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Spatial distribution of vehicle emission inventories in the Federal District, Brazil

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HIGHLIGHTS

- We used a bottom-up method to predict emissions and to characterize their spatial patterns using Global Moran's.
- Our findings suggested that light duty vehicles are primarily responsible for the main vehicular emissions.
- CO_2 is the pollutant with the highest emissions, over 30 million tons/year.

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ABSTRACT

Air pollution poses an important public health risk, especially in large urban areas. Information about the spatial distribution of air pollutants can be used as a tool for developing public policies to reduce source emissions. Air pollution monitoring networks provide information about pollutant concentrations; however, they are not available in every urban area. Among the 5570 cities in Brazil, for example, only 1.7% of them have air pollution monitoring networks. In this study we assess vehicle emissions for main traffic routes of the Federal District (state of Brazil) and characterize their spatial patterns. Toward this end, we used a bottom-up method to predict emissions and to characterize their spatial patterns using Global Moran's (Spatial autocorrelation analysis) and Getis-Ord General G (High/Low cluster analysis). Our findings suggested that light duty vehicles are primarily responsible for the vehicular emissions of CO (68.9%), CH_4 (93.6%), and CO_2 (57.9%), whereas heavy duty vehicles are primarily responsible for the vehicular emissions of NMHC (92.9%), NO_x (90.7%), and PM (97.4%). Furthermore, CO_2 is the pollutant with the highest emissions, over 30 million tons/year. In the spatial autocorrelation analysis was identified cluster ($p < 0.01$) for all types of vehicles and for all pollutants. However, we identified high cluster only for the light vehicles.

1. Introduction

Urban air pollution is considered as an important public health risk (Kheirbek et al., 2012; Nandasena et al., 2012; Gallardo et al., 2012). For example, the World Health Organization (WHO) reported that exposures to gaseous and particulate air pollutants are responsible for 223,000 deaths worldwide in 2010 due to lung cancer (OMSOMS, 2013).

Vehicles such as passenger cars, buses, trucks, and motorcycles are the main sources of air pollution in urban areas and their emissions account for 30% of NO_x and 14% CO_2 of global emissions (Vasconcellos, 2006). In Brazil, approximately 40% of CO_2 is associated with vehicular emissions (MCT, 2013).

Information about pollutant emissions released in urban areas is critical to public health policies for human health and environmental protection. In this context, air pollution monitoring networks are the main mechanism for obtaining information about gaseous and particulate air pollutants (Wallace et al., 2012; Hasenfratz et al., 2012). However, they are not available in many urban centers, since their capital and operation costs are high and require specialized professional personnel (Kanaroglou et al., 2005; Joly and Peuch, 2012).

In Brazil, for example, there are a total of 5570 cities, but only 1.7% of them have an air pollution monitoring network. Nationally,

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there are 252 monitoring stations, but not every station monitors all important pollutants such as PM_{10}, $PM_{2.5}$, O_3, SO_2, NO_x, and CO (Alves et al., 2014). In the Federal District (FD) the monitoring network is still incomplete. FD is a state where Brazil's capital, Brasilia, is located; an area of 5802 km^2 populated by of 2.5 million inhabitants. The monitoring network is composed of seven stations with only particle monitor which measures Total Suspended Particles – TSP. The number of stations per unit area or inhabitant in Brazil is considerably lower than those in USA and Europe. In Brazil, there are 0.03 stations per 1000 km^2, whereas in the USA and Europe, there are 0.5 and 1.7 stations per 1000 km^2, respectively. Also in Brazil there are 1.3 stations per 1 million inhabitants, while in the USA and Europe, the respective values are 16 and 14.8 stations per 1 million inhabitants (Alves et al., 2014). Specifically, in the FD, there are 1.38 stations per 1000 km^2 and 1.6 stations per 1 million inhabitants.

Obtaining air pollution inventories is considered to be a simple and inexpensive alternative method to meet the needs of cities with incomplete or non-existent monitoring networks (Nagpure and Gurjar, 2012). In general, air pollution inventory studies focus on emissions released within a large area. Thus, they do not necessarily consider the spatial distribution of sources emissions. Examples of locations where these emission inventories have been investigated include: Campinas, Brazil (Ueda and Tomaz, 2011), Rio de Janeiro, Brazil (Duarte et al., 2013), Bogotá, Colombia (Zárate et al., 2007), India (Nagpure and Gurjar, 2012), China (Huang et al., 2011; Zhou et al., 2014), Sardinia, Italy (Bellasio et al., 2007) and Houston, USA (Lee et al., 2014). Recent studies have examined the spatial distribution of source emissions such as: São Paulo, Brazil (Gallardo et al., 2012), Buenos Aires, Argentina (Gallardo et al., 2012) Norwich, UK (Nejadkoorki et al., 2008) and Santiago, Chile (Saide et al., 2009).

