Title: The application of three methods to measure the statistical association between different groups and the concentration of air pollutants in Montreal: a case of environmental equity

Abstract

Analyzing the spatial dispersion of pollutants has led to developing measures in order to determine whether certain population groups are disproportionately exposed to these hazards. The proxy of distance from major roads, mathematical modeling, and exposure as established by pollutant measurement are three of the main techniques developed to determine environmental inequity with regard to a particular group in the broader population. A few studies performed in different countries have concluded that low-income households and, to a lesser extent, ethnic minorities, tend to reside in the most polluted areas. The main objective of this article is to compare results obtained from three methods for analyzing the spatial concentration of polluting emissions on the Island of Montreal. The second objective is to determine whether groups vulnerable to air pollutants—namely individuals under 15 years old, the elderly, visible minorities and low-income households—are subjected to environmental inequity associated with air pollution. The results obtained by the three techniques for evaluating environmental equity firstly show that there are differences between these techniques. Secondly, they show that the groups selected based on age are not afflicted by environmental inequity. Finally, they indicate that low-income households in Montreal and, to a lesser extent, visible minorities, more frequently live near major roads and in areas with higher pollutant concentrations. However, this environmental inequity for low-income households can be compensated by positive aspects related to their urban environment.

1. Introduction

Transportation is a source of harmful particles that have an impact on health, namely nitrogen oxides (NO_x) [1] and, to a lesser degree, carbon monoxide (CO) and particulate matter (PM) [2, 3]. As a result, living within 200 metres of a major road is considered as a potential health hazard [3, 4], particularly for asthma [5, 6], lung development deficits among children [7], and heart problems [8-10]. The literature on environmental equity looks at interrelations between characteristics related to the environment and to inhabitants within one same territory. Researchers in this field attempt to find out whether resources or pollutants are distributed fairly [11]. In other words, are certain populations—defined according to various characteristics such as age, ethnic origin or low income—more commonly located in areas with fewer resources or more environmental pollutants? A number of studies have shown that areas with high proportions of low-income households are characterized by high concentrations of pollutants [12]. According to many authors [13-15], the combination of socio-economic inequalities and exposure to air pollutants contributes to physiological vulnerability among members of low-income households. Other studies have noted that the health impacts of pollution are stronger among children and the elderly. Indeed, children are more vulnerable to the consequences of air pollutants because their organs and nervous systems are not fully developed [12] and they breathe in more air per unit of mass [16]. In addition, because they are less mobile, they are more confined to their residential environments, as are the elderly [17-19]. If these environments offer poor conditions, they will be more affected than other age categories.

In the past 20 years or so, various methodological approaches have been proposed to evaluate pollutant exposure among vulnerable groups. The first step is to determine pollution levels. Among the techniques for evaluating pollution levels, the most often used are proximity to the source of pollution, modeling of pollution levels, and actual measurement of concentrations. Recently, certain authors such as Kingham and Dorset [20] and Maantay et al. [21] have suggested excellent syntheses of the literature that compare these techniques and identify their respective strengths and limits. The stakes are high: an imprecise measurement could lead to erroneous or unreliable results when evaluating environmental inequity for a given group [22]. Yet to our knowledge, no empirical analysis has simultaneously drawn upon these different techniques in a single study of one same territory in order to evaluate whether they would produce different results in line with environmental equity. Following on Kingham and Dorset [20] as well as Maantay et al. [21], we have therefore conducted an empirical evaluation of environmental equity related to pollution exposure in Montreal using the three above-described techniques.

2. Literature Review

In this section, we will briefly review the principal results of recent studies dealing with environmental equity in connection with air pollution. We will then address methodological questions by describing the three techniques most often used to evaluate pollution levels, while identifying their strengths and weaknesses. But first, it is important to define the concept of environmental equity, also called distributional justice. The current vision associated with environmental equity in the literature can be defined as follows: "Environmental justice policies seek to create environmental equity: the concept that all people should bear a proportionate share of environmental pollution and health risk and enjoy equal access to environmental amenities" [23]. Environmental equity studies therefore often tend to examine the distribution of health risks resulting from exposure to pollution for different groups defined by age, ethnic origin or socio-economic level [24]. Environmental equity is often confused with environmental justice. The distinction between the two concepts, according to Cutter [25], is that environmental justice involves more than an equal sharing of harmful environmental agents. It must, for instance, provide sufficient protection for various population groups exposed to such hazards [26].

2.1. Environmental Equity and Air Quality

Studies performed in Canada, the United Kingdom, New Zealand and the United States have shown that low-income households tend to be exposed to substantially higher levels of polluting emissions than the affluent classes, even though they have fewer vehicles [22, 24, 27, 28]. Research on ethnic minority population's exposure to higher pollution levels are less conclusive, as results vary depending on the context of the study [29]. In the United States, a number of studies and particularly those of Chakraborty [22] and Morello-Frosch et al. [28] have shown statistically positive relationships between the presence of ethnic minorities and concentrations of air pollutants. On the other hand, in Canada, with the exception of Latin Americans in Hamilton, Buzelli and Jerrett [30, 31] found no statistically significant and positive relationship between proportions of ethnic minorities and concentrations of polluting emissions in the cities of Hamilton and Toronto.

In spite of their physiological vulnerability to air pollution, children and the elderly have not often been addressed in environmental equity studies. Chaix et al. [32] have nevertheless reported that children under 15 years old from low-income households in Malmö, Sweden were in general exposed to statistically higher NO_2 levels than children of the same age with higher socio-economic status. As for populations over 65 years old, Brainard et al. [24], Mitchell and Dorling [33] and Chakraborty [22] found no environmental inequity experienced by this group in relation to air pollutant exposure.

2.3. Local Measurements of Air Pollution

Over the past two decades, three techniques have widely been used to evaluate the spatial concentration of air pollutants. First among these, is proximity to sources that generate air pollutants an approach that has often involved defining areas of proximity or 'buffer zones' varying between 0 and 300 m around highways or major roads [34, 35] or creating density indexes based on road network hierarchy [2].

More specifically, techniques within this approach consist in selecting territory adjacent to major roads, since pollution concentrations are thought to be higher there. Although they are easy to use—thanks to geographic information systems—and make it possible to calculate a potential indicator to identify the most at-risk areas for health, this approach has also been the focus of criticism. The strongest criticism is that it does not allow precise evaluation of a pollutant's concentration [20]; indeed, it merely represents a proxy of air pollution by positing that such pollution is higher around major roads. Without providing an exhaustive list, Table 1 shows studies that implement this approach, along with the context of the study and the statistical method used to assess environmental equity.

The table clearly shows that most studies use a distance of 200 m or less (150 or 75 m), either from highway sections or from both highway sections and major roads. Some authors such as Chakraborty et al. [36] and Chakraborty [34] have performed this same exercise but only for highway sections undergoing transportation system changes. To evaluate environmental equity, logistical regression is very often modeled with the binary dependent variable of whether a census tract or city block is located at least *n* metres from a highway stretch (200 m, for example), and with the independent variables of the proportions of targeted groups, for example ethnic minorities or low-income individuals.

Although very interesting, this approach has come under criticism since using a binary variable—the minimum distance of 200 m or not—can conceal substantial variations in exposure. Two different city blocks can, for instance, be located within 200 m: one at 10 m, the other at 190 m. Furthermore, some blocks can be located at the same distance from the highway (50 m, for example), but be surrounded by very different overall lengths of highway within a 200-metres radius (800 m versus 1600 m, for example). To solve this problem, some authors [2, 3, 37, 38] recommend creating density indexes, based on either traffic volume or roadway hierarchy. For example, Gunier et al. [38] created 200-metres buffer zones around city blocks, then summed the traffic volume per average day for the entire year, multiplied by the length (in miles) of the road section located within the zone. Finally, they divided the product by the total land area in the zone. As a result, for each block, they arrived at the number of vehicles per mile and per day, per square mile.

