Emissions and built form – an analysis of six Canadian cities

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A direct result of population growth in large cities is an increased demand for public transit, goods movement, and road transportation. This increase in transportation demand consequently results in increases in mobile source emissions. Given the large amount of greenhouse gas (GHG) emissions produced by the Canadian resource industries, Canadian cities must rein in mobile source pollution if the country is to improve its status on the world stage. This study addresses this issue through presenting a Canada-specific framework for estimating mobile source emissions at the citywide level. Several air pollutants – including CO_2, NO_2, particulate matters (PM2·5 and PM10), and air toxics – are considered in this exercise, and summarized using a principal component analysis (PCA). Aggregate emissions are compared to various built form and travel behavior attributes for each respective city. The results indicate that population, travel to work behavior, and various built form attributes indeed impact transportation emissions at the citywide level.

Keywords: Emission, Principal component analysis, Built forms

Introduction

Mobile sources are one of the major contributors to urban air pollution, which is coming under increasingly tighter regulation by environmental protection agencies because of its negative impacts on human health. Case in point, in the OECD countries alone, there are 3·5 million annual deaths attributed to urban outdoor air pollution, and of those 3·5 million deaths, 50% are because of outdoor air pollution caused by road transport (OECD, 2014). As populations have tended to migrate to large cities in search of a higher quality of life, urban population growth is one of the likely causes for increasing amounts of air pollution in the world's larger cities. The in-migration of population to large cities perpetuates opportunities for employment and new residential development, which results in the demand for more transportation facilities.

Though the magnitude of population is a good indication of air pollution in large cities, urban sprawl, unemployment rates, and the quality of public transportation are other factors that affect urban air quality. Given the importance of mitigating urban air pollution, it is essential to continue to explore these and other variables that affect aggregate urban emissions. Through understanding the effects of urban form and urban activity on transportation emissions, decision makers may better control the unintended consequences of urbanization.

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In the high income region of the Americas, which includes Canada and the USA, over 60% of the urban populations are exposed to levels of particulate matters (PM2·5 and PM10) that exceed the World Health Organization's (WHO) exposure guidelines (WHO, 2014). Under the Canadian Environmental Protection Act (1999), Environment Canada has announced that airborne PM $\leq$10 μm (PM10) is extremely toxic to human health. A recently released report by the WHO lists PM2·5, PM10, and NO_2 (three main road transport pollutants) to negatively affect human health. Given the noticeable contribution of the transportation sector to air pollution in Canada, there is a need for evaluating transportation emission levels in Canadian cities, and especially in the larger metropolitan areas.

When it comes to greenhouse gases (GHGs), Canada is one of the most significant air polluting industrialized countries in the world. Since 1990, Canada has increased GHG emissions – which include CO_2 – by 24·10% (Environment Canada Air Online, 2012), while Russia, Germany, and the UK all have reduced GHGs by 32·89%, 22·22%, and 18·45%, respectively. Among the G8 countries, Canada stands only marginally below the USA in tonnes of CO_2 equivalent emitted per capita: US: 22·74, Canada: 22·04, Russia: 15·42, Germany: 11·67, UK: 10·29, Japan: 10·04, Italy: 9·05, and France: 8·29 (Environment Canada Air Online). Within Canada, the provinces of Alberta and Ontario are the largest GHG contributors.

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Table 1 Population size and land area (sq km) of investigated census metropolitan areas (CMAs)

CMA name	Province	Population in 2011	Population in 2006	Land area/sq km
St John's	Newfoundland and Labrador	196 966	181 113	804·65
Halifax	Nova Scotia	390 328	372 858	5495·71
Toronto	Ontario	5 583 064	5 113 149	5905·71
Hamilton	Ontario	721 053	692 911	1371·85
Calgary	Alberta	1 214 839	1 079 310	5107·55
Vancouver	British Columbia	2 313 328	2 116 581	2882·55

Source: 2011 Canadian Census (Statistics Canada, 2011).

This paper serves to investigate six Canadian census metropolitan areas (CMAs): Toronto, Ontario; Vancouver, British Columbia; Calgary, Alberta; Hamilton, Ontario; Halifax, Nova Scotia; and St John's, Newfoundland. All, except Hamilton, are the largest CMAs in their provinces. Hamilton is included in the analysis because it and Toronto share in Canada's largest metropolitan region – the Greater Toronto and Hamilton Area. Though the CMAs vary significantly in size (both land area and population), they provide a representative cross-section of Canadian metropolitan areas. Table 1 presents the population and land areas of these sixe CMAs.

In this paper, both qualitative and quantitative analyses are performed to assess the impacts of built form and travel behavior characteristics on mobile emission levels. Given the links between transport emissions, urban air pollution, and health, this study investigates several pollutants including criteria air contaminants and CO_2 (see Table 2 for the full list of pollutants), from an inclusive set of road transport vehicle types. Total emissions for the base year of 2006 are estimated on an hourly basis and aggregated to the average annual level. A principal component analysis (PCA) is employed to summarize the impacts of the different pollutants into a smaller set of components, which represent the complete dataset. In the results section, a number of built form attributes for each CMA are measured and discussed including entropy, congestion, accessibility, percentage of certain land use types, and travel to work mode choice (in the case of passenger-related emissions).

The qualitative analyses come into play when comparing the overall emission levels with the built form attributes. Owing to the small sample size of case studies, testing correlations between various built form indices and aggregate emission levels is not warranted. Instead the results are shown graphically and qualitative comparisons are drawn.

The remainder of this paper is organized into the following sections: a review of the literature about the relationship between urban form and emissions; an outline of the methodology used for the emission estimation model, the PCA, and estimation of the built form indicators; a brief depiction of the aggregate emission results; a detailed discussion about the relationship between the built form indicators and the emission levels in each city; and conclusions and recommendations for future research.