In this paper we propose a method for predicting source emission emissions in an area with incomplete air pollution monitoring network. Specifically, we estimate vehicular emissions along the main traffic routes of the Federal District. Finally, we examine the spatial patterns of emissions and compare them to those from similar studies in Brazil.

2. Materials and methods

This study area was the urban area of the FD (Fig. 1). The region is located between the parallels of 15° 30′ and 16° 03′ South Latitude and the meridians of 47° 25′ and 48° 12′ West Longitude.

The input data consisted of the vehicle number along each of the main urban traffic routes of the FD. A total of 233 routes were considered in this study with a total length of approximately 615 km.

The study was conducted in two steps: first, air pollution emissions were calculated for each of the 233 routes; and second, the spatial patterns of the estimated emissions were analyzed. In both steps, ArcGIS software version 10.2 was used as the operational tool.

2.1. Spatial inventory

The selected inventory method was the bottom-up method. Equation (1) was used to predict emissions (MMA, 2011; Righi et al., 2013):

$$E_{a,y,z} = \frac{\left(Fr_{i,y} \times Iu_{i,y} \times Ef_{i,z,x}\right)}{10^6} \tag{1}$$

where $E_{a,y,z}$ is the annual emission in metric tons (t); *Fr* is the vehicle fleet (number of vehicles); *Iu* is the distance traveled (average distance in km/year); *Ef* is the emission factor (grams of pollutant per unit distance – g/km); *a* is the age of the vehicle fleet; *y* is the type of vehicle; *z* is the type of pollutant; and *x* is the type of fuel.

It was not possible to determine the age of the vehicles and the type of fuel used in the present study. Thus, variables *a* and *x* were not considered. Variable *y* was represented by three categories of vehicles: light vehicles (passenger cars), motorcycles, and heavy vehicles (buses and trucks). For the type of pollutant, variable *z*, we estimated emissions for carbon monoxide (CO), non-methane hydrocarbon (NMHC), methane (CH_4), nitrogen oxides (NO_x), total suspended particle matter (PM), and carbon dioxide (CO_2).

Equation (1) was used to calculate the emissions by pollutant, vehicle type and traffic route. To quantify total emissions from all three vehicles categories we used the following equation:

$$Et_z = E_{\text{light vehicles},\ z} + E_{\text{motocycles},\ z} + E_{\text{heavy vehicles},\ z} \tag{2}$$

Where, Et_z is the total annual emissions expressed in tons (t), and *z* is the type of pollutant.

The vehicle fleet data were obtained from three sources: the Transit Department of the FD (Detran, 2009), the Route Department (DER, 2010), and the report on Urban Transport of the FD - PDTU (GDFGDF, 2008). These data were generated from point counts of vehicle numbers (PDTU – visual counts; Detran and DER – electronic speed control devices). All point counts were transferred to the road segment, where the collection point was inserted. This was accomplished using the geographic traffic route network, provided by the Secretary of State for Habitation (Sedhab, 2012).

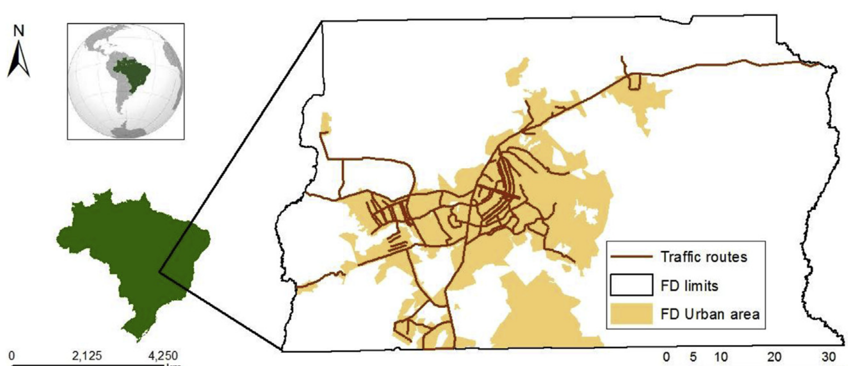

Fig. 1. Study area.