Table 1. Studies of environmental equity that use parameters of proximity to major roads

Study	Objective	Site	Statistical Method
Houston et al. [39]	To determine whether children under 6 years old belonging to ethnic minorities tend to be more frequently located **within 200 metres** of major roads with daily traffic of over 50,000 vehicles	South California	Logistic regression
Bae et al. [35]	To determine whether low-income households, ethnic minorities, the elderly and children are over-represented **within 200 metres** of highways	Portland and Seattle	Cluster analysis
Gunier et al. [38]	To determine whether individuals below 15 years old belonging to ethnic minorities or low-income households are more frequently located **within 200 metres** of major roads with daily traffic of over 500,000 vehicles	California	Chi-squared test and Spearman correlation
Cesaroni et al. [40]	To determine the population groups selected by age, income and education level that tend to reside **within 150 metres** of a major road	Rome	Logistic regression
Green et al. [41]	To determine whether public schools in California located **within 150 metres** of a major road with daily traffic of over 50,000 vehicles are more frequently composed of ethnic minorities (Hispanics and Blacks) and young people from low-income households	California	Logistic regression
Jacobson, Hengartner and Louis [42]	To compare the results of statistical approaches to determine the over-representation of low-income households and ethnic minorities located **within 200 metres** of a highway	New York	Logistic regression and linear regression
Chakraborty, Forkenbrock and Schweitzer [36]	To determine whether low-income households and ethnic minorities are over-represented **within 400 metres** of a roadway projected to undergo a transportation system change	Waterloo (USA)	Univariate statistics
Chakraborty [34]	To determine whether low-income households and ethnic minorities are over-represented **within 150 metres, 800 metres and 1600 metres** of a roadway projected to undergo a transportation system change	Tampa Bay (USA)	Two samples test of proportion
Amram et al. [43]	To characterize the income level of households in areas where Canadian elementary schools are located **within 75 metres** of a major road	Canada	Logistic regression

The second most frequently used technique is mathematical modeling. This approach consists in estimating pollutant concentration based on data relative to traffic data volumes as well as meteorological information such as temperature, wind force and direction, etc. [20]. The advantage of this technique is that it allows the generation of a spatial dispersion map for air pollutants on a large scale, for example a given city. However, some authors such as Kingham and Dorset [20] point out that the accuracy of these mathematical models can vary significantly depending on the data and parameters integrated into the model, particularly in line with meteorological factors. Indeed, inaccuracies are inevitable because of the complexity of meteorological processes and their spatio-temporal variability. Even so, this approach remains more accurate than one based solely on proximity to major roads.

Table 2 presents a few studies that draw upon a mathematical dispersion model to study environmental equity. Their general aim is to measure statistical associations between pollutant levels obtained through modeling, on the one hand, and several variables relative to deprivation and to proportions of ethnic minorities or children, on the other. To this end, several statistical methods have been used: regression models, nonparametric tests, etc.

Table 2. Studies of environmental equity based on mathematical modeling of air pollutants

Study	Objective	Site	Statistical Method
Kingham, Pearce and Peyman [27]	To measure associations between PM_{10} concentration and income level at the census tract (CT) scale	Christchurch, New Zealand	Comparison of the levels of PM_{10} by quintiles of deprivation
Pearce and Kingham [44]	To measure associations between PM_{10} concentration and income level, as well as ethnic origin, at the CT scale in New Zealand	New-Zealand	Comparison of the levels of PM_{10} by deciles of income, race, age and multivariate regression
Brainard et al. [24]	To measure associations between CO and NO_2 concentrations and percentages of ethnic minorities, young people, and deprivation level at the Enumeration District scale	Birmingham, United Kingdom	Kolmogorov-Smirnov test
Mitchell and Dorling [33]	To measure associations between NO_2 concentration and deprivation, ethnic origin and age at the Ward scale in Great Britain	United Kingdom	Comparison of the levels of NO_2 by deciles of income, race and age
Chakraborty [22]	To measure associations between the concentration of cancer and respiratory-related cases and traffic data volumes by integrating proportions of low-income households, ethnic minorities and elderly individuals at the CT scale	Tampa Bay, USA	Linear regression and multivariate regression
Chaix et al. [32]	To evaluate exposure of children under 15 years old to NO_2 according to deprivation level	Malmö, Sweden	Kulldorff spatial scan statistic and multivariate regression
Kruize et al. [45]	To measure associations between NO_2 concentration and income level at the scale of areas identified by zip code	Rinjimond, Pays-Bas	Cumulative frequency curves and chi-squared test
Briggs et al. [46]	To measure associations between spatial concentrations of NO_2, CO, PM, proximity to major roads and deprivation levels at the Ward level in England	England	Pearson and Spearman correlations, T-test

The final technique consists in constructing statistical or geostatistical models to predict pollutant levels for an entire territory based on sampled locations where pollutants are measured using sensors (most often for NO_2) over a given period. NO_2 is the pollutant used most often to measure pollution concentrations generated by road transportation, since it has high co-locational association with other types of pollutants such as particulate matter (PM) and CO [47, 48]. Once the pollution measurements are collected at *n* points in the studied area, two models can be used to generate a map of the territory: geostatistical interpolation methods such as kriging [30, 49], or land-use regression [31, 50-52]. It should be noted that land-use regression is now judged to be a more precise technique than kriging and spatial interpolation methods [53]. Briefly, it consists in constructing a regression equation with the observations being the *n* sampled points, the dependent variable being pollutant concentration (for example NO_2), and a whole series of independent variables including proximity to major roads, length of road sections near the sampled area, traffic data volumes, residential density, presence of industrial or commercial equipment or parks, etc. [1, 54]. Once a robust regression model is obtained (with high R^2), the equation is applied to the entire territory. For example, Crouse et al. [1] apply it to 5 m x 5 m cells overlaid on the entire territory, for which all values of independent variables have been calculated in GIS. The advantage of this technique, as Kingham and Dorset [20] have noted, is that it allows pollutants to be measured at a much finer scale, and at low cost. However, the technique has no longitudinal scope since it is based on pollution data measured at a specific time and under conditions specific to the time of sampling. Table 3 presents a few environmental equity studies that have used pollutant data measured using the land-use regression technique. For these reasons, most studies that employ land-use regression are primarily focused on methodological considerations, and much less toward assessing environmental equity in line with air pollution.

Table 3. Studies of environmental equity that draw upon data measurements and land-use regression

Study	Objective	Site	Statistical Method
Buzzelli and Jerrett [31]	To measure statistical associations between NO_2 concentrations and income levels, as well as the proportion of ethnic minorities per neighbourhood	Toronto, Canada	Logistic regression and linear regression
Crouse, Ross and Goldberg [50]	To measure statistical associations between NO_2 concentrations and income levels, as well as the proportion of ethnic minorities, lone -parent families and people living alone at the CT scale	Montreal, Canada	Pearson correlations
Richardson, Pearce and Kingham [51]	To measure statistical associations between PM_{10} and income level at the CT scale	Christchurch, New Zealand	Poisson negative binomial test
Su et al. [52]	To measure statistical associations between NO_2 concentration and household income, as well as the proportion of immigrants, at the CT scale	Vancouver and Seattle	Linear regression

2.4. Research Objectives and Questions

In light of this literature review, it is clear that all three approaches exhibit distinct advantages and disadvantages. It should be recalled that, even though it is very easy to operationalize, proximity to major roads is only a proxy of air pollution. Mathematical modeling for its part remains highly effective at the regional level, but somewhat inaccurate at the local level owing to the difficulty of integrating meteorological parameters at a finer scale. Finally, although the kriging and land-use regression approach of using data from pollution sensors can provide locally accurate measurements, they have no longitudinal scope since they measure pollution at a given time *t*, in spite of the wide agreement that pollution levels can vary depending on not only the season, but also the meteorological conditions. These observations lead us to pose two research questions. First, are the measurements obtained by the three techniques similar for one same city block or, to the contrary, do they show significant discrepancy? Despite their respective particularities, do these three types of measurements show very different results in terms of environmental equity for population groups that are vulnerable to air pollution (low-income population, visible minorities, children and the elderly)? Put otherwise, in statistical terms, what are the correlations between the three measurements, and can the same associations be observed between each of the four population groups studied and the pollution indicators obtained through the three techniques? Answering these questions seems highly relevant, since past studies have shown diverging results for environmental equity depending on the parameters used to measure pollution. Finally, revealing a situation of environmental inequity for a given group across all three measurement techniques would clearly demonstrate the existence of this inequity, compared to a traditional approach based on the use of a single method for measuring pollutants.