Literature review

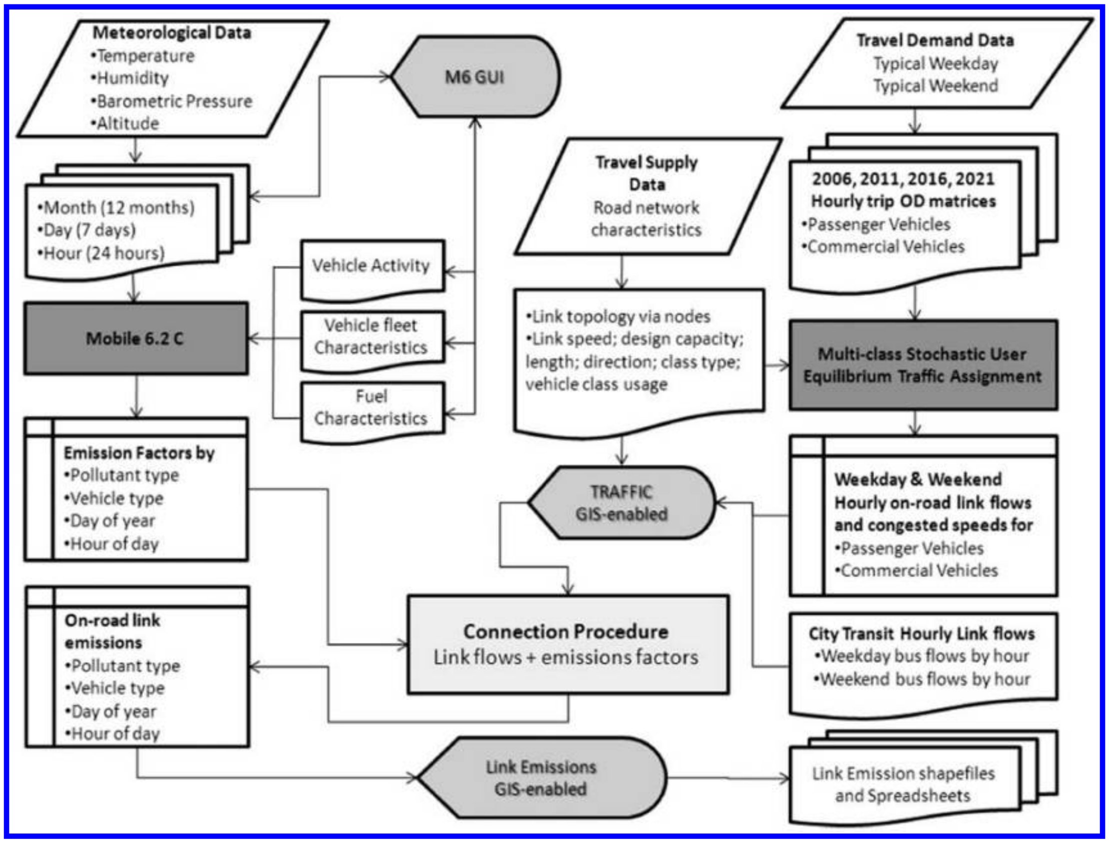
The literature on land-use and urban air pollution is directly related to studies on urban form, vehicle travel, and vehicle tailpipe emissions. However, relatively few studies have analyzed the impact of built environment variables on the macro-level air pollution in urban areas (Stone, 20080). Studies that focus specifically on transportation-related macro-level air pollution emission indicators are described in the following paragraph.

One of the earliest and most broadly cited attempts to study macro-level urbanization and fuel consumption included 32 different metropolitan regions from around the world (Newman and Kenworthy, 1989). In this study, the authors found a strong correlation between fuel consumption and population density, a measure of built environment. Further, Pucher and Lefevre (1996) studied vehicle miles travelled (VMT) or vehicle kilometers travelled (VKT) as a function of population density, where VKT may be used as an indicator for air-pollutant emissions. Finally, McDonald-Buller *et al.* (2010) investigated the impacts of two urban policy scenarios on VMT using a standard travel demand model: a business-as-usual scenario and a flat-rate carbon-based tax and congestion pricing policy. Though these studies illustrate important macro-level relationships between emissions and urban

Table 2 Principal component analysis (PCA) results for commercial vehicles

	Comp. 1	Comp. 2	Comp. 3
Proportion of variance	0·893	0·060	0·041
Cumulative proportion	0·893	0·953	0·994
Loadings			
HC	0·253		0·190
CO	2·520		0·176
NO_x	0·235		−0·450
CO_2	0·255		−0·137
SO_4		−0·979	−0·203
OCARBON	0·249		−0·138
ECARBON	0·253		0·152
GASPM	0·225	0·106	−0·558
SO_2	0·247		−0·307
NH_3	0·252		0·221
Brake	0·252		0·207
Tire	0·255		0·115
Benzene	0·252		0·207
Butadiene	0·251		0·237
Formaldehyde	0·256		
Acetaldehyde	0·256		
Acrolein	0·255		−0·117

HC: hydrocarbons; CO: carbon monoxide; NO_x: nitrogen oxides; OCARBON: organic carbon portion of diesel exhaust particulate; ECARBON: elemental carbon portion of diesel exhaust particulate; GASPM: total carbon portion of gasoline exhaust particulate.



1 Modeling framework for estimating on-road link emissions with Mobile 6·2C

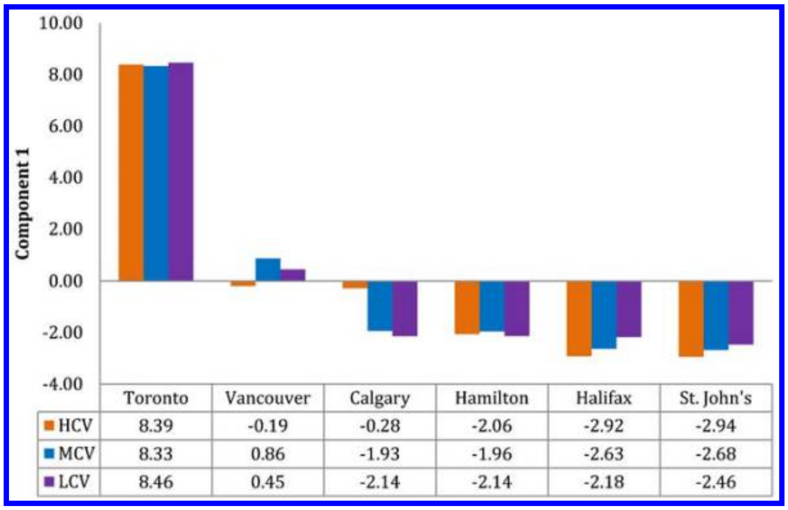
variables, their relative scarcity shows a clear need for more research in the area of citywide emission modeling.

In contrast, there are considerably more studies that investigate the impact of built environment variables on air-pollutant emissions at the disaggregate level. For instance, Frank *et al.* (2000) studied vehicle emissions per household as a function of land-use variables. Given that human activity patterns and household travel decisions are greatly influenced by built environment variables, vehicular emissions are inherently a function of built environment variables such as urban shape and land-use pattern (Salis *et al.*, 2004; Ewing and Cervero, 2001; Frank, 2000; Saelens *et al.*, 2003; Giles-Corti and Donovan, 2003). Public health and its dependence on air quality have also been studied in conjunction with vehicle emissions (Frank and Engelke, 2005).