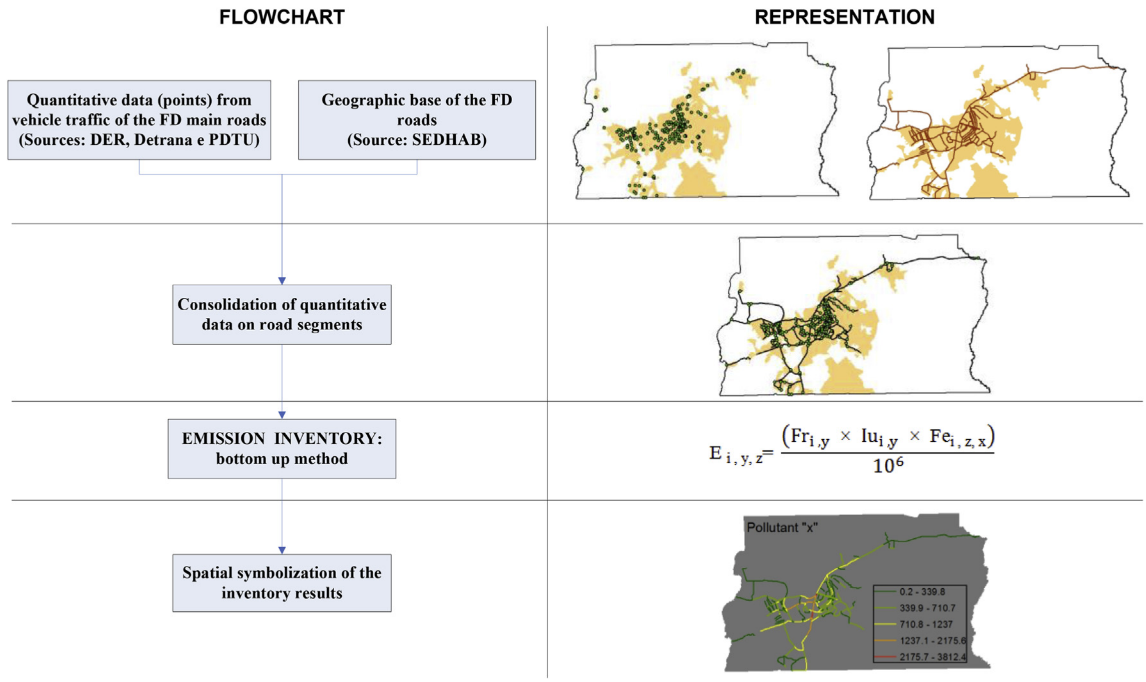

Fig. 2. Study stages developed for inventory calculation.

Distance traveled depends on the vehicle age, according to the Brazilian Ministry of the Environment (MMA, 2011). However, it was not possible to obtain data on vehicle age. Therefore, we assumed a maximum vehicle use of 15 years. According to Denatran (2012), 90% of vehicles in the FD had a maximum age of 15 years. Thus, an average use for vehicles between 0 and 15 years for the period 1995–2010 was used. In this study the values of vehicle use per year were 14,875 km/year for light vehicles; 8625 km/year for motorcycles; and, 70,085 km/year for heavy vehicles.

The emission factors were provided by the Environmental Agency of São Paulo (Cetesb, 2012) and MMA (2011) (See Table S1, supporting information), which were determined for Brazilian vehicles. The emission factor is a function of vehicle age and we adopted the same procedure as for vehicle use.

Fig. 2 presents an overview of the four study steps followed for predicting emission inventories. In the first, we collected and spatially projected the data. In the second, we consolidated the data for road segments. Finally, for the third and fourth step, we calculated emissions and characterized their spatial patterns, respectively.

2.2. *Characterization of spatial patterns*

Two geostatistical methods were applied to evaluate the spatial patterns of estimated emission rates. The first geostatistical test aimed to characterize the distribution pattern; specifically, we identified the existence of spatial autocorrelation of emissions among the 233 routes in the FD. Therefore, Global Moran's I test (value I) was employed, which examines whether the spatial distribution is dispersed ($I < 0$), random ($I = 0$), or clustered ($I > 0$). Equation 3 gives the algebraic formulation used for this test (Anselin, 1995) (supporting information).

The second geostatistical test was aimed at identifying the level of clustering between the 233 studied routes. This test identifies high clusters (routes clustered due high emission rates) or low clusters (routes clustered due low emission rates). Therefore, the Getis-Ord General G test was employed (Getis and Ord, 1992), which is estimated as Equation 4 (supporting information).

A significance test was applied to both tests using the procedures shown in Figure S1 (supporting information).

