ENVS 653

TERM PROJECT - PHASE 3

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Executive Summary

Within the field of air pollution studies, an increasing area of interest is pollution equity, defined by Tessum et al. (2019) as the “difference in the environmental health damage caused by a racial-ethnic group and the damage that group experiences.” Studies so far indicate that socioeconomically advantaged groups tend to commit more damage than they experience. Using a variant of the pollution equity idea that takes into account climate change-related emissions, we explore whether this phenomenon exists in the Greater Montreal area.

Specifically, we examine the level of air-pollution exposure risk across the city and suburbs of Laval and Longueuil and relate them to average household emissions of pollutants—greenhouse gases (GHG). The aim is to assess whether the burden of air pollution is equitably shared across neighbourhoods, regardless of income and private vehicle usage, or some high emitters evade air pollution while low emitters reside in more highly polluted areas.

We accomplished this by creating two maps, one representing the potential for air pollution exposure, and one representing GHG emissions, each at the level of the census dissemination area (DA). The air pollution potential map was constructed with data on land use, point source pollution, surface temperature, and road network proximity. The GHG emissions map was built with combined income and private vehicle usage data as a proxy for GHG emissions. We then related GHG emissions to pollution exposure risk in a bivariate map.

Our analysis suggests several spatially correlated trends. Primarily, it was evident that suburban areas outside of the island of Montreal represent high household GHG emissions and low pollution exposure. This trend of high emissions and low risk pollution exposure is also present in central high-income residential areas in Montreal, such as Notre-Dame de Grace and Westmount, as well as some of the neighborhoods surrounding Parc Mont Royal. We also discerned a distinction between the east and west ends of the island. The east generally represents higher exposure to pollutants than the west. Overall, this analysis points out several spatial trends in which we find evidence of unequal burdens of exposure risk.

Introduction

Within the field of air pollution studies, an increasing area of interest is pollution equity, defined by Tessum et al. (2019) as the “difference in the environmental health damage caused by a racial-ethnic group and the damage that group experiences.” Studies so far indicate that socioeconomically advantaged groups tend to commit more damage than they experience. Using a variant of the pollution equity idea that takes into account climate change-related emissions, we explore whether this phenomenon exists in the Greater Montreal area.

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An investigation into where the burden of air pollution in Montreal lies in relation to individual emissions has multiple implications and real-world applications. The most important is education. The findings of the study could help the general public take action to reduce emissions, as individuals, and as voters who shape politicians’ agendas for correcting injustices. More specifically, the findings could shape public policy, for example, by identifying socioeconomically disadvantaged neighbourhoods where the mitigation of air pollution should be prioritized. At the same time, the findings could identify high-emitting neighbourhoods where alternatives to or incentives to reduce private vehicle ownership should be prioritized, for example, where investments for public transportation infrastructure should be located.

Methods

GHG Emissions

A. Data Collection & Formatting

Data for GHG emissions per household were not available therefore, we used census data as a proxy to estimate household GHG emissions. Disposable household income was chosen as an indicator for GHG emissions, as research has shown a strong positive correlation between carbon footprint and household income (Kuzyk, 2011; Mackenzie et al., 2008). Then we wanted to somehow incorporate vehicle use into our GHG equation as in 2005 Statistics Canada found that personal vehicle use accounted for nearly two-thirds (63%) of total household emissions. We used % of residents who drive their car into work as a mode of commuting as an indicator of personal vehicle use. To obtain these variables, we accessed the Statistics Canada census data from CHASS Data Center (University of Toronto, 2021).

Since these two variables were only available in non-spatial data formats, to transform the census data to spatial form, a boundary shapefile of the dissemination areas (DAs) of

Greater Montreal was obtained from Statistics Canada. Once the spatial data was collected a spatial join was performed with income and vehicle use. Finally, the data was projected to MTM8.

Table 1. GHG data descriptions and sources.