Researchers (see for example Mage *et al.*, 1996), studying the impacts of urban form on air pollution, tend to concentrate on specific air pollutants such as carbon monoxide (CO), hydrocarbons (HC), nitrogen oxides (NO_x), O_3, PM2·5, and PM10. The latter are also known as criteria air contaminants in Canada (Environment Canada, 2014). Though interesting, the passenger car is the dominant type of vehicle considered for estimating air pollution, while air pollution is mainly attributed to commercial vehicles and public transit vehicles (Mayer, 1999).

Urbanization, and hence urban form, has also been shown to influence regional meteorological conditions, which in turn affect air quality and pollution dispersion. For example, the heat island effect is the most widely recognized meteorological effect of urbanization. This effect is demonstrated by the difference in air temperatures of urban centers relative to adjacent rural areas, and has been shown to be a several degree increase in temperature in large cities (Oke, 1987). Shepherd *et al.* (2002) show another example of the effect of urban form on meteorological conditions. In this instance, they claim that the approximate 20% increase in rainfall in the metropolitan Atlanta region can be explained in terms of urban activity in the upwind control region during the period of 1998–2000.

The above review indicates that there are a number of opportunities to contribute to the literature as there are few existing studies looking at the relationship between estimates of macro-level transportation pollution and built form (Stone, 2008). The first opportunity lies in estimating macro-level air-pollutant emission levels using a broad range of air pollutants and a full spectrum of transport vehicle types. Further to this, there appears to be no existing attempt at estimating macro-level transport emissions for Canadian cities. Though it is difficult to derive direct policy implications from citywide comparisons, the information gained from macro-level pollution estimation provides insight into the interactions between built form and air quality in the Canadian context, and points to future research work in the area of Canadian transport emissions.



	Toronto	Vancouver	Calgary	Hamilton	Halifax	St. John's
HCV	8.39	-0.19	-0.28	-2.06	-2.92	-2.94
MCV	8.33	0.86	-1.93	-1.96	-2.63	-2.68
LCV	8.46	0.45	-2.14	-2.14	-2.18	-2.46

2 Component 1 estimates for commercial vehicles

Methodology

This section is split into three subsections in each of which the related methodology is explained. First, the methodology for estimating the emission for each pollutant is discussed. This estimation is conducted at the highly disaggregate level of links, requiring a complex system of algorithms, which are integrated with the emission estimation models. The estimated emission values are aggregated to the city level and used then in the PCA model, which is explained in detail in the second subsection. Following that, the used methods for quantifying land-use attributes are discussed.

Implementation of modeling framework

For the purpose of establishing an inventory of traffic emissions, the authors developed an integrated system to model link-based traffic flows on an hourly basis, for the subsequent estimation of emissions. The proposed framework combines an intra-urban traffic model with emission factors calculated with the help of Mobile 6·2C, the Canadian version of the USEPA Mobile 6·2 Vehicle Emission Modeling Software (USEPA, 2003). In this model, the authors differentiate passenger vehicles, transit buses, and three types of commercial vehicles: light, medium, and heavy duty. The pollutants considered are HC, CO, NO_x, PM, and air toxics. Traffic flows are modeled using origin–destination (OD) matrices of trips for each vehicle type. The road network consists of links connected through nodes, with relevant attributes such as speed, length, the design capacity, link direction, and vehicle class usage. A stochastic user equilibrium (SUE) algorithm (Sheffi, 1985) assigns trips efficiently along the network, simulating the choice of links by the travelers. The traffic flows are integrated with emission factors for the relevant vehicle types at various speeds on highways and arterial roads. Figure 2 displays the modeling framework for estimating the link-based emissions.

Emission factors

The authors developed a graphical user interface, M6, for the Mobile 6·2c software. *MOBILE6·2C* generates emission factors for pollutants as follows:

1. HC
2. NO_x
3. CO
4. PM2·5 and PM10 with components:

a. SO_4 – sulfate portion of exhaust particulate
b. OCARBON – organic carbon portion of diesel exhaust particulate
c. ECARBON – elemental carbon portion of diesel exhaust particulate
d. GASPM – total carbon portion of gasoline exhaust particulate
e. Lead – lead portion of exhaust particulate
f. SO_2 – sulfur dioxide (gaseous)
g. NH_3 – ammonia (gaseous)
h. Brake – brake wear particulate
i. Tire – tire wear particulate

5. Air toxics

a. Benzene
b. Methyl tertiary butyl ether
c. 1,3-Butadiene
d. Formaldehyde
e. Acetaldehyde
f. Acrolein

6. Carbon dioxide

Emission factors are calculated for 28 types of motorized vehicles under different travel speeds but for the purposes of this project, 26 of the 28 vehicle types were considered and collapsed into five major vehicle classes *g*, in order to match the five vehicle classes of the utilized travel data. Each vehicle class is associated with an age distribution for number of registrations in Canada, in the MOBILE6·2C package. The five classes of vehicles are light-duty passenger vehicle (LDPV), light-duty commercial vehicle (LDCV), medium-duty commercial vehicle (MDCV), heavy-duty commercial vehicle (HDCV), and Heavy Duty Diesel Transit and Urban Buses (HDDBT). Motorcycles and school buses were excluded.

Emission factors produced by *MOBILE6·2C* are influenced by fleet characteristics such as vehicle type, age, fuel type, mode of operation, and external variables such as meteorology and road type. Many of these variables are defined by default distribution tables customized for the Canadian fleet of cars. Meteorological variables of hourly temperature, humidity, and daily barometric pressure for the Calgary CMA were obtained for the meteorological station at the Calgary International Airport, from the Environment Canada climate data website (Environment Canada, 2007). The links of the street network comprise the arterial roads and major highways.

As shown in Fig. 1, for a specified pollutant *p*, travel speed *s* and road type *h*, *MOBILE6·2C* initially reads in the meteorological information along with data on vehicle characteristics and activities. It then produces a table summarizing the estimated emissions $e(p, s, h, v, a)$ in grams per kilometer for each of the 26 vehicle types *v* and a given age group *a* in which vehicles type *v* belong. The table also provides the distribution of vehicles $r(v, a)$ across all ages *a* for each vehicle type *v*. Each distribution per vehicle type *v* provides the fraction of *v* among 25 ages (a=1,2,…,25), where $\sum_a r(v, a)=1$.

M6 processes the calculated $e(p, s, h, v, a)$ to produce the emission factors $ef(p, s, h, g)$ needed to estimate the on-road link emissions from the link flows generated by vehicle class *g*. Factors $ef(p, s, h, g)$ are obtained via the following algorithm:

Step 1: Select all records for a given vehicle group *g*

Step 2: Average $e(p, s, h, v, a)$ over all vehicle types *v* corresponding to vehicle class *g*

$$e_{\text{avg}}(p,s,h,g,a)=\frac{\Sigma_{\text{v}=1}^{\text{n}}e(p,s,h,v,a)}{n} \quad (1)$$

where *n* is the number of vehicle types in vehicle group *g*.