3. Methodological Approach

3.1. Territory of Study, Targeted Groups and Scale of Analysis

This study focuses on the Island of Montreal (Canada), which, in 2006, was home to 1.85 million inhabitants across 499 km^2.

Research studies in the field of environmental justice initially concentrated on the presence of environmental hazards in neighbourhoods dominated by poor populations or particular racial groups. Today, researchers introduce new social categories [55] defined by age [34], level of disability or gender [56]. Buckinham and Kulcur [55] suggests that different categories of people be taken into account, especially owing to differentiated vulnerabilities that vary from one group to another.

The study identified four targeted groups, namely 1) people belonging to low-income households, 2) people who declared belonging to visible minorities, 3) young people under 15 years old, and 4) people 65 years old and over. We are therefore interested in two ‘traditional’ groups of study in environmental equity: low-income individuals and members of visible minorities[1] (the Canadian reality makes this last group a more relevant category than Afro-American or Hispanic). Our study also examines two groups that are especially vulnerable to air pollutants, as mentioned earlier, namely the young and the elderly. The number of individuals in these groups and for the total population were extracted from the 2006 census by Statistics Canada at the ‘Dissemination Area’ scale, that is, the most accurate unit of analysis in which 400 to 700 people reside.

[1] The variable of visible minorities refers to all non-white individuals except for Amerindians, i.e., the census categories of Chinese, South Asian, Filipino, Latin American, Black, Arab, Korean, Japanese, South East Asian, West Asian and South Sea Islander (Statistics Canada, 2006).

Determining the existence of environmental inequity for a given group requires analysis at a fine geographical level, since pollution levels can greatly vary at the scale of a neighbourhood and even a census tract or dissemination area. As a result, we selected the city block as a spatial division from which to generate pollution indicators and the variables relative to the four studied groups. It should be noted, however, that Statistics Canada only provides data on the total population and the number of dwellings at the city block scale. To address this issue, we estimated the numbers of each group consistent with the approach recently put forward by Pham et al. [57]:

$$t_i = t_a \frac{T_i}{T_a}$$

where t_i represents the estimated population of the group (low-income individuals, for example) in the block, t_a the group's population in the dissemination area, and T_i and T_a respectively the total population in the block and the dissemination area. The descriptive statistics for the populations estimated in each of the groups are presented in Table 4.

Table 4. Univariate statistics of studied groups at the city block scale

Groups	Abbr.	N	Mean	SD	Min	Median	Max
0-14 years old	Pop014	10 372	27,40	31,35	0,00	19,00	676,00
65 years old and over	Pop65	10 372	26,95	50,43	0,00	16,00	1810,00
Visible minorities	VisMin	10 372	43,91	80,60	0,00	18,00	1481,00
Low-income population	LowInc	10 372	50,84	80,97	0,00	24,00	1641,00
0-14 years old (%)	Pop014Pct	10 372	15,91	5,35	0,00	15,97	41,38
65 and over (%)	Pop65Pct	10 372	14,92	8,37	0,00	13,92	95,15
Visible minorities (%)	VisMinPct	10 372	21,11	16,52	0,00	17,31	96,60
Low-income population (%)	LowIncPct	10 372	23,69	16,17	0,00	21,26	94,42

S.D.: Standard deviation

3.2. Indicators of Proximity to Major Roads

To construct our first measurement for estimating pollutants, we proceeded as follows. Based on road network data for the Island of Montreal (Geobase), we constructed different indexes of road density in buffer zones within a radius of 200 m created around centroids of city blocks, specifically 1) the proportion of the highway structure (length of highway sections divided by total length of the network within the buffer zone); 2) proportion of secondary roads—collector, arterial and expressway—and finally 3) the proportion of local streets.

The selected distance was 200 m, since the effects of air pollutants are rarely experienced beyond this distance [4]. It is also worth noting that to improve the accuracy of these measurements, the location of the city block centroid was adjusted according to the occupation of residential land as illustrated in Figure 1. These operations were performed in GIS using ArcGIS version 10 [58].

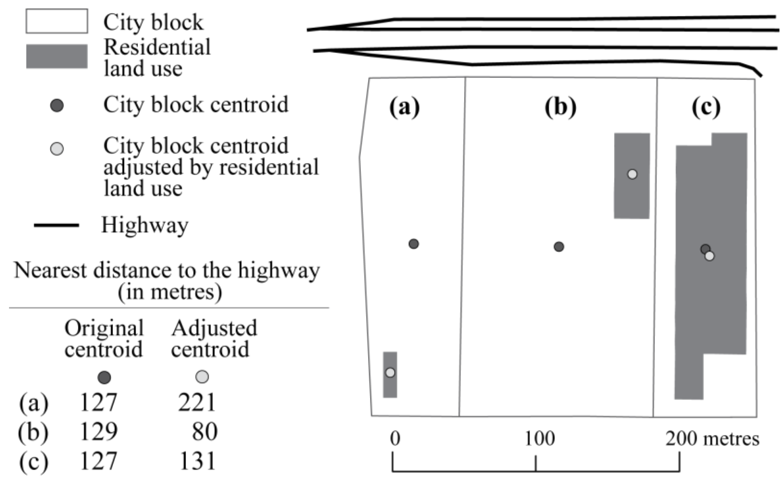

Figure 1. Adjustment of location for the city block centroid

3.3. Pollution Indicators Obtained through Mathematical Modeling

For pollution indicators obtained through mathematical modeling, we used data from the MOTREM model developed by the Ministère des Transports du Québec (MTQ) in 2011. MOTREM models the levels of three pollutants (CO, NO_x and $PM_{2.5}$ particles) over 12,691 road sections on the Island of Montreal at five times during a fall day: morning peak hours (6:30 a.m. to 9:30 a.m.), daytime (9:30 a.m. to 3:30 p.m.), afternoon peak hours (3:30 p.m. to 6:30 p.m.), evening (6:30 p.m. to 12:00 a.m.) and night (12:00 a.m. to 6:30 a.m.). These 12,691 road sections cover the entire island of Montreal and represent a sample of 45% of the total length of the Montreal road network. The parameters integrated into the MOTREM model also include traffic data volumes, vehicle typology, road geometry and average meteorological conditions [59]. In a reference document on MOTREM, the MTQ is careful to specify the limitations of its mathematical model: polluting emissions produced by the MOTREM model are at the regional level—since this model includes only the upper hierarchy of the road network—and, as such, these emissions do not necessarily take into account phenomena produced at the micro-local level.