3. Results

The majority of vehicles were light vehicles, totaling 6,283,337, which accounts for 91% of all vehicles. Motorcycles and heavy vehicles represented 4 and 5%, respectively. The number of vehicles across the 233 routes varied significantly as suggested by the estimated coefficient variations. The smallest coefficient was observed for light vehicles, 0.79, while those of motorcycles and heavy vehicles were greater than one indicating high variance of the data (Table 1).

Due to high heterogeneity of the vehicle number among routes, it is possible to observe outliers in the statistical analysis. The greatest number of outliers was observed for motorcycles. The locations of outliers were similar especially among motorcycles and heavy vehicles (Fig. 3).

The descriptive statistics for the air pollution inventories presented in Table 2 suggested that light vehicles were responsible for a large fraction of CO (68.9%), CH_4 (93.6%), and CO_2 (57.9%) emissions, while heavy vehicles accounted for the majority emission of NMHC (92.9%), NO_x (90.7%), and PM (97.4%) emissions.

Table 1
Descriptive statistics for the vehicles studied in the FD.

Statistical Parameter	Light vehicles	Motorcycles	Heavy vehicles
Minimum	15	0	0
Maximum	150,100	13,900	16,967
Total	6,283,337	265,785	345,352
Average	26,967	1140	1482
SD	21,457	2097	2169
CV	0.79	1.83	1.46

Note: SD = standard deviation; CV = coefficient of variation.

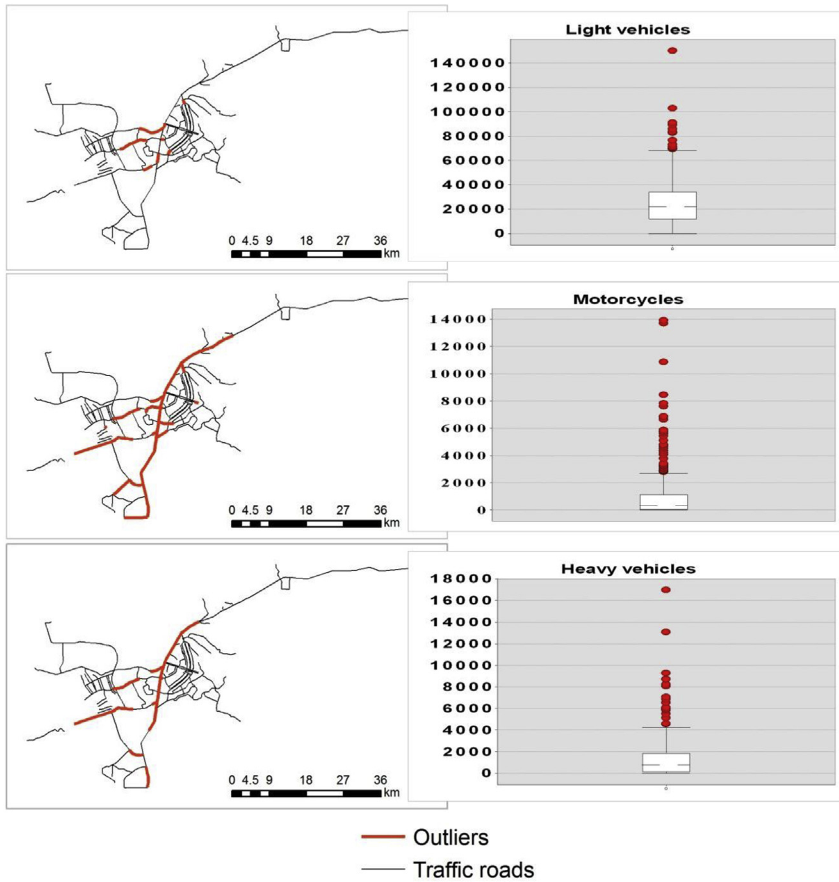

Fig. 3. Box plot graphs of the outliers (left) and vehicle numbers (right).

Fig. 4 shows the spatial distribution of emissions per vehicle type. Light and heavy vehicles presented the highest emissions among the 233 routes. Additionally, we must emphasize that the routes with the outliers shown in Fig. 3 are almost identical to those with high emission depicted in Fig. 4.

CO_2 was the pollutant with the highest emissions, at more than 30 million tons. On average, approximately 130,000 tons of CO_2 are emitted per year among the 233 routes. Conversely, CH_4 exhibited the lowest emissions, approximately 4000 tons (Table 3).

Additionally, all pollutants presented high outliers, due to the heterogeneity of vehicles numbers circulating among the routes (Fig. 5).

Regarding the spatial distribution of the total pollutant emissions (Fig. 6), similarities between maps were observed. The highest rates are found for the routes with the most vehicles at peak times and routes with the highest traffic of heavy vehicles.