Step 3: Average $r(v,a)$ over all vehicle types *v* corresponding to vehicle class *g*

$$r_{\text{avg}}(g,a)=\frac{\Sigma_{\text{v}=1}^{\text{n}}r(v,a)}{n} \quad (2)$$

Step 4: Calculate the emission factor for a given pollutant *p*, travel speed *s*, road type *h*, and vehicle type *g* as follows

$$ef(p,s,h,g)=\Sigma_{\text{a}}e_{\text{avg}}(p,s,h,g,a)\times r_{\text{avg}}(g,a) \quad (3)$$

Traffic assignments

To determine emissions at the road link level, hourly traffic flow estimates for each vehicle class *g* for a typical weekday and weekend were required. Passenger and commercial flows were determined from hourly OD trip matrices that were either derived from household travel surveys in the case of passenger trips or estimated from spatial interaction models as in the case of commercial trips. Traffic flows were modeled with a GIS-based implementation of the SUE traffic assignment algorithm (Sheffi, 1985) and the resulting computer program that the authors have called *TRAFFIC*. The program is coded in the C programming language and includes basic GIS capabilities of the ESRI MapObjects spatial components (Moah *et al.*, 2009). *TRAFFIC* reads OD matrices for the designated traffic assignment zoning system, along with the road network connected to that zoning system. The program processes the input information to simulate and map traffic flows on the road network.

The road network used is a planar graph, which is divided into a set of mutually exclusive links connected through nodes. Each link has attributes including posted speed $s(l)$, length $k(l)$, the design capacity $\underline{dc}(l)$, link direction (one way versus two ways), class type $\overline{h}$ (freeway versus arterial), and vehicle class usage (i.e. passenger versus truck usage). The SUE algorithm assigns trips to particular paths connecting origin *i* and destination *j* under the principle of user equilibrium (Moah *et al.*, 2009). Here, travel time on all used paths in the city is less than or equal to travel time on any un-used path. As such, no traveler will be able to reduce travel times by unilaterally altering the used path. The algorithm attempts to simulate how travelers choose their paths to go from a given origin to a given destination.

A multiclass algorithm utilizing the SUE assignment is designed to simultaneously assign the trips generated by different vehicle classes on the road network. Before the algorithm is engaged, LDCVs, MDCVs, and HDCVs OD matrices are expressed in passenger car equivalency (PCE) units. That is, one HDCV trip is translated into 2·5 passenger trips using a PCE value of 2·5, for instance. This conversion is important since the traffic assignment uses link design capacity measures $\underline{dc}(l)$ in passenger car units. Typical PCE values for heavy-, medium-, and light-duty commercial vehicles are 2·5, 2·0, and 1·0, respectively (Kanaroglou and Buliung, 2008).

The steps for multiclass traffic assignment algorithm to estimate link flows $x^{\text{t}}(g,l)$ for vehicle class type *g* (*g* = LDPV, LDCV, MDCV, HDCV) and road link *l* are as follows:

Step 0 (Defining link performance function):

Define a link performance procedure to calculate travel times on a given link *a*

$$t^{\text{c}}(l,t)=t^{\text{f}}(l)\left(1+a\left(\frac{x^{\text{t}}(\text{LDPVs},l)+x^{\text{t}}(\text{LDCVs},l)+x^{\text{t}}(\text{MDCVs},l)+x^{\text{t}}(\text{HDCVs},l)+x(\text{CTRVs},l)}{dc(l)}\right)^{\beta}\right) \quad (4)$$

where $t^{\text{f}}(l)$ is free flow travel time on link *l, dc*(*l*) is the design capacity of link *l*, and α and β are constants set to 0·15 and 4, respectively.

Step 1 (Iteration t = 0):

Initialize iteration number t = 0; initialize the link flows for the different vehicle types to 0. That is

$$x^0(\text{LDPVs},l)=0;\; x^0(\text{LDCVs},l)=0;\; x^0(\text{MDCVs},l)=0;$$
$$x^0(\text{HDCVs},l)=0 \text{ for all links } l.$$

Step 2 (Assigning PCE HDCVs):

Calculate travel times for each link *l* using the link performance function in equation (4). Assign the PCE HDCVs OD matrix to the truck network. This will result in an updated array for heavy-duty CV link flows, that is x^0 $(\text{HDCVs},l)\geq 0$ for all *l*.

Step 3 (Assigning PCE MDCVs):

Calculate travel times for each link l using the link performance function in equation (4). Assign the PCE MDCVs OD matrix to the truck network. This will result in an updated array for medium-duty CV link flows, that is x^0 (MDCVs,l) ≥ 0 for all l.

Step 4 (Assigning PCE LDCVs):

Calculate travel times for each link l using the link performance function in equation (4). Assign the PCE LDCVs OD matrix to the entire road network. This will result in an updated array for light-duty CV link flows, that is x^0 (LDCVs,l) ≥ 0 for all l.

Step 5 (Assigning LDPVs):

Calculate travel times for each link l using the link performance function in equation (4). Assign the LDPV OD matrix to the entire road network. This will result in an updated array for LDPV link flows, that is x^0 (LDPVs,l) ≥ 0 for all l.

Step 6 (Increase iteration counter):

Increase iteration number by 1, that is $t=t+1$.

Step 7 (Convergence test):

If $t=1$, repeat steps 2–5 to generate $x^1(g,l)$ $\forall g$

If $t>1$ then, if $\mathrm{Max}|x^{t+1}(g,l)-x^t(g,l)|\leq \varepsilon$ then traffic assignment is completed, otherwise repeat steps 2–5 to generate a new $x^t(g,l)$ $\forall g$. Here, ε is an arbitrarily small number.

Upon convergence, assigned flows for heavy, medium, and light commercial vehicles are translated to actual truck flows by re-scaling the assigned flows by the used PCE values. Once flows are assigned to the network, congested speeds $s^c(l)$ can be calculated for each link l based on the achieved congested travel times $t^c(l,t)$ per link l.