Based on the MOTREM model, we constructed three indicators of air pollution: average concentration of CO, NO_x, and $PM_{2.5}$ particles in a 200-metres radius from the adjusted centroid of the city block. This exercise was performed in two steps. First, we calculated pollutant concentrations for each period. For example, for period t, the CO measurement within the buffer zone of 200 m around the centroid adjusted to the city block is calculated as follows:

$$CO_{it} = \sum \frac{l_s CO_s}{L}$$

where CO_{it} is the measurement of pollutant CO within buffer zone i for period of the day t, l_s is the road section length included within the buffer zone, CO_s is the measurement of this pollutant that the model attributes to the section, and L is the total length of the network for which modeling within the zone was performed. Next, we carried out a weighted summation according to the number of hours in each period as follows:

$$CO_{it} = \sum \frac{3CO_{Am\ peak} + 6{,}5CO_{Day} + 3CO_{Pm\ Peak} + 5{,}5CO_{Evening} + 6CO_{Night}}{24}$$

where CO_{it} represents the measurement of CO pollution for the entire day.

3.4. Pollution Indicators Obtained through Land-Use Regression

To implement this technique, we used a data set produced by a team of researchers from McGill University who measured NO_2 concentrations during the months of August, December and May 2006 at more than 133 locations on the Island of Montreal sampled according to population density and proximity to major roads [1]. Next, they generated a pollution map encompassing the entire island of Montreal using land-use regression (Crouse, Goldberg and Ross, 2009). Based on this map, we simply propose to calculate the average value of NO_2 for the 10,372 city blocks in Montreal whose total population is above 0.

3.5. Statistical Analyses

Once all of the indicators are generated for the three types of techniques—density of major roads, mathematical modeling and land-use regression—we can see whether these measurements are relatively similar or not based on Spearman correlation coefficients. Then, to determine whether environmental inequities exist in relation to our four targeted groups (low-income individuals, members of visible minorities, young people and the elderly), we suggest four statistical analyses largely used in studies on environmental equity [27, 46, 57, 60]: 1) univariate statistics of pollution indicators weighted by the population of each group at the city block scale, 2) a T-test between each group and the rest of the population to compare their respective averages in terms of pollution indicators (for example between the population under 15 years old and the population over 15 years old), 3) Spearman correlation coefficients between proportions of the different groups and pollution indicators, and finally 4) a T-test for the extreme quintiles (quintile 1 versus quintile 5 in the percentage of low-income individuals, for example). These analyses were conducted in SAS version 9.2 [61].

4. Results

4.1 Comparison of the Different Pollution Indicators

Before analyzing pollution-related environmental inequity for the various population groups under study, it is important to begin by succinctly describing the spatial distribution of pollution indicators obtained, then measuring their associations. The indicators of proximity to major roads and of NO_2 concentrations from land-use regression were calculated for all the 10,372 city blocks on the Island of Montreal that are populated. As for indicators from the MOTREM model (mathematical modeling), they are only available for 9,029 city blocks, since this model has not been used for all road sections on the Island of Montreal, particularly local streets. The univariate statistics of the seven pollution indicators are reported in Table 5, while their mapping, in quartiles, can be found in Figures 2 and 3 in Annex 1 and 2.

Table 5. Univariate statistics of pollutant indicators in a 200-metres radius from populated city blocks

Indicator	Abbr.	N	Mean	S.D.	P25	P50	P75
Proximity indicators to major roads							
A. Highways (%)	P_Highways	10372	1.07	4.69	0.00	0.00	0.00
B. Collectors or arterials (%)	P_CollExp	10372	17.88	16.52	0.00	16.74	29.16
C. Local streets (%)	P_Local	10372	80.10	18.61	68.28	82.28	100.00
Pollutant indicators from MOTREM model							
D. CO concentration	CO	9029	3343.55	6287.04	876.31	1636.08	3117.30
E. NO_x concentration	NO_x	9029	363.30	757.07	86.80	157.95	314.01
F. $PM_{2.5}$ concentration	$PM_{2.5}$	9029	6.97	14.40	1.62	2.97	5.96
Pollutant indicator from land-use regression							
G. NO_2 concentration	NO_2	10372	11.68	3.02	9.69	11.33	13.71

S.D.: Standard deviation; P25: first quartile; P50: median; P75: third quartile.

Not surprisingly, the city blocks with higher proportions of highways are adjacent to highway sections (Figure 2.a). The blocks exhibiting the greatest proportions of collector streets are mainly located at boroughs in the city core, while those with a high proportion of local streets are much more present at the far ends of the island (Figure 2.b and c). As for the mathematical modeling (MOTREM model), the highest concentrations of three pollutants (CO, NO_x, $PM_{2.5}$) are situated in city blocks near the highway network and the main roads that cross the Island of Montreal running north and south (Figures 3.a to c). Finally, the NO_2 indicator generated by land-use regression is fairly high in areas near an intersection of two or more highways, along highways 40 and 15, and in the central boroughs of the Island of Montreal (Ville-Marie, Plateau-Mont-Royal, Rosemont–La Petite Patrie, Villeray–Saint-Michel–Parc-Extension) (Figure 3.d).

To compare the seven indicators, we calculated Spearman correlation coefficients (Table 6). Overall, with the exception of correlations between the three indicators from mathematical modeling (CO, NO_x, $PM_{2.5}$) which are indeed quite strong (>0.95), all other correlations are moderate or low, but significant ($p<0.0001$). More specifically, first, the correlations between the indicators of proximity to major roads and of pollutants from the MOTREM model are moderate (from 0.30 to 0.50 in absolute value). This can be explained by the intrinsic construction of the MOTREM model, i.e., the parameters used, namely average speed, number of traffic lanes, traffic data volumes and the proportion of heavy vehicles. As a result, the concentrations of these pollutants are higher in the city blocks with a higher proportion of highway sections; and, conversely, lower in those with a higher proportion of local streets.

Table 6. Spearman correlation coefficients between the pollution indicators

		Proximity to major roads			MOTREM model			Land-use regression
Indicators		A	B	C	D	E	F	G
A	P_Highways	--	0.057	-0.322	0.400	0.405	0.407	0.154
B	P_CollExp	0.056	--	-0.947	0.346	0.356	0.370	0.197
C	P_Local	-0.321	-0.947	--	-0.458	-0.469	-0.481	-0.223
D	CO	0.407	0.346	-0.458	--	0.977	0.963	0.205
E	NO_x	0.405	0.356	-0.449	0.977	--	0.995	0.207
F	$PM_{2.5}$	0.405	0.370	-0.481	0.963	0.995	--	0.197
G	NO_2	0.154	0.197	-0.223	0.205	0.207	0.197	--

All the values are significant ($p<0.0001$). N=10372 for P_Highways, P_CollExp and P_Local. N=9029 for CO, NO_x and $PM_{2.5}$.

Second, the correlation coefficients are relatively low (±0.20 in absolute value) between indicators of proximity to major roads and from the MOTREM in relation to the land-use regression indicator (NO_2). At first glance, one might have expected stronger correlations. Two principal factors might explain this result. The first has to do with the timeframe for data collection. The MOTREM model uses data on traffic data volumes for a day during the fall—a time of year where traffic data volumes are at their highest—while the NO_2 data represent an average of measurements collected in the summer, winter and spring. It is important to note that major differences in these pollutant concentrations were measured in different cities according to changes in seasonal traffic data volumes [62] and atmospheric conditions [63]. Hours of sunlight, amount of precipitation, and wind-related characteristics are also as many meteorological factors that influence seasonal variations in pollution dispersion [64]. The second explanatory factor has to do with geographical scale: the MOTREM model has a regional scope while the use of NO_2 sensors has a local scope. It should be noted that a number of studies have shown significant spatial variability in pollution at the intra-urban level [65, 66] caused by the interaction between meteorological factors [67], urban functions and local particularities of traffic [1].

