios.

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Figure 2
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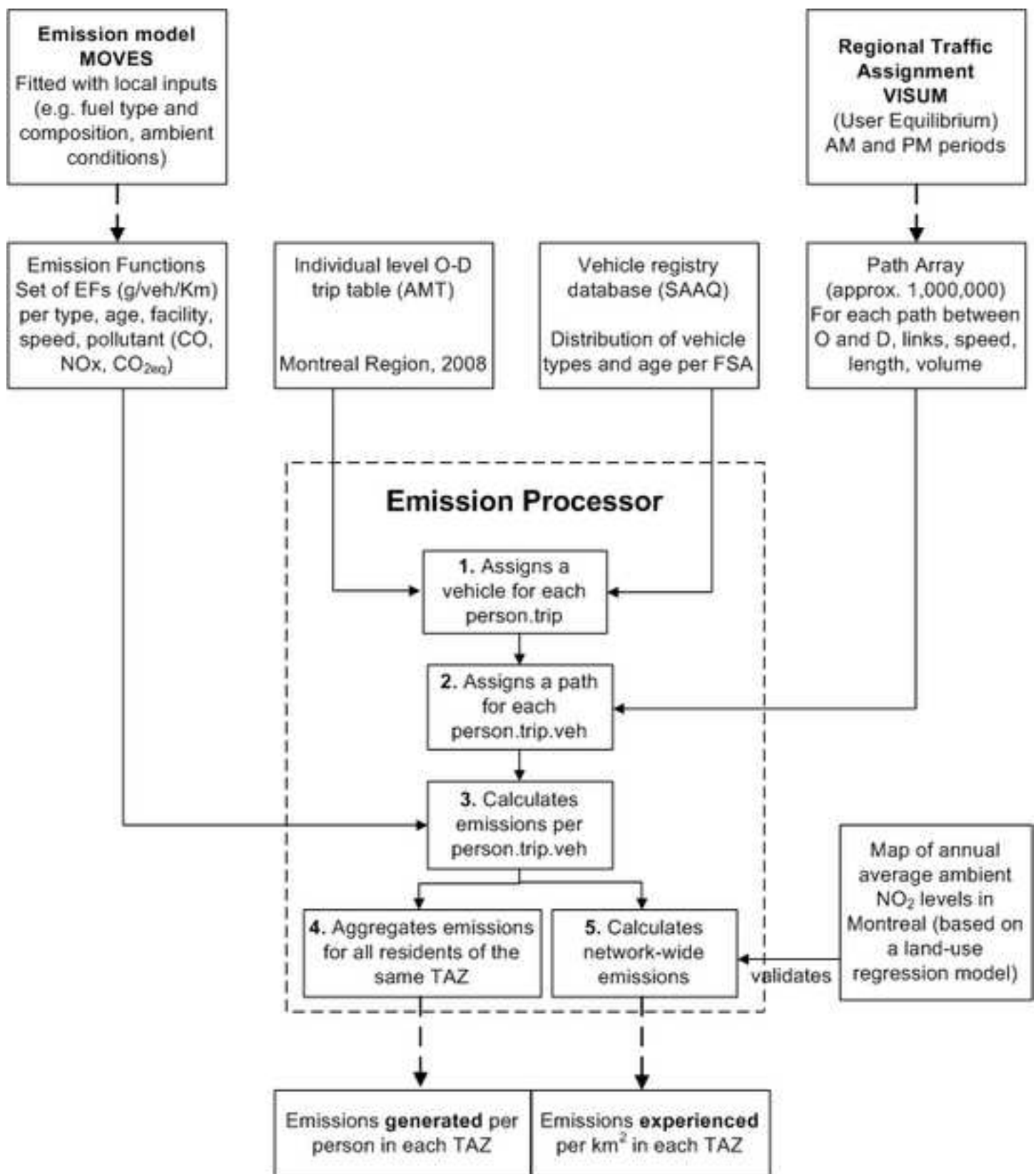