Emission estimates

Following the approach in Anderson *et al.* (1996), *TRAFFIC* calculates the emissions on a given link using the estimated link flows $x(g,l)$, link congested speeds $s^c(l)$, link length $k(l)$, and the generated emission factor $ef(p,s,h,g)$from the *M6* program. For a given link l, the congested travel speed $s^c(l)$ is utilized to obtain its corresponding emission factor. Consequently, the total emissions (in grams) on link l during a particular hour of the day for pollutant p and vehicle class g are calculated as follows

$$le(p,g,l)=x(g,l)\cdot ef(p,s^c(l),h,g)\cdot k(l) \qquad (5)$$

Another useful measure that can be calculated is the density of emission on the link, which measures the total grams per kilometer. This is calculated as follows

$$led(p,g,l)=x(g,l)\cdot ef(p,s^c(l),h,g) \qquad (6)$$

The total emission of pollutant p because of the overall generated traffic is calculated as follows

$$te(p,l)=\Sigma_g le(p,g,l) \qquad (7)$$

Notice that link l should belong to road class type h, where h = freeways or arterials since all minor and local roads were excluded from the inventory. Using the estimated link emissions, a total measure depicting aggregate emission for the entire urban area can be calculated by summing across all links, that is

$$E(p)=\Sigma_l te(p,l) \qquad (8)$$

Note that bus flows x(CTRVs,l) are determined exogenously since bus traffic by its nature is essentially predetermined.

Principal component analysis

Principal component analysis is a mathematical procedure, which uses an orthogonal transformation to convert a set of possibly correlated variables (in this case, emissions for 17 different pollutants from 5 Canadian CMAs) into a new set of independent (uncorrelated) variables or principal components (Pearson, 1991). The principal components are linear products of the original variables (see equation (9)), while the number of components is equal or less than the number of variables. In the PCA transformation, the first component explains the major part of the variance in the data. Each succeeding component explains the highest possible portion of the remaining variance in the data. Therefore, the initial few components may be used to represent the original data.

The loadings used to linearly transform the original variables to the independent components are estimated such that the greatest variance by any projection of the data comes to lie across the first principal component. Similarly, the second greatest variance lies on the second coordinate, and so on. It should be noted that if the variables are not in the same scale, then they should be standardized before calculating the principle component. Equation (9) represents the relationship between the standardized variables and the components

$$\mathrm{PCA}_i=\sum_{j=1}^{N} L_{ij}Z_j \qquad (9)$$

PCA_i is the ith component, Z_j is the jth standardized variable (i.e. emission level of the jth pollutant), L_{ij} is the loading factor for jth pollutant and ith principle component, and N is the number of variables (or pollutants). L_{ij} may be interpreted as the importance of jth pollutant in the ith component.

Although the application of PCA in emission modeling is not new (Smeyers-Verbeke *et al.*, 1984), it is infrequently implemented. Outside of the traditional PCA, researchers have utilized other types of eigenvector-based multivariate analyses to merge several environmental factors (Montero *et al.*, 2010).

Built form indicators

The following briefly explains the derivations of the three built form indicators, which are derived from the DTMI files and used in the subsequent analysis of emissions and built form. Each of the built form indicators discussed below is normalized and aggregated to the macro-level. Other built form indicators are used in the analysis;

however, they require less explanation and will be addressed later in the text.

Accessibility index

The accessibility index of one location (zone) represents the total opportunities from other locations (zones) that are available to it, while considering the impact of the spatial impedance between it and any other location. Following the methodology by Kockelman (1997) and Maoh and Kanaroglou (2009), a set of accessibility statistics are calculated as shown in equation (10) using the land-use data available in the DMTI files (www.dmtispatial.com). DMTI Spatial offers various products including street maps, census data, boundary information, postal geography, topographic maps, and geographic features for all Canadian urban areas

$$\mathrm{ACC_i} = \Sigma_\mathrm{j} \frac{A_\mathrm{j}}{t_\mathrm{ij}^2} \tag{10}$$

$\mathrm{ACC_i}$ refers to the accessibility index of TAZ i, A_j is the attraction of zone j based on the resources, open area, etc., available in zone j, and t_ij is the travel time from zone i to zone j. The accessibility indices of each TAZ are then weighted by the population of the TAZ, and normalized by the total zonal population to be aggregated to the CMA level, which includes the urban core area and adjacent areas that have a high level of interaction with the core.

In general, the accessibility index should be positively correlated with total emission levels, as increasing accessibility implies an increase in opportunities that are available and accessible in a city. Though higher accessibility leads to a higher travel demand, this does not explain the entire picture of people moving emissions. If the city's land uses are also well mixed, the built form would be conducive to walking and biking, which would support lower levels of personal vehicle emissions. Thus, the accessibility index alone cannot explain a city's built form context.

Entropy index

The entropy index for TAZ i is used to quantify the land-use balance (Cervero, 1989) and is calculated as shown in equation (11) using the land-use data extracted from the DMTI files

$$\mathrm{Entropy_i} = \frac{\Sigma_\mathrm{j} P_\mathrm{j} * \ln(P_\mathrm{j})}{\ln(J)} \tag{11}$$

P_j is the percentage of land use type j within each TAZ, while J is the number of land use types existing in the TAZ. To make these entropy measures comparable across different cities, the entropy for each CMA is normalized by the number of TAZs.

Contrary to the accessibility index, the entropy index should be negatively correlated with emissions, as a higher mixture of land uses indicates lower travel distances. Again, the entropy index does not explain the full picture of a city's built form; however, it provides important supplementary information about the mixture of land uses in a city.

Congestion index

Citywide traffic congestion levels are calculated to reflect the performance of the road system. This congestion indicator is simply estimated by using the link flow and capacity. Then, the city level congestion indices are calculated as shown in equation (12)

$$\mathrm{Congestion} = \frac{\Sigma_\mathrm{k}^\mathrm{N} \frac{x(l)}{dc(l)}}{L} \tag{12}$$

$x(l)$ and $dc(l)$ are previously defined and L is the total number of traffic links of a city's road network.

The congestion index (CI) is expected to be positively correlated with emissions, as higher congestion levels imply inefficient operation of a city's road system. The CI is important, as it is the only indicator that provides information about the performance of a city's road network.

Aggregate emission results

Two separate PCA estimates were completed. The first represents the total citywide emission estimates for the goods moving vehicle types: light-duty, medium-duty, and heavy-duty commercial vehicles. Given that road transportation makes up the largest share of goods transport, the commercial vehicle emission estimates are assumed to represent the main share of urban goods movement emissions (Jiang *et al.*, 1999). The second represents the per capita emission estimates for the people moving vehicle types: passenger vehicle and transit bus. Per capita emission estimates are shown for people moving vehicle types in order to control for the effects of population.