Categories	Variable	Relevance	Formatting	Sources
General	Dissemination areas (DAs) for Census Metropolitan Area	Set the scale for the analysis and incorporate spatial data.	Project to MTM 8	Statistics Canada (2016)
GHG Emissions	Median household after-tax income	As income increases, GHG emissions increase (Kuzyk, 2011; Mackenzie et al., 2008).	Join to DA shapefile. Conversion to raster. Reclassify based on income deciles (See Appendix B.1).	Statistics Canada (2016), CHASS Data Center
	Private vehicle use: Main mode of commuting for the employed labour force - car, as a driver	Personal vehicle use accounted for nearly two-thirds (63%) of total household emissions. Over 75% of households use their personal vehicle to commute to work and about 80% travel alone (Statistic Canada, 2012).	Join to DA shapefile. Conversion to raster. Reclassify based on quantile groups (See Appendix B.1).	Statistics Canada (2016), CHASS Data Center

B. Methodology

The objective of the GHG emissions was to obtain an overall GHG emissions classification (from high emission levels) to low per DA. To quantify GHG emissions, median household income was categorized into income deciles and associated with a GHG emissions index on a scale of 0 – 10 increasing by income, a method adapted from Mackenzie et al., 2008. Therefore, the highest income category is assigned the highest GHG emission level at 10. With the distribution varying greatly between DA, and in order to categorize each DA, we reclassified the data using the equal quantiles. Each category was then reclassified and given a score from 1 to 8, each score being the double of the previous category. For details about the classification, refer to Appendix B.1 Then we performed a weighted overlay with the two datasets. During this step, we decided to give income a slightly higher weight since literature has shown that income alone is a great indicator of overall GHG emissions (Kuzyk, 2011).

Once the overlay was performed, we wanted to represent the data back to the scale of DA. Therefore, we then used the zonal statistics tool to compute the average GHG emissions index per DA. At this point we reclassified GHG emissions per DA based on a categorical scale of high, medium, and low and the results appear in Appendix A.1. An overview of the methods used in this section is displayed in Figure 1 below.

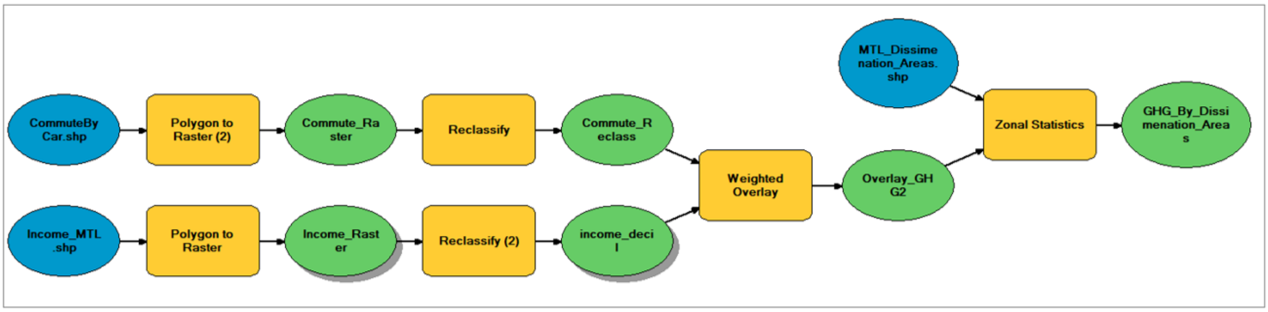

Figure 1. The ArcMap model of the GHG indicators overlay.

Air Quality Exposure

A. Data Collection & Formatting

Table 2. Air quality data descriptions and sources.

Category	Variable	Relevance	Formatting	Source
Air Quality	Land Use	Land use is a strong predictor of air pollution levels (Yang et al., 2017; Henderson et al., 2007).	Merging multiple shapefiles, conversion to raster, and reclassification based on pollution risk of land use category.	Communauté métropolitaine de Montréal (2020)
	Montreal Surface Temperature	Heat can exacerbate the health risks posed by air pollution (Lam, 2014; Rainham, 2003; Kalisa, 2018).	Conversion to MTM8 and reclassification based on pollution risk of surface temperature category.	Données Québec (2015)
	NPRI Facilities	Atmospheric and effluent releases of pollutants to air (Taylor et al., 2020).	Create point shapefile from data, spatial interpolation using Radial Basis Function and reclassification based on resulting exposure interpolation.	National Pollutant Release Inventory (2021)
	Road Networks	Highways and major roads have a noted correlation with PM2.5 pollutants as a source (Ryan & LeMasters, 2007).	Creating buffer zones, converting from polyline to raster, and assigning air quality influence ranks.	Données Québec (2021)

Air quality is an inherently complex phenomenon shaped by multiple environmental variables, including: proximity to roads, type of road, traffic volume, land use, point sources of pollution, wind patterns, and surface temperature (Henderson et al., 2007). Studies of air quality in urban environments typically employ some or all of these variables, often with land-use regression techniques or, more recently, machine-learning algorithms. Statistically robust models of air quality are tested with at least 80 point measurements (Hendereson et al., 2007). Only 15 monitoring stations are operated across Montreal, which we deemed insufficient for our analysis. We opted instead to evaluate air quality on a qualitative scale, using four variables: land use, surface temperature, major point sources of pollution (from National Pollutant Release Inventory (NPRI) sites), and highways and major roads (see Table 2).