Furthermore, we analyzed the spatial patterns of emissions. We determined and classified spatial autocorrelation by vehicle

Table 2
Descriptive statistics for air pollutant inventories (tons/year).

Vehicle	Pollutant	Minimum	Maximum	Total	Average	Standard deviation	CV
L	CO	0.21	1964	82,249	353	281	0.80
	NMHC	0.03	267	11,216	48	38	0.80
	CH_4	0.01	89	3739	16	13	0.80
	NO_x	0.03	335	14,020	60	48	0.80
	PM	0.0003	3	112	0.48	0.38	0.79
	CO_2	45	421,615	17,649,236	75,748	60,273	0.80
M	CO	0	620	11,865	51	94	1.84
	NMHC	0	74	1421	6	11	1.84
	CH_4	0	13	254	1.09	2.01	1.84
	NO_x	0	17	325	1.39	2.57	1.85
	PM	0	1.08	20	0.09	0.16	1.78
	CO_2	0	10,790	206,313	885	1628	1.84
H	CO	0	1237	25,172	108	158	1.46
	NMHC	0	8102	164,902	707	1036	1.46
	CH_4	–	–	–	–	–	–
	NO_x	0	6873	139,899	600	878	1.46
	PM	0	244	4974	21	31	1.46
	CO_2	0	619,538	12,610,308	54,121	79,232	1.46

Note: L = light vehicles, M = motorcycles, H = heavy vehicles, CV = coefficient of variation.