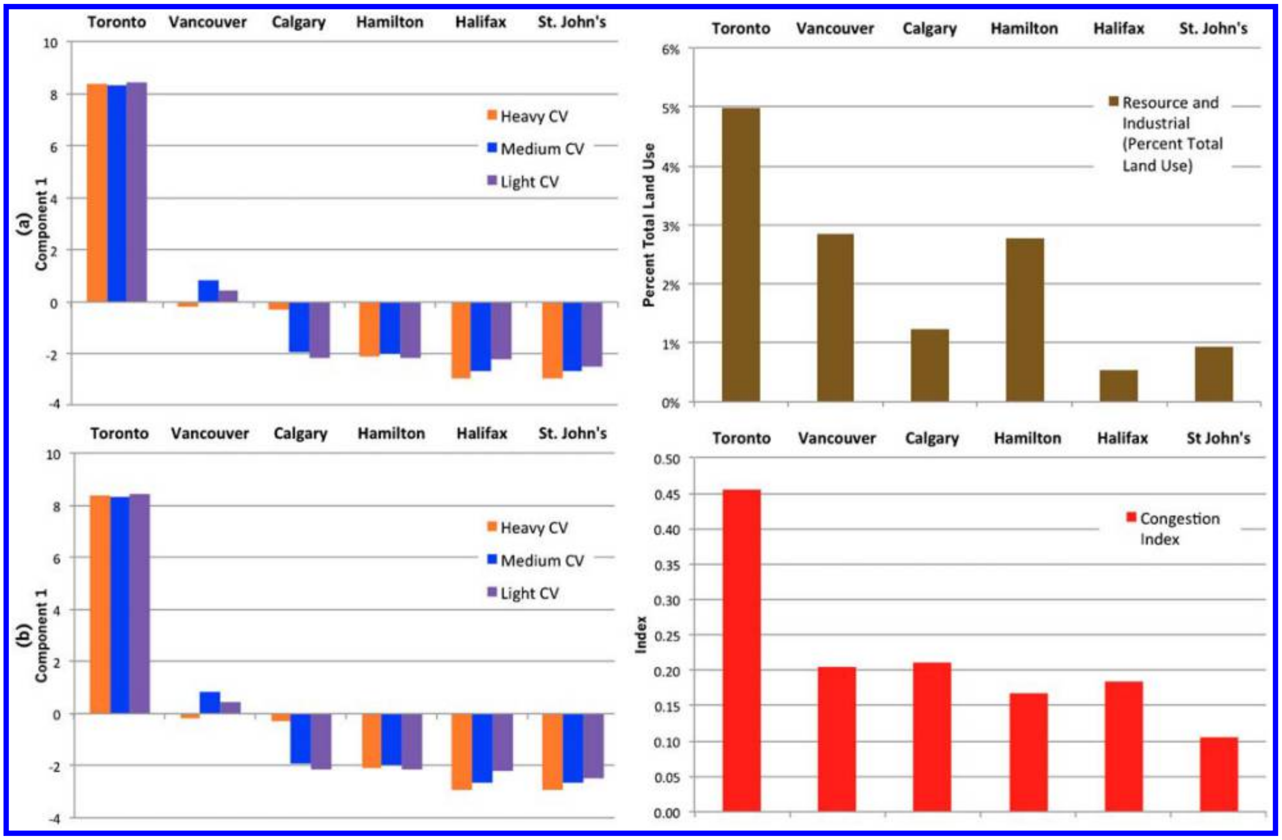
Commercial vehicle emissions

Table 2 shows the results of the PCA on the total emission data for the six metropolitan areas for commercial vehicles. Only the first three components are shown as they represent the majority of the variance in the data.

As the first component represents 89·3% of the variance in the data, it will be used to represent total emissions in the following analysis. This is inline with other findings (Henderson *et al.*, 2007), which show that air pollution variables are highly correlated and may be represented by a single component.

Passenger vehicle and transit bus emissions

By doing a PCA similar exercise on the per capita emission data for the six CMAs for the passenger vehicle and transit bus, a similar result is obtained. Similar to the estimated components obtained for commercial vehicles, it is found that the amount for different emission types are highly correlated and the first component represents 93·4% and 99·2% of the variance in the data for auto and bus, respectively. This finding will be used to represent per capita emissions in the following analysis. Again, this finding is consistent with the literature (Henderson *et al.*, 2007).



3 **Charts comparing *a* commercial vehicle emission versus per cent resource and industrial land use and *b* commercial vehicle emissions versus congestion index (CI)**

Discussion

The following analysis of built form characteristics and aggregate emissions is broken into two sections according to the freight moving vehicles and people moving vehicles, as described in the previous section. In each of Figs. 2–5, the CMAs are shown from left to right, in order from largest to smallest 2006 population (Toronto: 5 113 149; Vancouver: 2 116 581; Calgary: 1 079 310; Hamilton: 692 911; Halifax: 372 858; St John's: 181 100).

Commercial vehicle emissions

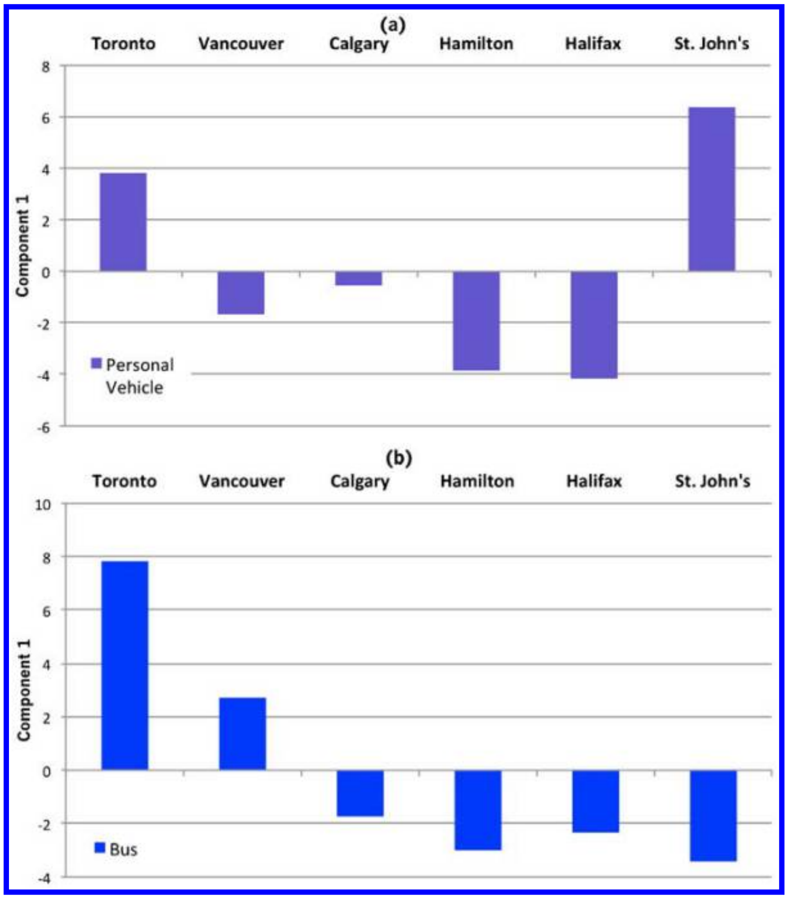
Figure 2 is a graphical representation of the component 1 results for each of the commercial vehicle types for each of the six cities.