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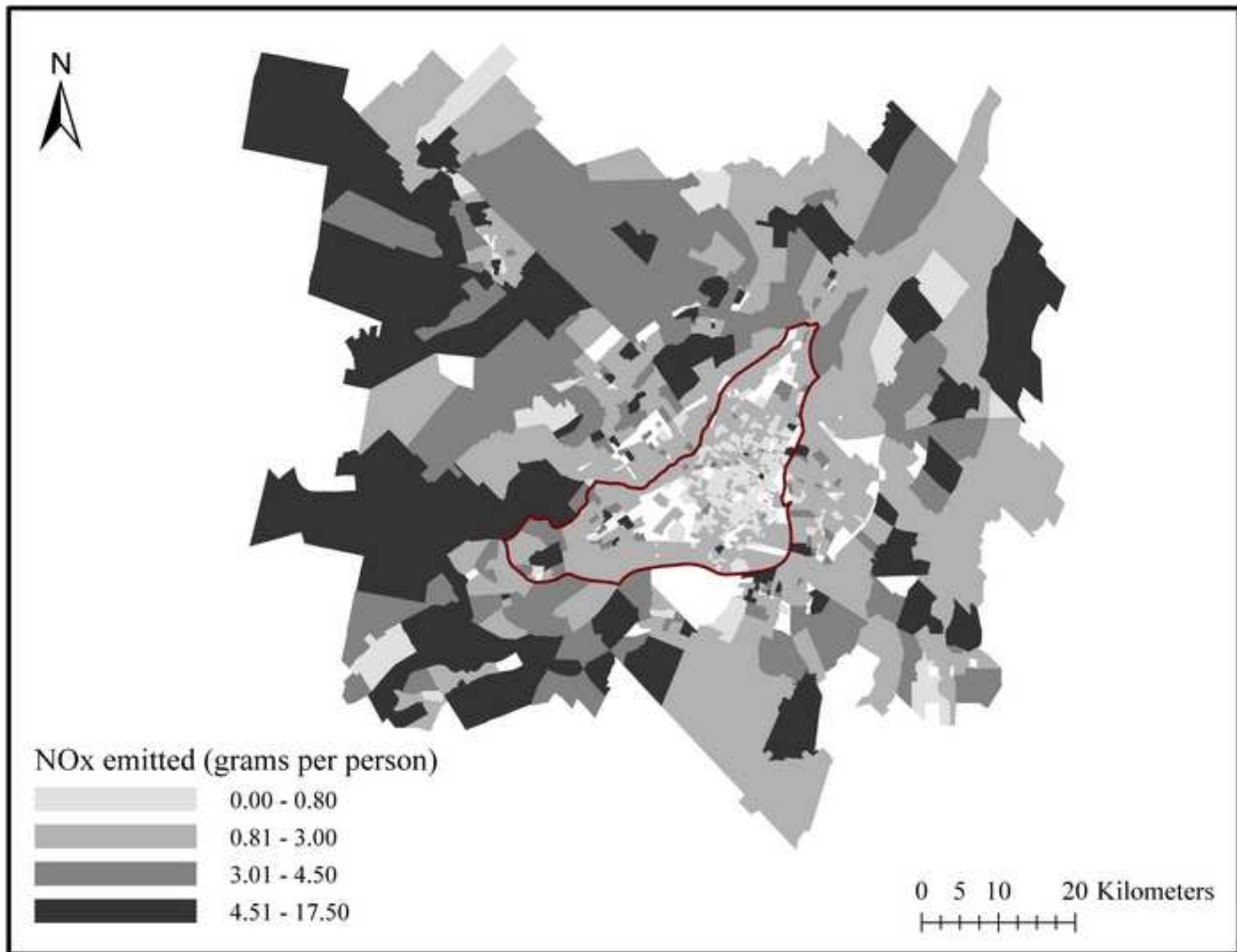