Using ArcGIS, the four variables were represented as rasters, combined in a weighted overlay, and generalized to the unit of the census DA to achieve a final map where the risk of pollution exposure in a particular DA is low, medium, or high. Below we describe these steps in greater detail.

B. Methodology

I. Land Use

Numerous studies over the past 15 years have used land use categories to predict pollution levels of PM2.5, NO_2 and NO (Jerrett et al., 2005; Henderson et al., 2007). Yang et al.'s (2017) study of Nanchang city in China provided the clearest guidance on how to rank land use categories by pollution risk on a standard scale. The study found that the highest levels of PM2.5 occur in commercial spaces followed by industrial areas. Control or effectively zero-pollution creating zones are ecological areas. In the middle are residential land uses, closely followed by institutional ones.

Montreal land use data contains many land use categories which were combined to reduce complexity and approximate land uses described by Yang et al. (2017). The standardization to five categories on a 0 to 10 scale was done as illustrated in the table in Appendix B.2. Importantly, street land uses were removed to avoid doubling the influence of roads, which was captured in a separate raster.

II. NPRI Facilities

The National Pollutant Release Inventory (NPRI) is Canada's legislated, publicly accessible inventory of facilities that are required to disclose their pollutant releases (to air, water, and land) to Environment Canada under the Canadian Environmental Protection Act(CEPA). Included within the reports are measurements for PM2.5 per year in tons per facility. Proximity to NPRI facilities has been demonstrated as being a significant contributor to lowering air quality in surrounding neighborhoods (Shairsingh et al. 2018). As per Zhou et al (2015) we used Radial Basis Function to perform a spatial interpolation within ArcGIS spatial for the spread and extent of the release of PM2.5 from the facilities within the greater Montreal area (GMA). We then reclassified the outputs as from 10 (poor air quality closest to facilities) to 1 (normal air quality, farthest from the facilities).

III. Road Proximity

Highways and major roads are a source of PM2.5 pollutants (Ryan & LeMasters, 2007). We worked under the assumption that PM2.5 decreases in concentration away from its source at a specific rate (Beckerman et al, 2008). A series of buffer zones were created around highways and major roads in the Greater Montreal area to assign likelihood of high PM2.5 concentration. These consisted of 100 m, 200 m, and 300 m buffers which were assigned an air quality rank from 10 (poor air quality due to PM2.5) to 1 (normal air quality level). In accordance with a study by Hitchins, Morawska, Wolff & Gilbert (2000), the assumption that a 50% decrease in PM2.5 concentration within approximately 100-150 m of roads was applied.

IV. Surface Temperature

The surface temperature data for Montreal is a raster of zones classified from cool to very hot on a 0 to 9 scale. Only categories above 7 are labelled to reflect that they may pose a health risk. In the literature, the dynamics of air pollution and temperature appear to be somewhat poorly understood, although there is indication that heat exacerbates pollution impacts (Lam, 2014; Rainham, 2003; Kalisa, 2018). Therefore, a subjective but conservative reclassification to a standard 0 to 10 scale was made, ranking serious heat islands 10 and cool areas 0. Details are included in Appendix B.3.