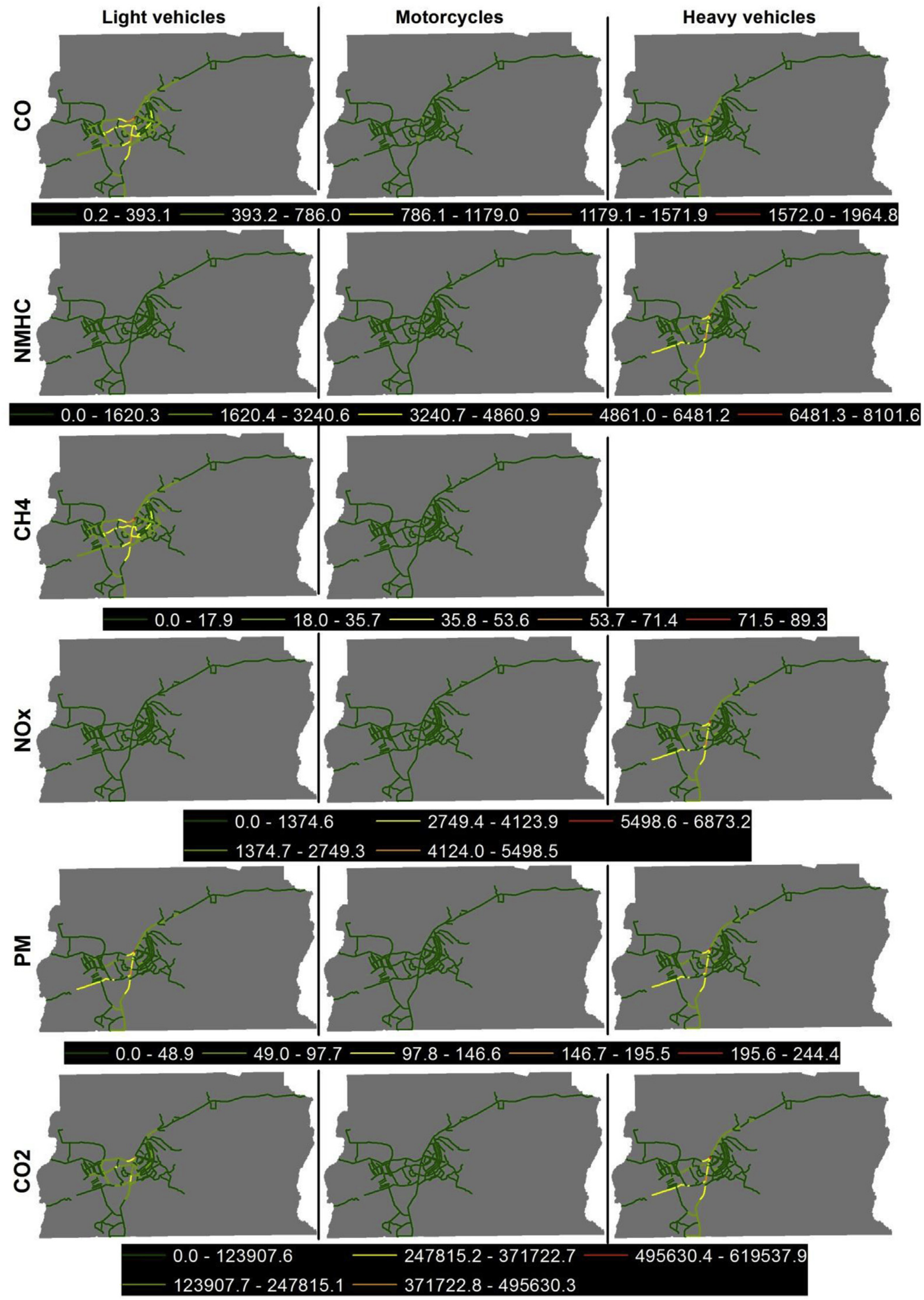

Fig. 4. Spatial distribution of pollutant emissions (ton/year). Note: Was used equal interval as classification method for each map.

Table 3
Descriptive statistics for the pollutant total emissions (ton/year).

Pollutant	Minimum	Maximum	Total	Average	Standard deviation
CO	0.21	3812	119,287	512	473
NMHC	0.03	8442	177,539	762	1069
CH_4	0.01	102	3993	17	14
NO_x	0.03	7224	154,245	662	911
PM	0.0003	248	5107	22	32
CO_2	45	1,051,773	30,465,857	130,755	127,056

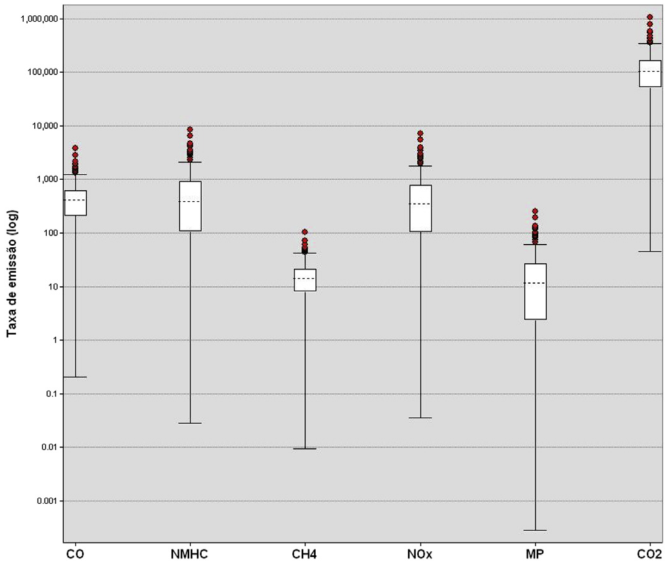

Fig. 5. Box plot graph of the overall inventory.

Table 4
Global Moran's I test results.

Group	Moran's index	z-score	p-value	Classification
Lights vehicles	0.071	6.529	<0.01	Clustered
Motorcycles	0.053	5.085	<0.01	Clustered
Heavy vehicles	0.024	2.515	<0.01	Clustered
Total emission - CO	0.055	5.230	<0.01	Clustered
Total emission - NMHC	0.025	2.623	<0.01	Clustered
Total emission - CH_4	0.070	6.509	<0.01	Clustered
Total emission - NO_x	0.025	2.640	<0.01	Clustered
Total emission - PM	0.024	2.553	<0.01	Clustered
Total emission - CO_2	0.042	4.092	<0.01	Clustered

type and total emissions using Moran's Index which ranged from 0.071 to 0.024. This result suggests of presence of clusters (Table 4).

Regarding the presence of high or low emission clusters, only the light vehicles were identified as showing high clusters. We did not identify high or low emission clusters for the other vehicle types and total emissions (p-value > 0.10); therefore, these emissions were classified as exhibiting a random distribution (Table 5).