Finally, what might explain the weak correlations between NO_2 estimates and the indicator of proximity to highways (coefficient = 0.154)? As some authors have pointed out [20, 21], the mere presence of a highway within a 200-metres radius is insufficient to explain NO_2 concentration since highway sections can have different traffic volumes. In addition, NO_2 pollution is not generated only by highways, but also by other road types.

4.2 Determining Environmental Inequity

Having noted these relatively moderate or low correlations between different pollution indicators, we will now address our second research question: Can inequities in the exposure of different targeted groups be observed, regardless of the indicator used? In other words, does choosing one indicator rather than another have a significant effect on results related to the presence of environmental inequity? To address this question, four statistical analyses, currently used in studies on environmental equity, have been performed. The first two are based on the number of individuals belonging to the targeted groups (weighted univariate statistics and T-Test) and the second two, on proportions (Spearman correlation and T-Test on extreme quintiles).

Weighted univariate statistics for the pollution indicators

We began by calculating the univariate statistics for the seven indicators obtained at the city block scale by weighting them by the number of the total population, then by the number of the four population groups (Table 7). These statistics clearly show that the pollutant level (for CO, NO_x, $PM_{2.5}$, NO_2) and the proportion of highways are always higher when weighted by low-income populations and visible minorities. To take an example, average and median values for NO_2 are respectively 12.86 ppm and 12.78 ppm for the low-income population and 12.60 ppm and 12.46 ppm for visible minorities, versus 12.21 ppm and 11.95 ppm for the total population. However, the gaps found between the statistics obtained for the total population and for young people and the elderly are very limited.

The young people 15 years old and under reside in city blocks with a slightly lower concentration of NO_2 (average = 11.99 ppm, median = 11.72 ppm versus 12.21 ppm and 11.95 ppm for the total population), but not other pollutants (CO, NO_x, $PM_{2.5}$). In addition, compared to the total population, collector, arteries and expressways are less present in their residential area (average and median of 18.07% and 16.48% versus 19.68% and 18.12%), while local streets are more present (average and median of 79.84% and 82.36% versus 78.24% and 80.64%). The situation also seems to be more complex for people 65 years old and over: they live in residential areas with more highways and collector roads/arteries/expressways, and less local streets. However, the modeled or measured levels of pollutants (CO, NO_x, $PM_{2.5}$, NO_2) show averages similar to those observed for the total population in addition to medians that are slightly lower than those for the total population and similar to those for people under 15 years old.

Table 7. Univariate statistics of pollutant indicators weighted by total population and studied groups

Indicator	Weighting	Mean	P5	P25	P50	P75	P95
P_Highways	Total population	*1.03*	0.00	0.00	0.00	0.00	*6.86*
	Pop014	1.07	0.00	0.00	0.00	0.00	9.17
	Pop65	1.18	0.00	0.00	0.00	0.00	11.94
	VisMin	**1.33**	0.00	0.00	0.00	0.00	**15.16**
	LowInc	**1.19**	0.00	0.00	0.00	0.00	**13.89**
P_CollExp	Total population	19.68	0.00	0.00	18.12	31.88	49.20
	Pop014	*18.07*	0.00	0.00	*16.48*	*30.07*	*47.74*
	Pop65	**21.27**	0.00	0.00	**19.57**	**34.07**	**51.19**
	VisMin	19.78	0.00	0.00	18.50	31.97	49.35
	LowInc	**21.55**	0.00	**5.90**	**20.40**	**33.51**	**49.86**
P_Local	Total population	78.24	43.50	65.52	80.64	100.00	100
	Pop014	**79.84**	**45.11**	**67.14**	**82.36**	100.00	100
	Pop65	76.37	*39.19*	*63.11*	78.75	100.00	100
	VisMin	77.63	**42.31**	**64.43**	**79.68**	100.00	100
	LowInc	*76.06*	42.04	63.16	*77.72*	*92.05*	100
CO	Total population	*3232.51*	308.49	923.78	1661.92	*3129.09*	11424.67
	Pop014	3289.82	275.35	*885.60*	1625.74	3177.05	**12374.67**
	Pop65	3234.79	*274.57*	906.97	*1623.75*	3151.37	*11207.69*
	VisMin	**3658.79**	**315.33**	**949.70**	**1798.23**	**3498.00**	**14138.26**
	LowInc	**3317.07**	**348.56**	**972.17**	**1761.20**	**3281.11**	12117.53
NO_x	Total population	350.62	35.07	91.02	161.16	*317.86*	*1304.29*
	Pop014	362.31	32.91	*87.53*	*158.99*	318.63	**1480.43**
	Pop65	*350.44*	*31.21*	89.12	*158.99*	324.80	1351.57
	VisMin	**407.24**	**37.06**	**95.98**	**180.88**	**356.27**	**1737.82**
	LowInc	**363.07**	**41.10**	**96.53**	**171.94**	**334.51**	1432.35
$PM_{2.5}$	Total population	*6.79*	0.64	1.70	3.02	*6.05*	*26.39*
	Pop014	7.04	0.60	*1.62*	2.98	6.06	**28.81**
	Pop65	*6.79*	*0.59*	1.66	*2.95*	6.26	26.77
	VisMin	**7.99**	**0.66**	**1.82**	**3.37**	**7.08**	**33.09**
	LowInc	**7.08**	**0.74**	**1.82**	**3.22**	**6.52**	27.74
NO_2	Total population	12.21	8.16	10.22	11.95	14.29	16.97
	Pop014	*11.99*	*7.96*	*10.03*	11.72	14.03	16.84
	Pop65	12.05	8.30	10.17	*11.69*	*13.95*	*16.79*
	VisMin	**12.60**	**8.35**	**10.53**	**12.46**	**14.71**	**17.22**
	LowInc	**12.86**	**8.71**	**10.84**	**12.78**	**14.88**	**17.17**

P5= 5th percentile; P25= first quartile; P50= median; P75= third quartile; P95= 95th percentile. Bold typeface indicates the strongest values for each statistical measurement; italics, the weakest.

Comparison of averages between the groups and the rest of the population (T-test)

We carried out a T-test to compare the average of the seven indicators weighted by the number of people in each group compared to that of the rest of the population (Table 8). The most significant differences can be observed for low-income individuals and visible minorities for the four pollutants (CO, NO_x, $PM_{2.5}$, NO_2) and the proportion of highways, even if these differences are more limited for the latter group. This points to the existence of environmental inequities for both population groups. The average NO_2 value weighted by the low-income population is 12.86 ppm versus 11.95 ppm for the population that is not low-income, for a difference of 0.90 ppm. Although not as substantial, a gap can also be noted for visible minorities, at 0.51 ppm. A situation of distributional inequity can thus be observed, but it is very low, particularly for visible minorities. There is no significant difference in terms of exposure to the modelled pollutants (CO, NO_x and $PM_{2.5}$) for young people and the elderly, although it is worth noting lower and significant exposure for the measured pollutant (NO_2). Averages for highways are likewise non-significant for these two age groups. In other words, these groups are not victims of environmental inequity in line with exposure to pollutants and highway proximity.