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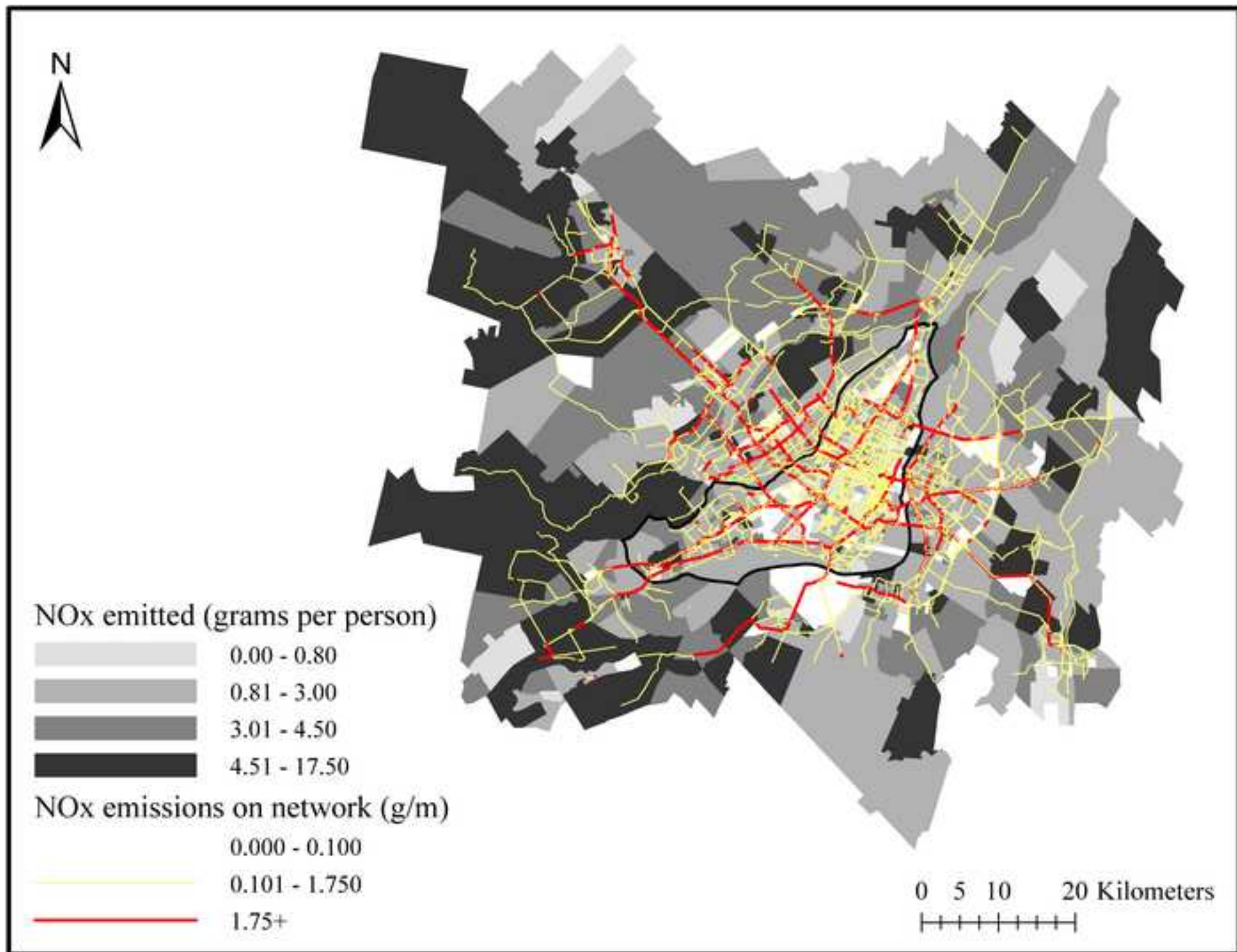