The component 1 estimates shown in Fig. 2 should not be interpreted as real emission values for each city. The component 1 estimates provide a relative magnitude of emissions in each city, to be used as a comparison between CMAs. As such, the y-axis represents the average emission level of the six CMAs, where positive component 1 estimates indicate above average commercial vehicle emissions and negative component 1 estimates indicate below average commercial vehicle emissions. Thus, Toronto has the highest heavy commercial vehicle emissions of the six CMAs, followed by Vancouver, Calgary, Hamilton, St John's, and Halifax.

To understand the magnitude of emissions estimated for each of the CMAs, two built form indicator variables are employed: per cent resource and industrial land within the metropolitan area, and the CI, as shown in Fig. 3. The other built form indicators were found to have little relationship with commercial vehicle emissions and, therefore, will not be discussed in this section.

As shown in Fig. 3*a*, there is some relationship between industrial land use and commercial vehicle emissions. The per cent industrial and resource land use in each city would indicate that the commercial vehicle emissions should be higher in Toronto, Vancouver, and Hamilton, slightly lower in Calgary and St John's, and the lowest in Halifax. Though the pattern is representative for Toronto, Vancouver, Calgary, and Halifax, it does not explain Hamilton and St John's. Unlike the other four CMAs, a large share of Hamilton's industrial land use is attributed to the steel industry, which relies on marine transportation and not trucks. Therefore, while Hamilton's share of manufacturing land use is equivalent Vancouver's share, the level of commercial goods movement would typically be much lower. As for St John's, the results may be as a result of inconsistencies in land development. Unlike the other larger CMAs, St John's has undeveloped land within its boundary and the industrial land-use indicator may not accurately represent the currently built proportions of these land uses. Also, it may be that large areas of St John's CMA are designated as resource land use because of the fishery industry in that Atlantic CMA.

The CI, shown in Fig. 3*b*, again explains the large magnitude of commercial vehicle emissions in Toronto;



4 Component 1 estimates for *a* passenger vehicle emissions and *b* transit bus emissions

however, there is no clear relationship between the CI and the commercial vehicle emissions for the other cities. This relationship is further analyzed by looking at the correlation between the first component estimate for commercial vehicles and the percentage of land use for industrial and resources and the CI. Table 3 shows the results of the correlation matrix. As it can be seen from Table 3, there is a strong correlation between congestion and emission from commercial vehicles. Further, there appears to exist a moderate correlation between the level of total emission from commercial vehicles and industrial and resources opportunities in the studied CMAs.

It is possible that the magnitude of commercial vehicle emissions within a given CMA is more related to the economic activity of the CMA rather than the CMA's built form characteristics. It is also possible that the magnitude of emissions in Toronto is so high compared to the other cities that the relationship between the other five CMAs is being dominated by Toronto. In order to accurately assess whether specific land-use variables impact commercial vehicle emissions in a given CMA, it would be constructive to isolate CMAs with similarly sized populations and economic activity, and analyze the results among the different strata of CMA sizes. However, even without gleaning specific context about the correlation between built form and commercial vehicle emissions, the relative magnitudes of commercial vehicle emissions shown in this case study provide an instructive comparison across the six CMAs.

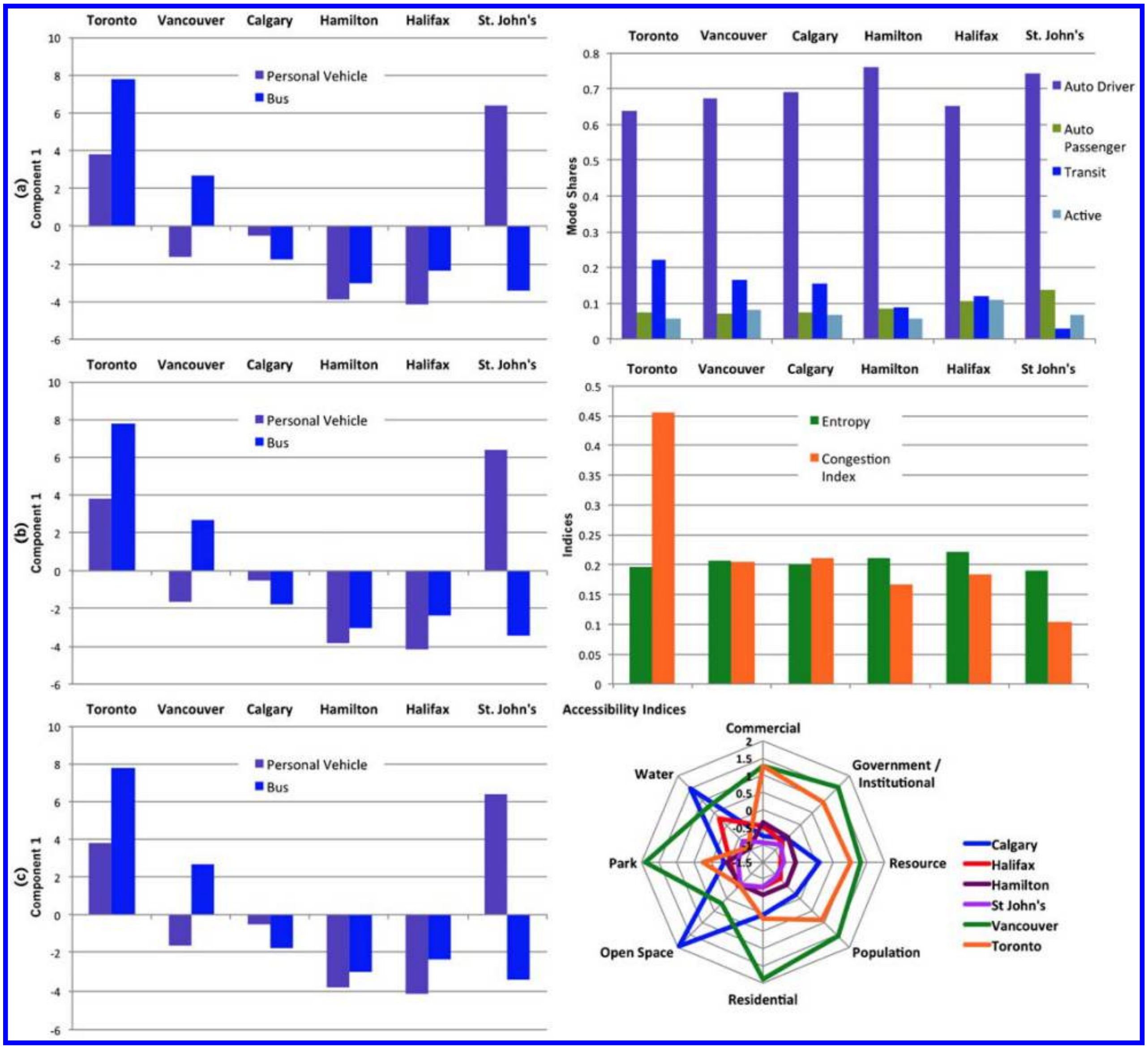
Table 3 Correlation between the PC1 of commercial vehicles and resource and industrial built form indicator (RIBFI) and congestion index (CI)