Table 8. Averages of pollutant indicators from the T-test for the four studied groups and the rest of the population

		Highways (%)*				**Collectors, arterials and express roads (%)**			
		Mean		Difference		Mean		Difference	
Group 1 (G1)	**Group 2 (G2)**	**G1**	**G2**	**Moy**	**P**	**G1**	**G2**	**Moy**	**P**
0-14 years old	> 15 years old	1.07	1.03	0.04	0.5637	18.07	19.98	-1.91	0.0001
65 years old and over	less than 65years old	1.19	1.00	0.18	0.1291	21.27	19.40	1.87	0.0001
Visible minorities	No visible minorities	1.33	0.93	0.40	0.0001	19.79	19.65	0.14	0.6310
Low-income population	No Low-income population	1.19	0.97	0.22	0.0006	21.55	18.93	2.62	0.0001
		Local streets (%)				**CO***			
0-14 years old	> 15 years old	79.84	77.95	1.89	0.0001	3289.8	3222.2	67.60	0.2313
65 years old and over	less than 65years old	76.37	78.58	-2.21	0.0001	3234.8	3232.1	2.71	0.2318
Visible minorities	No visible minorities	77.63	78.45	-0.81	0.0093	3658.8	3086.8	572.00	0.0001
Low-income population	No Low-income population	76.07	79.13	-3.06	0.0001	3317.1	3195.9	121.20	0.0001
		NO_x*				**$PM_{2.5}$***			
0-14 years old	> 15 years old	362.3	348.5	13.79	0.5969	7.04	6.75	0.29	0.9250
65 years old and over	less than 65years old	350.4	350.7	-0.21	0.4836	6.79	6.80	-0.01	0.8177
Visible minorities	No visible minorities	407.2	331.3	75.98	0.0001	7.99	6.38	1.61	0.0001
Low-income population	No Low-income population	363.1	345.2	17.85	0.0001	7.08	6.67	0.41	0.0001
		NO_2							
0-14 years old	> 15 years old	11.99	12.25	-0.26	0.0001				
65 years old and over	less than 65years old	12.05	12.24	-0.19	0.0007				
Visible minorities	No visible minorities	12.60	12.09	0.51	0.0001				
Low-income population	No Low-income population	12.86	11.95	0.90	0.0001				

* For the four indicators, the p-value is computed after transformation of the variable due to no-normality. However, the mean for each indicator is displayed at the original scale to facilitate interpretation.

Correlation between pollutants and group proportions

Environmental equity is also often assessed using the share of targeted groups within the total population of given spatial units [27, 33, 50, 60]. In this vein, we calculated Spearman correlation coefficients to verify the existence of significant linear relationships between the shares of the four studied groups across the seven indicators of pollution exposure (Table 8).

The first thing to note is that only three correlations are judged to be average: between the share of low-income individuals and the network of collector roads, arteries and expressways (0.302) as well as NO_2 (0.437), showing a situation of environmental inequity; and between the share of young people and NO_2 (-0.301), in which case the group benefits a much more advantageous situation. Another observation is that correlations are always positive and significant between the seven indicators and the percentages of low-income individuals and members of visible minorities, suggesting a situation of inequity, which is nevertheless not striking since the values of the correlation coefficients are mostly low.

As for the statistical measurements calculated based on the number of people within the studied groups, the situation is more advantageous for young people and the elderly in light of the Spearman coefficients. For those 65 years old and over, only one correlation is significant and, additionally, it is negative (with NO_2: -0.065). In addition, for the share of people under 15 years old, correlations are all negative and significant with the four types of pollutants and the road network excluding highways.

Table 9. Spearman coefficients between the pollution indicators and the presence of different groups by city block

	Proximity to major roads			MOTREM model			Land-use regression
Group	P_Highways	P_CollExp	P_Local	CO	NO_x	$PM_{2,5}$	NO2
0-14 years old (%)	0.011	**-0.262**	**0.241**	**-0.069**	**-0.055**	**-0.051**	**-0.301**
65 years old and over (%)	0.023	-0.009	0.004	-0.031	-0.017	-0.014	**-0.065**
Visible minorities (%)	**0.083**	**0.117**	**-0.122**	**0.094**	**0.128**	**0.139**	**0.134**
Low-income population (%)	**0.057**	**0.302**	**-0.293**	**0.118**	**0.144**	**0.151**	**0.437**

Bold: significant at the level of P<0.0001. N=10372 for P_Highways, P_CollExp and P_Local
N=9029 for CO, NO_x and $PM_{2.5}$.

Comparison of averages between the extreme quintiles of group proportions

Although the Spearman correlations are significant and globally moderate, associations between the shares of the different groups and pollution indicators may not be linear. Consequently, we suggest one final analysis aiming to compare the averages of extreme quintiles based on a T-Test, an exercise conducted, among others, by Kingham et al. [44] and Briggs et al. [46]. The output of this analysis, shown in Table 10, further highlights environmental inequity for the low-income population and visible minorities. For example, the NO_2 average for the last quintile in the percentage of low-income individuals is 13.27 ppm versus 9.84 ppm for the first quintile, representing a difference of -3.43 ppm in exposure to this pollutant. In comparison, the gap between NO_2 averages weighted by the number of low-income people and those not belonging to this category was only 0.90 ppm (Table 8). The results are similar for the group of visible minorities and the average for the pollutant NO_x—which is almost twice as low in the first quintile as in the last (277.7 g versus 468.0 g; difference of -190.3 g)—and the average for the pollutant CO, for which the discrepancy between extreme quintiles is -1455 g.

Finally, as with the three preceding analyses, it appears that elderly people are not subject to inequity: only one T-test is significant, namely the one for NO_2. Furthermore, the value for pollution is lower in the last quintile than in the first.

The situation appears somewhat complex for individuals under 15 years old. One positive point to note is that the averages for proportions of collector arteries and the pollutant NO_2 are significantly lower in the last quintile, and higher for the proportion of local streets. In other words, city blocks with a strong concentration of young people show lower levels of NO_2 pollution and a lower presence of superior road networks other than highway. However, the results appear contradictory for two of the modeled pollutants (CO and NO_x): averages are higher for the last quintile, which represents an inverse relationship compared to the one observed with the Spearman coefficients, which were slightly negative. This can be attributed to the fact that the MOTREM model did not estimate pollution for roughly 1,000 city blocks—located mainly in the western suburbs of Montreal where proportions of young people are very high—since these areas almost exclusively contain a network of local streets with low traffic data volumes. If values had been assigned to these blocks, they would probably have been very low and would therefore have contributed to lowering or inverting the discrepancy between extreme quintiles.

Table 10. Comparison of values for pollutant indicators associated with the minimal and maximal quintiles of the studied groups

		Highways (%)*				**Collectors, arterials and expressways (%)**			
		Mean		Difference		Mean		Difference	
Quintile 1	**Quintile 5**	**Q1**	**Q5**	**Moy**	**P**	**Q1**	**Q5**	**Moy**	**P**
0-14 years old (%)	> 15 years old (%)	0.97	1.13	-0.16	0.3261	24.69	12.49	12.19	0.0001
65 years old and over (%)	less than 65years old (%)	1.07	1.50	-0.44	0.0046	19.90	19.85	0.05	0.9247
Visible minorities (%)	No visible minorities (%)	0.51	1.58	-1.06	0.0001	14.77	20.04	-5.27	0.0001
Low income pop. (%)	No low income pop. (%)	0.84	1.25	-0.41	0.0001	10.54	23.77	-13.23	0.0001
		Local streets (%)				**CO***			
0-14 years old (%)	> 15 years old (%)	73.24	85.55	-12.30	0.0001	2964.7	3501.0	-536.4	0.0001
65 years old and over (%)	less than 65years old (%)	77.76	77.45	0.31	0.6080	3395.5	3475.2	-79.72	0.4608
Visible minorities (%)	No visible minorities (%)	84.02	76.96	7.06	0.0001	2693.9	4149.0	-1455	0.0001
Low income pop. (%)	No low income pop. (%)	87.86	73.68	14.18	0.0001	3229.3	3330.3	-101.0	0.0001
		NO_x*				**$PM_{2.5}$***			
0-14 years old (%)	> 15 years old (%)	301.8	397.8	-95.96	0.0001	5.72	7.65	-1.93	0.1752
65 years old and over (%)	less than 65years old (%)	359.7	383.5	-23.73	0.9212	6.85	7.26	-0.41	0.9293
Visible minorities (%)	No visible minorities (%)	277.7	468.0	-190.3	0.0001	5.17	9.33	-4.16	0.0001
Low income pop. (%)	No low income pop. (%)	350.8	365.0	-14.19	0.0001	6.38	7.23	-0.85	0.0001
		NO_2							
0-14 years old (%)	> 15 years old (%)	13.06	10.63	2.42	0.0001				
65 years old and over (%)	less than 65years old (%)	11.97	11.63	0.34	0.0011				
Visible minorities (%)	No visible minorities (%)	10.96	12.48	-1.53	0.0001				
Low income pop. (%)	No low income pop. (%)	9.84	13.27	-3.43	0.0001				

* For the four indicators, the P-value is computed after transformation of the variable due to no-normality. However, the mean for each indicator is displayed at the original scale to facilitate interpretation.