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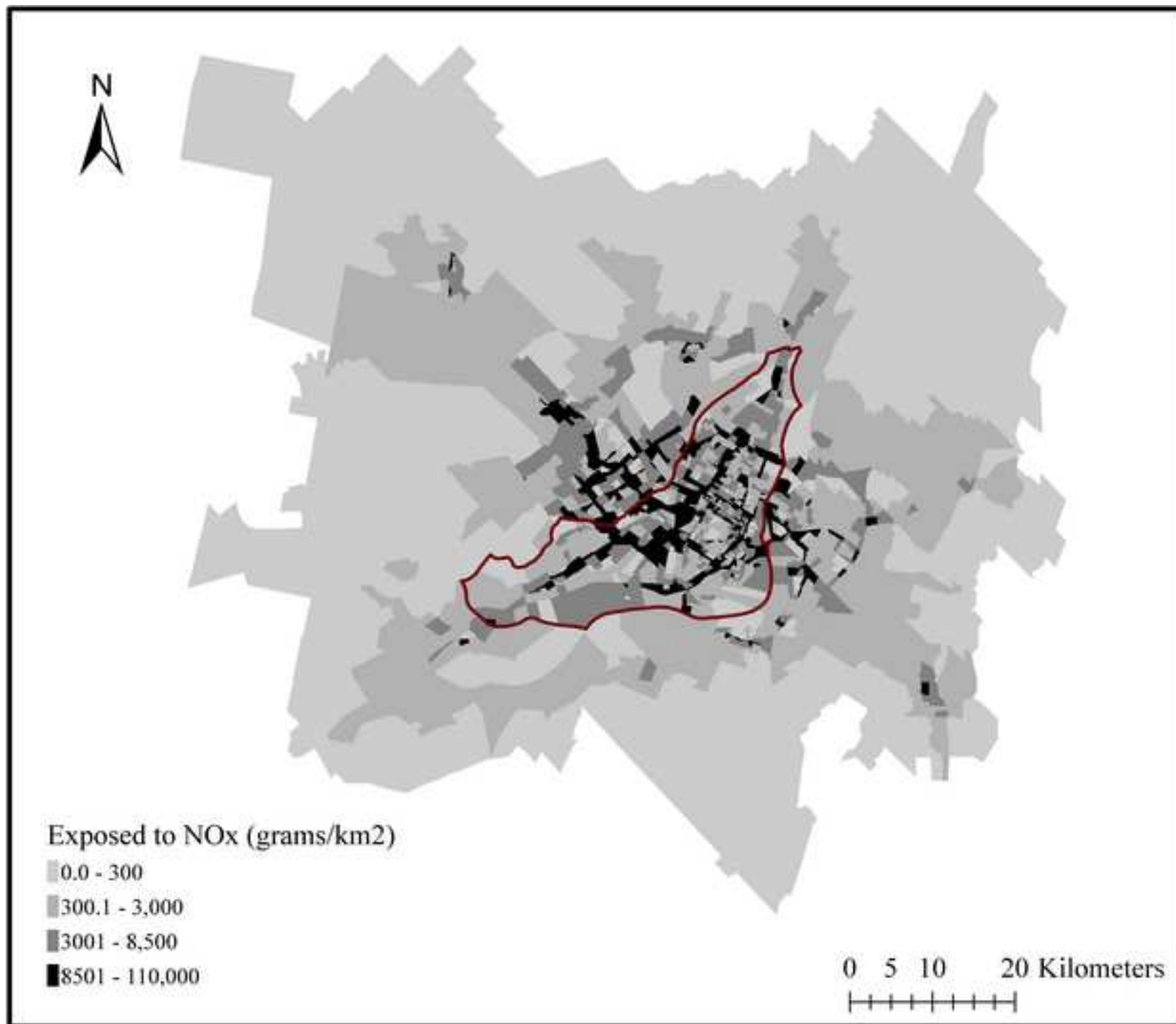