	HDCV	MDCV	LDCV	CI	RIBF
HDCV	1				
MDCV	0·97	1			
LDCV	0·97	0·99	1		
CI	0·97	0·95	0·95	1	
RIBFI	0·35	0·45	0·39	NA	1

Passenger vehicle and transit bus emissions

The results of the component 1 estimates for (a) personal vehicle emissions and (b) transit bus emissions are shown in Fig. 4, which as previously mentioned, represent the relative per capita emission levels for each city.

Again, the component 1 estimates shown in Fig. 4 should not be interpreted as real emission values for each city. These estimates provide a relative magnitude of emissions in each city, to be used as a comparison between cities. Thus, St John's has the highest level of per capita personal vehicle emissions, followed by Toronto, Calgary, Vancouver, Hamilton, and Halifax. The pattern for transit bus emissions is more representative of the population in each city, where Toronto has the highest level, followed by Vancouver, Calgary, Hamilton, Halifax, and St John's.



5 **Charts comparing *a* passenger and bus vehicle emission versus travel mode choice, *b* passenger and bus vehicle emission versus entropy and congestion indices, and *c* passenger and bus vehicle emission versus accessibility indices**

To better understand the results presented in Fig. 4 and the previous sections, a number of built form indicators are used: travel to work mode choice (Statistics Canada, 2007a, 2007b, 2007c, 2007d, 2007e, 2007f), the entropy index, the CI, and the accessibility indices. These comparisons are shown in Fig. 5.

Figure 5*a* indicates that there is indeed a relationship between people moving vehicle emissions and the aggregate travel behavior in each CMA. St John's has the highest combined automobile (driver and passenger) mode share of any of the CMAs, which is correlated to it having the highest rate of personal vehicle emissions. The transit mode share in St John's is the lowest of the six CMAs, which further suggests why it has the lowest rate of transit bus emissions. Halifax's low auto share and high transit and active mode shares indicate why it has the lowest personal vehicle emission rates of the six CMAs, and higher bus emissions than St John's and Hamilton. Hamilton's rate of personal vehicle emissions is not well explained by the CMA's auto mode share; however, the low rate of bus emissions in Hamilton corresponds to the low level of transit use in the CMA.

Although the relative proportion of automobile use in Calgary and Vancouver corresponds each CMA's level of personal vehicle emissions, the relationship between travel behavior and emissions in Calgary, Vancouver, and Toronto is more complicated. Each of these three CMAs has higher-order transit networks such as light rail transit (LRT) or subway, and therefore, specific portion of bus transit users is unclear. With that said, Toronto's high rate of transit bus emissions are likely representative of the relative level of transit users in the CMA. In the future, CMAs providing multiple different modes of transit service should be analyzed separately, and an indicator representing the proportion of bus transit service in each metropolitan area should be investigated.

The entropy and congestion indices shown in Fig. 5*b* further explain the emission results. It is clear that Toronto stands alone in terms of congestion levels, which shows that regardless of the aggregate travel behavior in the city, congested networks impact the magnitude of region wide emissions. The comparison of Vancouver and Calgary shows that Vancouver has higher entropy and lower congestion, and adds context to Vancouver's lower rate of personal vehicle emissions. Hamilton's low level of congestion and high level of entropy also help to explain the CMA's low rate of emissions for both vehicle types. Similarly, Halifax's highest relative entropy provides a good explanation for the CMA's low emission rates.

Each land use shown in Fig. 5*c* is assumed to be an attraction for personal vehicle and transit travel. As such, the general hierarchy of accessibilities should indicate the attraction of land uses in each metropolitan area. Vancouver, Toronto, and Calgary have the highest overall accessibility indices, which is compatible with the result of higher people moving emission rates in the three urban regions.

Conclusion and future research

Given the impact of air pollution on human health, and the impact of mobile source emissions on air pollution, it is crucial to understand more about transportation emissions in the urban setting. This emission analysis work is particularly important in the Canadian context, as there has been no prior attempt to analyze macro-level emissions of Canadian cities using an inclusive set of vehicle types and pollutant types. Although diesel vehicles, such as buses and trucks, emit the highest levels of PM, NO_x, CO, and HC, they are rarely the focus of emission models. Thus, this paper specifically targets commercial vehicles and buses, as well as passenger vehicle types, to ensure that diesel vehicles are well represented in the analysis.

The methodology employed in this paper is a valuable first step in the realm of emission modeling in Canada. Incorporation of the PCA allows for the results of the macro-level mobile source emission estimates to be compared across metropolitan areas. Though there is a clear indication that certain urban variables – per cent resource, industrial land, travel to work behavior, congestion, entropy, and accessibility – affect the mobile emission rates in each region, the population of each metropolitan area appears to have a dominant effect on emissions. The results are clearly stated for all types of commercial vehicles, and though transit bus and passenger vehicle emissions were analyzed on a per capita basis, there is still an obvious positive relationship between total emission levels and urban population. In the future, when this work is enhanced with additional case studies, these positive relationships should be statistically tested to prove correlation. Therefore, it is recommended that additional case studies be completed such that statistical correlations may be drawn between particular built form attributes and mobile source emissions for a sample of greater than the six studied areas.

In this analysis, urban areas were selected based on their status as the largest metropolitan regions in their province. Given that a clear link has been shown between the population of the cities and total mobile source emission levels, future case studies should consider analyzing cities within strata of similar populations. In controlling for the effects of urban population, the impacts of built form variables on macro-level emissions may be better understood across different scales of cities. For transit buses and commercial vehicles in particular, comparing cities of different magnitudes is difficult, as the transportation and economic systems in larger cities function quite differently than those in smaller cities.

While this study analyzes air-pollutant emissions at the city level, it does not investigate built form variables on disaggregate emission levels, such as the census tract or neighborhood. For this type of analysis, care must be taken to account for spatial correlation issues across the smaller disaggregate units. This task, however, has been left for future research.

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