5. Discussion

Our results regarding environmental equity for four population groups in Montreal deemed to be vulnerable to air pollution essentially corroborate those of past studies. First, we demonstrated over-exposure to pollutants for low-income individuals and, to a lesser extent, for visible minorities. Secondly, as in other studies [22, 24, 33], we did not find a situation of inequity for young people and the elderly, although we did not introduce control variables, for example deprivation. Such results for these four groups can largely be explained by the urban landscape and the social geography of Montreal.

To begin with, it is not surprising that low-income individuals are more exposed to pollutants since they are concentrated in Montreal's central neighborhoods [68]. These spaces are above all characterized by greater residential density, the diversity of urban functions, higher concentrations of collector roads, arteries, expressways, and highways that link together the downtown area; hence higher traffic data volumes. All these factors lead to higher pollution levels, whether modeled or measured.

Visible minorities on the Island of Montreal for their part are victims of over-exposure to pollutants, although this exposure remains much weaker than for low-income individuals. This corroborates two recent Canadian studies in environmental equity, namely those of Buzzelli and Jerrett [30, 31] on air quality in Hamilton and Toronto as well as that of Apparicio et al. [60] on the accessibility of parks in Montreal. Moreover, the lower degree of ethnic residential segregation in large Canadian cities compared to their American counterparts might well explain these significantly lower levels of environmental inequity in line with pollution.

Young people under 15 years old appear to reside in urban environments with more local streets, less high-level roads, and lower pollution levels, especially as reflected by NO_2 measurements. Since the 1950s, the presence of young people under 15 years old has been dropping in central boroughs while it has considerably increased in suburbs on the outskirts of the Island of Montreal [60]. These areas are characterized by low urban density and low functional diversity—the vast majority of homes being single-family houses—along with a roadway network organized so as to serve residential neighborhoods, hence minimizing the presence of major roads.

Finally, individuals 65 years old and over residing on the Island of Montreal do not appear to be faced with environmental inequity either. This is not surprising since a recent study on the evolving distribution of elderly people in Montreal between 1981 and 2006 has demonstrated that this group has become decentralized [69]. In other words, the elderly are increasingly dispersed across the island and, in particular, they are increasingly present in the inner suburbs.

Environmental inequity or pollutant exposure inequity?

One of the main issues in environmental equity is to assess the health risk associated with living in a residential area with higher concentrations of air pollutants [11]. The objective then becomes to establish whether the targeted groups may be exposed to pollutant concentrations that can affect health [70]. The World Health Organization (WHO) has determined that annual concentrations of NO_2 should not exceed 40 $\mu g/m^{-3}$ [71]. The average concentration of this pollutant is 13.27 ppm[2] in city blocks with high concentrations of low-income households (last quintile), which equates to 24.68 μg/m^{-3}, a level much lower than the threshold set by the WHO. This finding nuances the observation of environmental inequity in connection with low-income households in Montreal. Although this group does live in more polluted areas than the rest of the population, the concentration is deemed 'not harmful' to health according to the WHO. In addition, low-income households that reside near the downtown area can benefit from certain amenities related to their location. Apparicio and Séguin [72] have demonstrated that central neighbourhoods, especially deprived ones, have better access to services and equipment compared to those in the periphery of the Island of Montreal. Moreover, residential proximity to major roads sometimes offers better access to public transportation networks, hence improving mobility for households without vehicles [73]. However, it should also be kept in mind that, owing to their socio-economic position and hence their limited mobility, low-income individuals have fewer resources to be able to protect themselves from high concentrations of pollutants in their areas of residence [74]. Conversely, more wealthy households that reside in significantly more polluted environments can more easily get out of the city, for example by acquiring a second house. It therefore appears important to consider several elements relating to the urban environment before making an observation on environmental inequity for a group within the population. Indeed, studies in environmental equity, including this one, have tended to focus on one single element in the urban environment, a fact that has recently come under criticism [11, 45].

Comparability of the three techniques used

We have shown that average or weak correlations exist between the three techniques used (Spearman coefficients between 0.15 and 0.50 in absolute value). At first glance, the most surprising element is the relatively weak correlation between the measured pollutant (NO_2) and the modeled pollutants (CO, NO_x, $PM_{2.5}$) (± 0.20). Because of the typical co-localization of NO_2 with the pollutants PM and CO, one might have expected higher correlation coefficients. This situation can be explained in part by the varying spatial scale of the two approaches: one is at the regional level and takes into account the characteristics of the upper road network, while the other is more local and takes into account characteristics of the road network, but also of the built environment and population density.

What can be deduced from these differences in the diagnosis of environmental equity? It should be noted that the four statistical analyses here performed have all shown a much stronger situation of inequity for low-income individuals with regard to NO_2 exposure than with regard to pollutants modeled at a more regional scale. Indeed, the correlation between this group and NO_2 is three times higher compared to the modeled pollutants (0.44 versus values below or equal to 0.15). In a context where the literature on environmental equity seeks to measure health consequences associated with pollutant exposure, the variable of exposure must be as accurate as possible according to the scale of analysis [75]. The land-use regression method—which uses several elements from the built environment and urban functions, at a fine scale, to predict pollutant levels—therefore appears more appropriate for studies of environmental equity. This is particularly true in light of the existence of micro-spaces of poverty in Montreal [76].

6. Limits of the Study

Operationalizing these techniques has shown the approximate level of pollutants for a period of time *t*, i.e., their concentration [70]. It is important, however, to distinguish between the notions of pollutant concentration and exposure. Exposure has to do with the period of time an individual spends in an environment and the quantity of pollutants to which the person is exposed [70]. This makes it complex to measure individuals' actual exposure to pollutants, since it is difficult to ascertain the time period during which they remained at their residence [20, 21]. In addition, this analysis only takes into account certain pollutants, while individuals can also be exposed to other pollution sources [1].

7. Conclusion

The results of this analysis corroborate those of a number of studies in environmental equity: low-income households do tend to reside in more polluted areas. Yet while a situation of distributional inequity is associated with pollution in Montreal, it would be hasty to conclude that this represents a situation of flagrant environmental inequity that is highly harmful to the health of low-income populations. Indeed, the measured NO_2 concentrations are well below the thresholds set by the WHO.

We have also shown that diagnoses of environmental equity relating to air pollution vary from one technique to another. According to numerous authors [75, 77], it is primordial to accurately measure a studied phenomenon in order to properly assess health risks for targeted groups. Although in the context of this study, associations were stronger with the land-use regression method, it is difficult for us to conclude that this is the most appropriate technique irrespective of the data, the scale of analysis, and the context of a given study. However, our results do clearly show that the combined use of different approaches to measure pollutants offers a way to refine diagnoses of environmental equity and air quality.