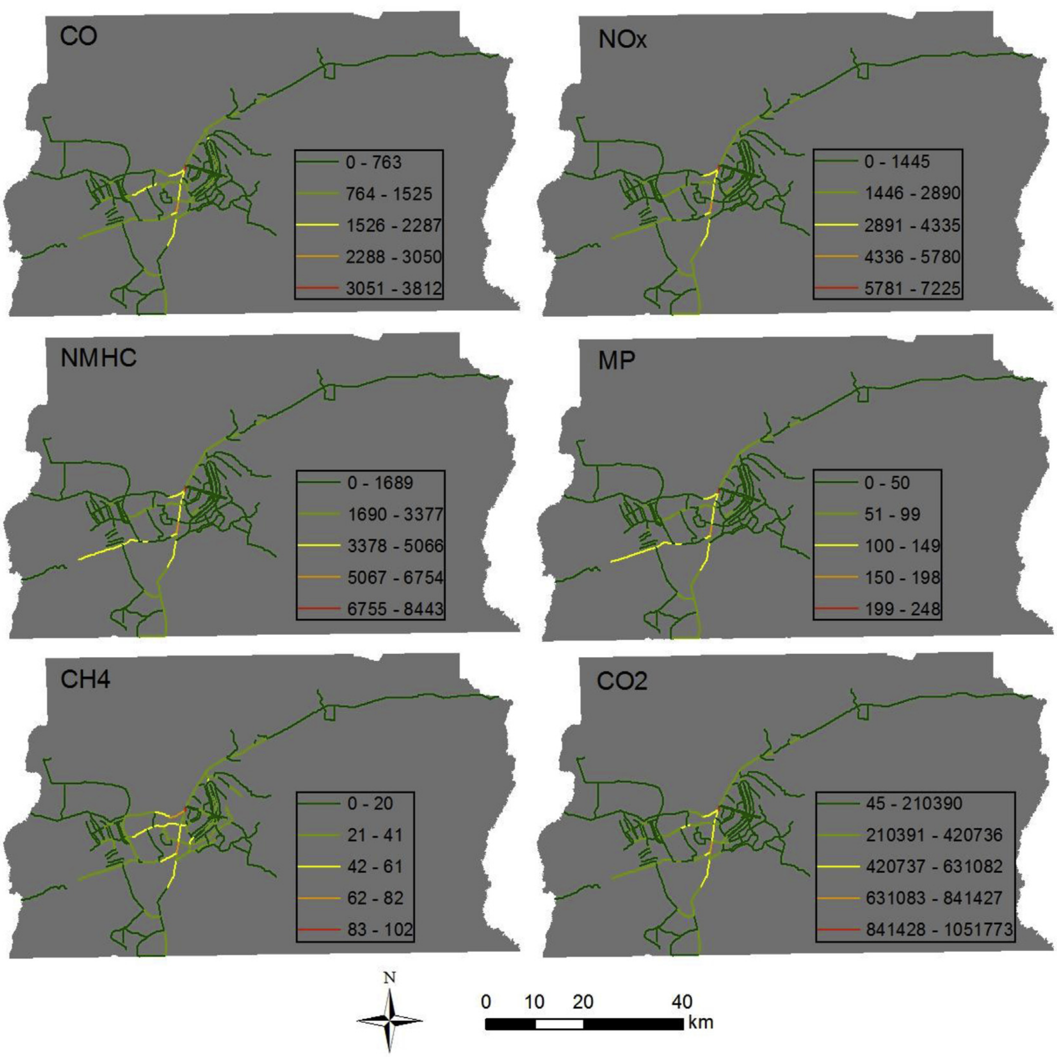

Fig. 6. Spatial patterns of the total pollutant inventories (ton/year). Note: Was used equal interval as classification method for each map.

Table 5
Getis-Ord General G test results.

Group	General G	z-score	p-value	Classification
Lights vehicles	<0.001	3.228	<0.01	High-Clusters
Motorcycles	<0.001	−0.662	0.51	Random
Heavy vehicles	<0.001	−0.587	0.55	Random
Total emission – CO	<0.001	1.359	0.17	Random
Total emission – NMHC	<0.001	−0.491	0.62	Random
Total emission - CH_4	<0.001	1.715	0.21	Random
Total emission - NO_x	<0.001	−0.437	0.66	Random
Total emission – PM	<0.001	−0.556	0.58	Random
Total emission - CO_2	<0.001	0.999	0.32	Random

4. Discussion

Light vehicles accounted for 91% of the total vehicle fleet and were responsible for 68.9% of CO (82.2 thousand tons), 93.6% of CH_4 (3.7 thousand tons), and 57.9% of CO_2 (17.6 million tons) emissions. Heavy vehicles represented only 5% of the total vehicle fleet; however, because of their high emission factors they accounted for a large fraction of pollutant emissions: 92.9% of NMHC (164.9 thousand tons), 90.7% of NO_x (139.8 thousand tons), and 97.4% of PM (4.9 thousand tons) emissions.

Ueda and Tomaz (2011) conducted a study using information from the city of Campinas, Brazil, and found similar results where 74% of CO is emitted from light vehicles, and 61% of NO_x and 99.9% of PM are associated with heavy vehicle emissions.