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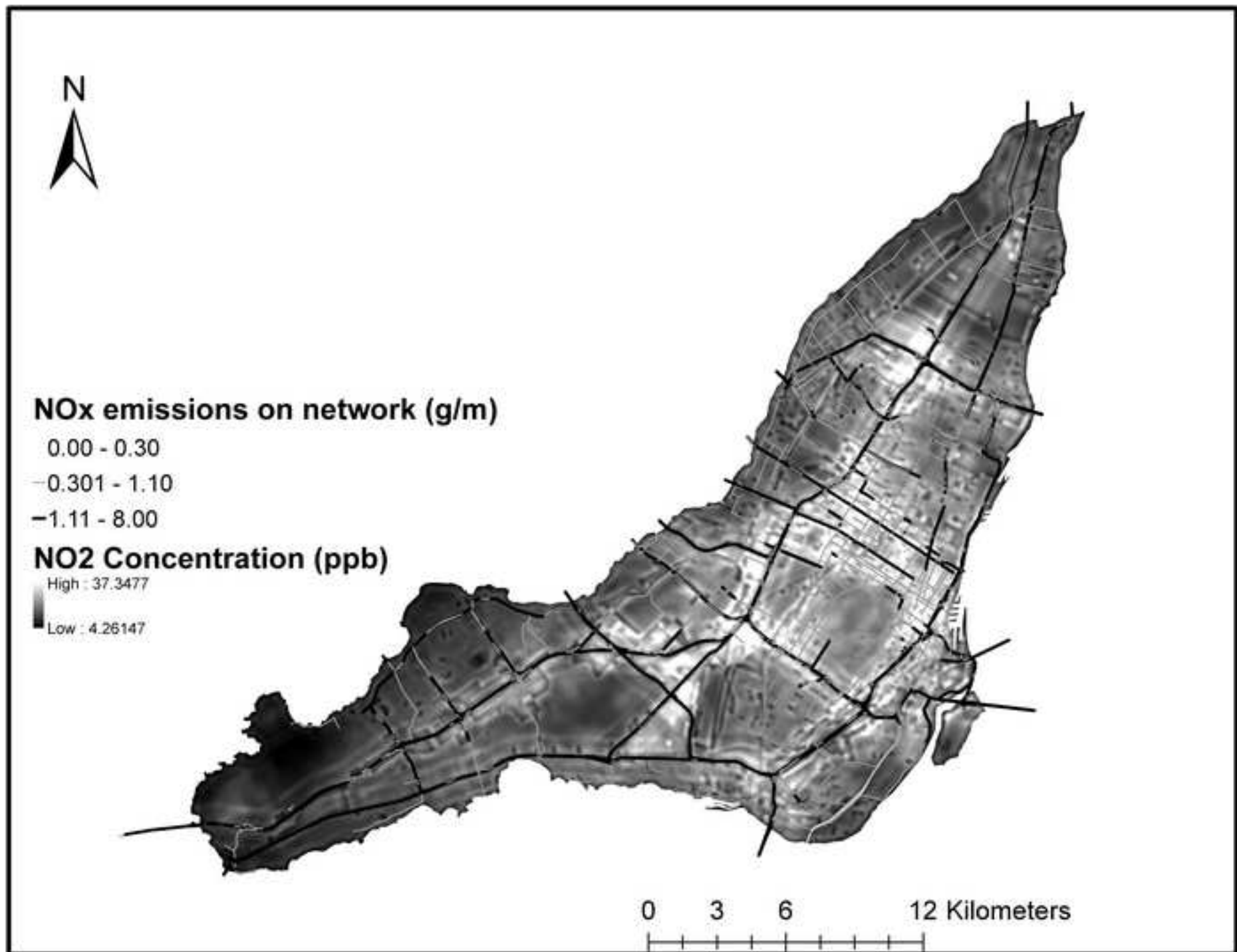