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Annex 1

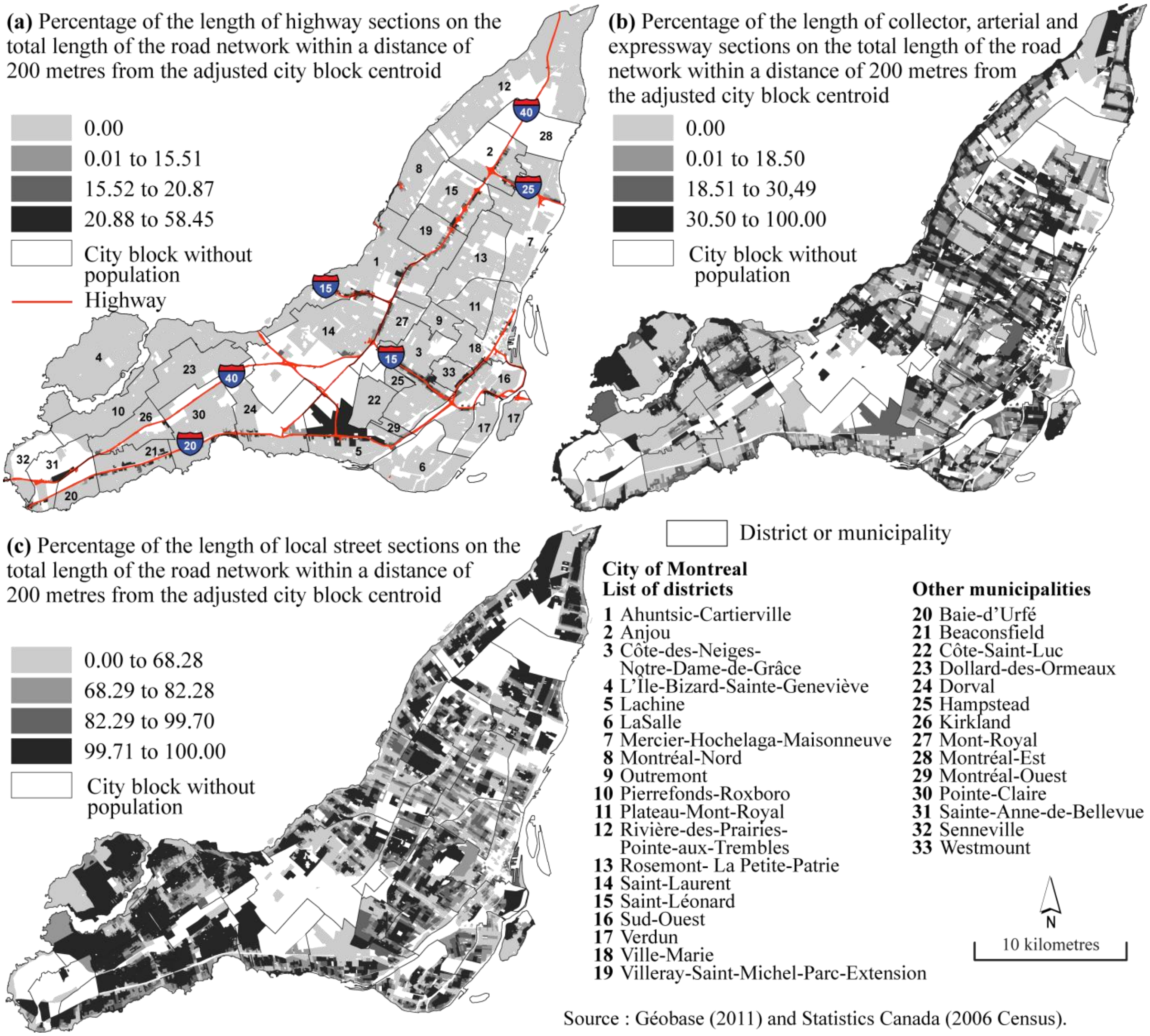

Figure 2. The three indicators of proximity to major roads calculated at the city block scale, Island of Montreal

Annex 2

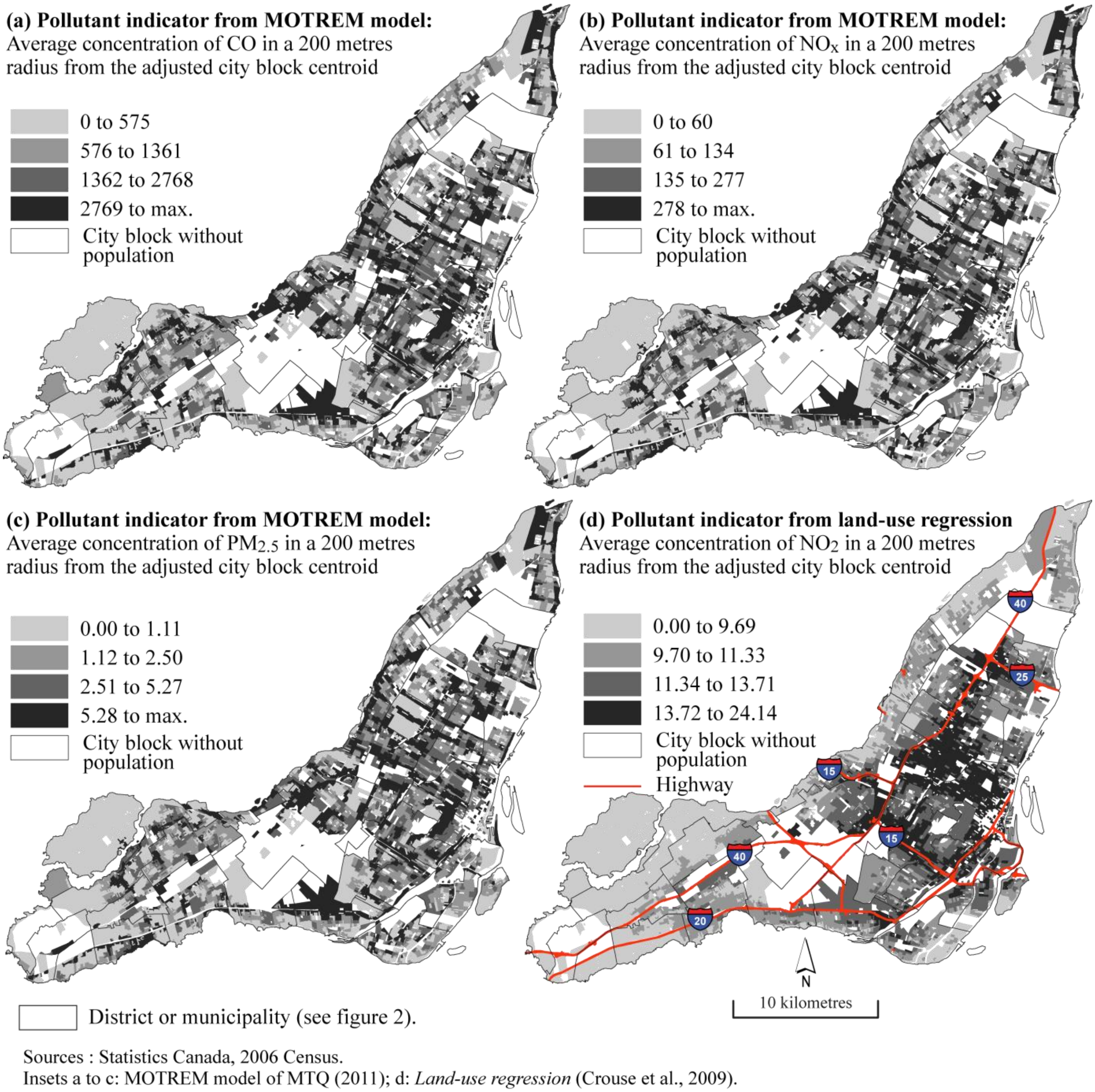

Figure 3. The three indicators of pollution modeled or measured at the city block scale, Island of Montreal