Rio de Janeiro is another city in Brazil with high emissions. Duarte et al. (2013) estimated that light vehicles emit annually approximately 51,000 tons of CO (60% of the total), 8000 tons of NO_x (17% of the total), and 25 tons of PM (2.9% of the total). Heavy vehicles and motorcycles emit 5.9 and 90% of the total of PM, respectively.

The findings of our study are in agreement with those of Campinas and Rio de Janeiro cities similar. In addition, they are similar to those reported by a national study, conducted by Brazilian Ministry of the Environment (MMA, 2011). Table 6 shows these comparisons.

Whereas FD is located in an area of 5802 km^2 populated by of 2.5 million, highlights that Campinas and Rio de Janeiro have respectively an area of 790 km^2 and 1200 km^2. As population, Campinas has 1.2 million and Rio de Janeiro 6.4 million.

Table 6
Comparisons between FD, Rio de Janeiro, Campinas and National inventories.

Study	Vehicle	Pollutants					
		CO	NMHC	CH4	NOx	PM	CO_2
FD	L	68.9%	6.3%	93.6%	9.1%	2.2%	57.9%
	M	9.9%	0.8%	6.4%	0.2%	0.4%	0.7%
	H	21.2%	92.9%	*	90.7%	97.4%	41.4%
	Total	100%	100%	100%	100%	100%	100%
RJ	L	54.7%	**	**	15.6%	2.7%	**
	M	33%	**	**	1.4%	5.9%	**
	H	12.3%	**	**	**	91%	**
	Total	100%	–	–	100%	100%	–
CP	L	74%	**	**	38.07	*	**
	M	6.5%	**	**	0.93%	*	**
	H	19.5%	**	**	61%	99.9%	**
	Total	100%	–	–	100%	100%	–
BR	L	48%	49%	68%	8%	2.5%	35%
	M	35%	26%	32%	*	0.5%	3%
	H	17%	25%	*	92%	97%	62%
	Total	100%	100%	100%	100%	100%	100%

Note: L = light vehicles, M = motorcycles, H = heavy vehicles, FD = Federal District -present study, RJ = Rio de Janeiro, CP = Campinas, BR = Brazil – national study, (*) = Negligible value, (**) not calculated.

Regarding total emission, CO_2 was the pollutant with the highest emissions exceeding 30 million tons. On average, approximately 130 thousand tons of CO_2 are emitted among the 233 traffic routes in the FD. In contrast, CH_4 was the pollutant with the lowest emissions at approximately 4000 tons. Ueda and Tomaz (2011) showed that in Campinas, the total emission of CO is 244,000 tons, while that of NO_x is 46,000 tons and PM is 2000 tons.

The spatial analysis of the predicted emissions revealed spatial autocorrelation (clustering) among the 233 routes in the FD indicating that neighboring routes exhibited similar emissions. Regarding low values *versus* high emission clusters, the only cluster identified was a high cluster for light vehicles (Table 5). Probably, the main reason of this result is that the light vehicles are the majority, 91% of all vehicles, and with the lower coefficient of variation (Table 1). Also the spatial distribution of light vehicles, especially the outliers, is different from other vehicles (Fig. 3). The urban land use is the main factor linked with this different spatial distribution for light vehicles. While the heavy vehicles emission are concentrated on the highways (outside the urban center), the emissions from light vehicles is concentrated on streets and avenues (inside the urban center). Therefore, the high cluster for light vehicles can be explained for the following issues: high spatial density of streets and avenues and the high numbers of light vehicles.

Our study has some limitations. We were unable to consider the difference between old and new vehicles; emissions during time of the day; emission from cold start; and idle periods at traffic signals. However, highlights that our data are from 233 roads in the FD, approximately 615 km, in an area of 5802 km^2. In Brazil, and maybe in most of the development countries, there are no very accurate traffic information (vehicles age, traffic per hour, speed etc.) for huge data.

Also we were unable to validate the results for three reasons. First, as we mentioned on the introduction, the air pollution monitoring in the FD has some problems, for instance, it is missing several data in terms of temporal and spatial samples. Second, the network in the FD is composed of seven stations with only TSP monitor. Third, our results are in mass (tons) and the results of each TSP monitor in FD are in concentration ($\mu g/m^3$). The way that we used to validate our results was to compare with similar studies in Brazil, which have used the same emission factor.

Finally, the method applied in this study can enhance our ability to develop cost effective air pollution control policies for urban areas, especially for those where air pollution monitoring networks are nonexistent or inadequate such as in the FD. The obtained results show that in the FD public policies regarding transport and the environment need to be applied considering the spatial dependence among air pollution emission in terms of land use, types of roads and types of vehicles.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.atmosenv.2015.04.029.

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