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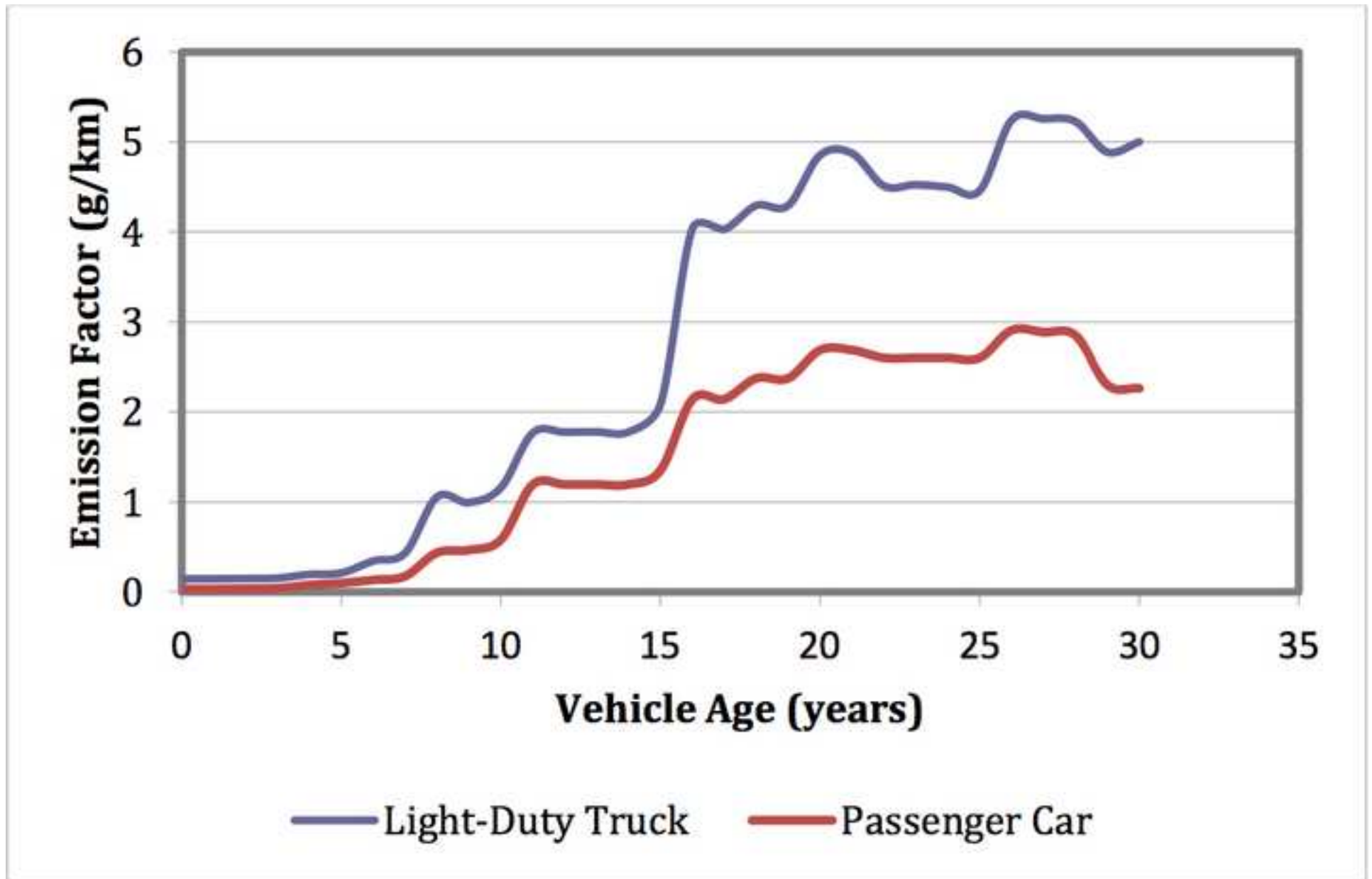
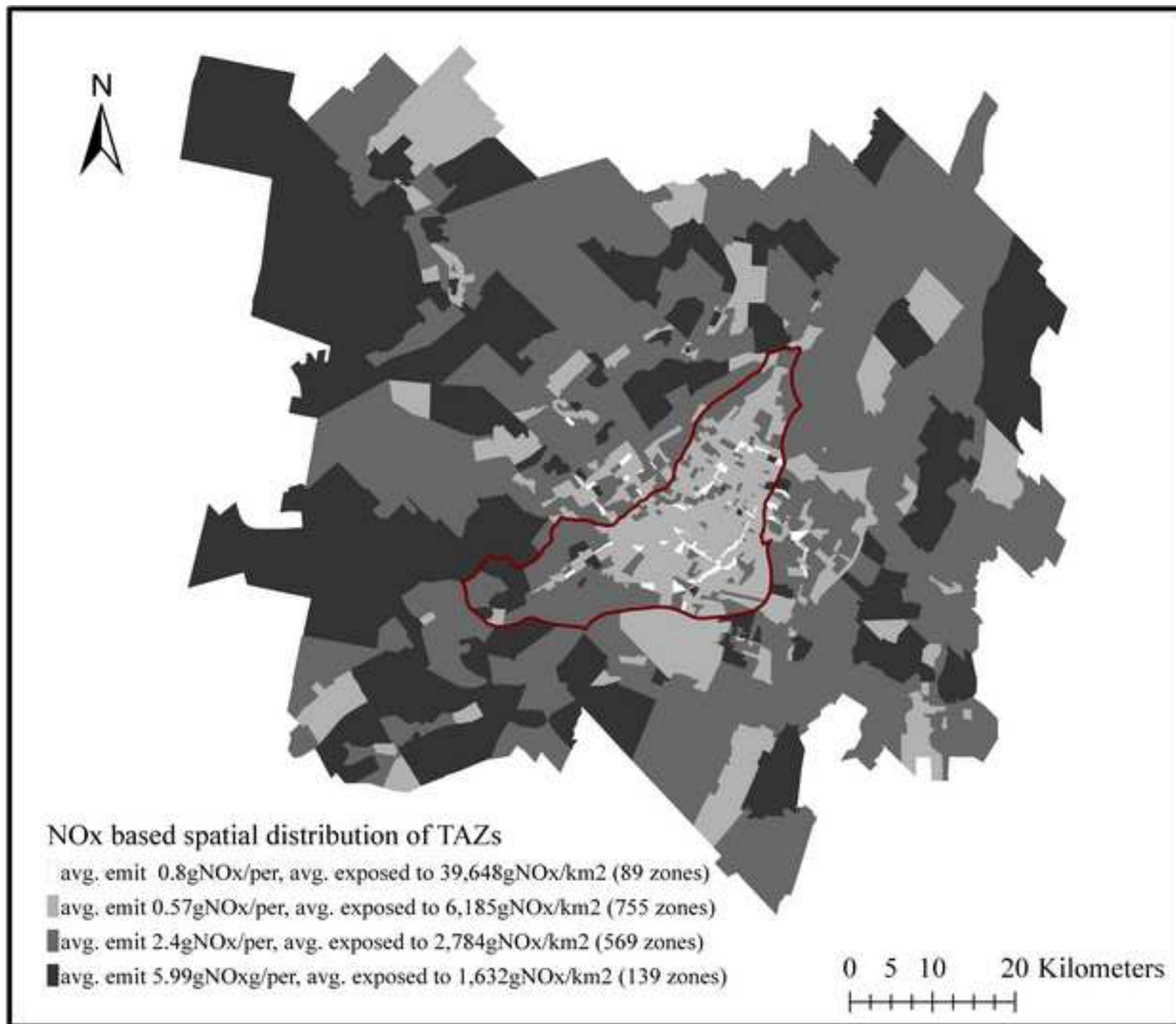


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TABLE 1

Demand Factors^b	Components		
	High income, newer vehicles	High vehicle ownership, larger vehicles	Older vehicles
TAZ average income	0.657		
Vehicles per household		0.884	
Ratio of light-duty trucks vs. cars		0.772	
Fraction of model year: 1981 to 1990			0.949
Fraction of model year: 1991 to 2000	-0.966		
Fraction of model year: 2001 to 2011	0.956		
Summary Statistics			
Eigen Value	2.32	1.44	1.13
Variance accounted for by the component (%)	38.62	24.03	18.89
Supply Factors^b	Components		
	Dense, walkable and TOD	Commercial	Government & institutional
TAZ Walkscore	0.690		
Residential density (%)	0.732		
Length of highways (kilometres)	-0.630		
Local road density (%)	0.862		
Open water density (%)	-0.803		
Bus stop density (%)	0.638		
Commercial area (km ²)		0.935	
Government and institutional area (km ²)			0.981
Summary Statistics			
Eigen Value	3.21	1.04	1.03
Variance accounted for by the component (%)	40.08	13.00	12.91

^a Principal components estimation, varimax rotation and kaiser normalization were used in creating the factors

^b Factor loadings below 0.4 are considered insignificant and not shown in the table

TABLE 2

Factors	Ln (emitted NO_x / person)		Ln (exposed to NO_x / km²)	
	B	t-stat	B	t-stat
Constant	0.077	2.543	7.103	96.02
Dense, Walkable, TOD zones	-0.082	-2.166	0.687	7.883
Government & Institutional	-0.042	-1.390	-0.120	-1.610
Commercial	-0.111	-3.497	0.238	3.147
Older Vehicles	-0.304	-9.702	-0.408	-5.507
High car ownership, larger vehicles	0.666	15.74	-0.856	-9.747
High income, newer vehicles	-0.096	-3.134	0.115	1.535
Summary Statistics				
Adjusted R ²	0.314		0.192	

TABLE 3

Fraction of model year 1981 to 1990	Vehicles per Household							Total
	0-0.5	0.5-1	1-1.5	1.5-2	2-2.5	2.5-3	3+	
0-0.01	2	0	0	0	0	0	0	2
0.01-0.15	32	8	22	33	3	0	0	98
0.015-0.02	55	67	114	121	20	3	1	381
0.02-0.025	66	181	180	163	26	1	0	617
0.025-0.03	73	78	48	41	7	0	0	247
0.03-0.04	42	39	17	49	22	1	1	171
0.04-0.05	18	3	4	7	3	0	0	35
0.05+	1	0	0	0	0	0	0	1
Total	289	376	385	414	81	5	2	1552