V. Weighted Overlay

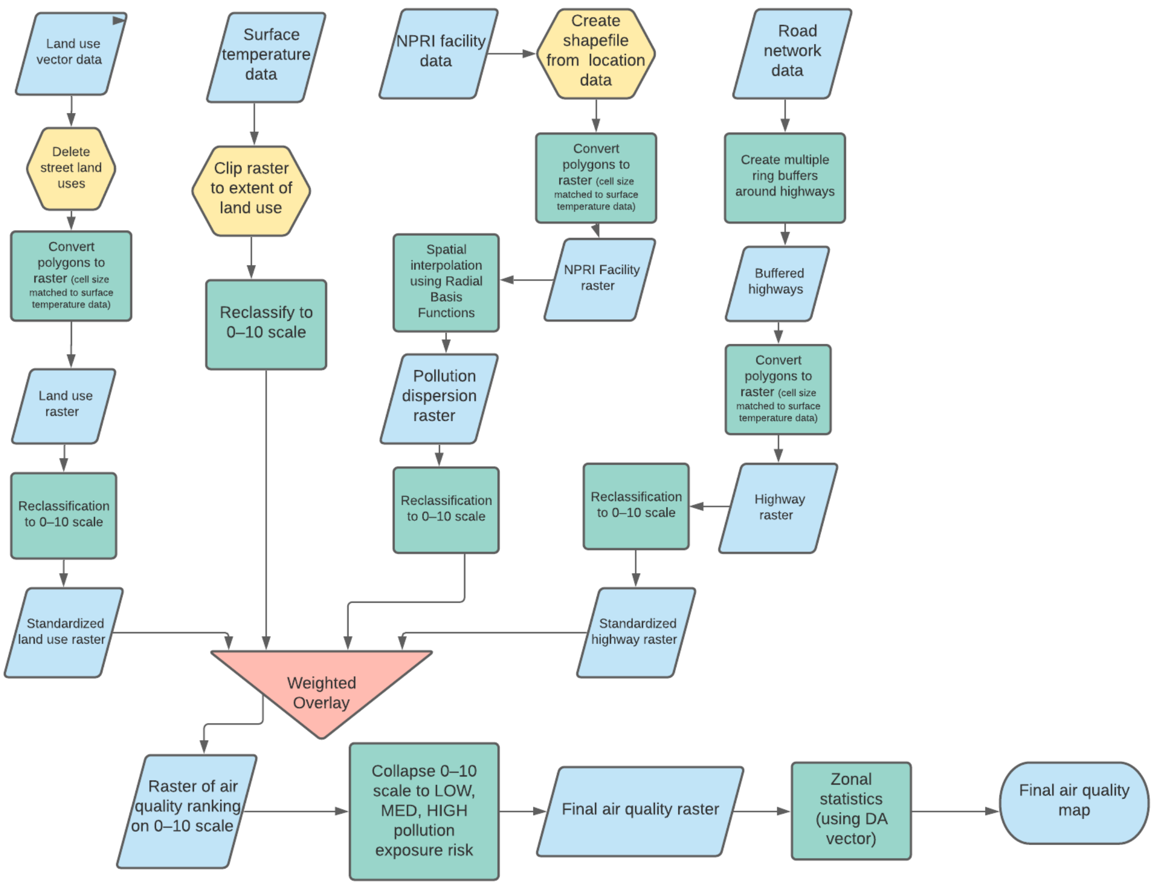

Figure 2. Model of Air Quality predictions overlay.

After each variable was prepared as a standardized raster, the layers were combined by weighted overlay to reflect relative influence on pollution exposure risk. From most to least influence, the variables were ranked as follows: road proximity (35%), land use (30%), NPRI facilities (25%) , and surface temperature (10%). This resulted in a single raster of pollution exposure risk on a 0 to 10 scale, which was generalized to three categories: low, medium, and high risk. To prepare this raster for the bivariate analysis, the majority category for each census DA was tabulated and added as an attribute to the DA shapefile.

Bivariate Map

To compare GHG emissions to pollution exposure risk by census DA, the attributes were matched in R. Low, medium, and high GHG emissions were labelled 1, 2, and 3, while pollution exposure risk became A, B, C. Thus, for example, DAs with low GHG emissions and low pollution were coded “A1” while high GHG emissions and high pollution were coded “C3”. This coding was translated into the colour representation (choropleth) seen in Figure 3.

Results & Conclusions

Several spatial trends emerge in the final bivariate map (Figure 3). Foremost, suburban areas off the island of Montreal create high household emissions and experience low pollution exposure risk. This also appears true of residential areas on the island, such as Notre-Dame de Grace and Westmount. We attribute the low exposure risk in these areas to the land use category and the absence of major roads. Large areas of green space, includingPark Mont-Royal, lower the pollution exposure risk.. Finally, we also discern some distinction between the east and west ends of the island. In the eastern end are areas of deep red (moderate emitters, high exposure risk), reflecting lower income households in proximity to industrial zones and NPRI facilities. In the west end, particularly along the Saint-Lawrence River, are higher-income neighbourhoods with few exposure risk sources. This result aligns with well-known persistent socio-economic disparities between the east and west island. Overall, our analysis provides a preliminary answer to the question of where within Greater Montreal high-emitters evade the burdens of exposure risk.

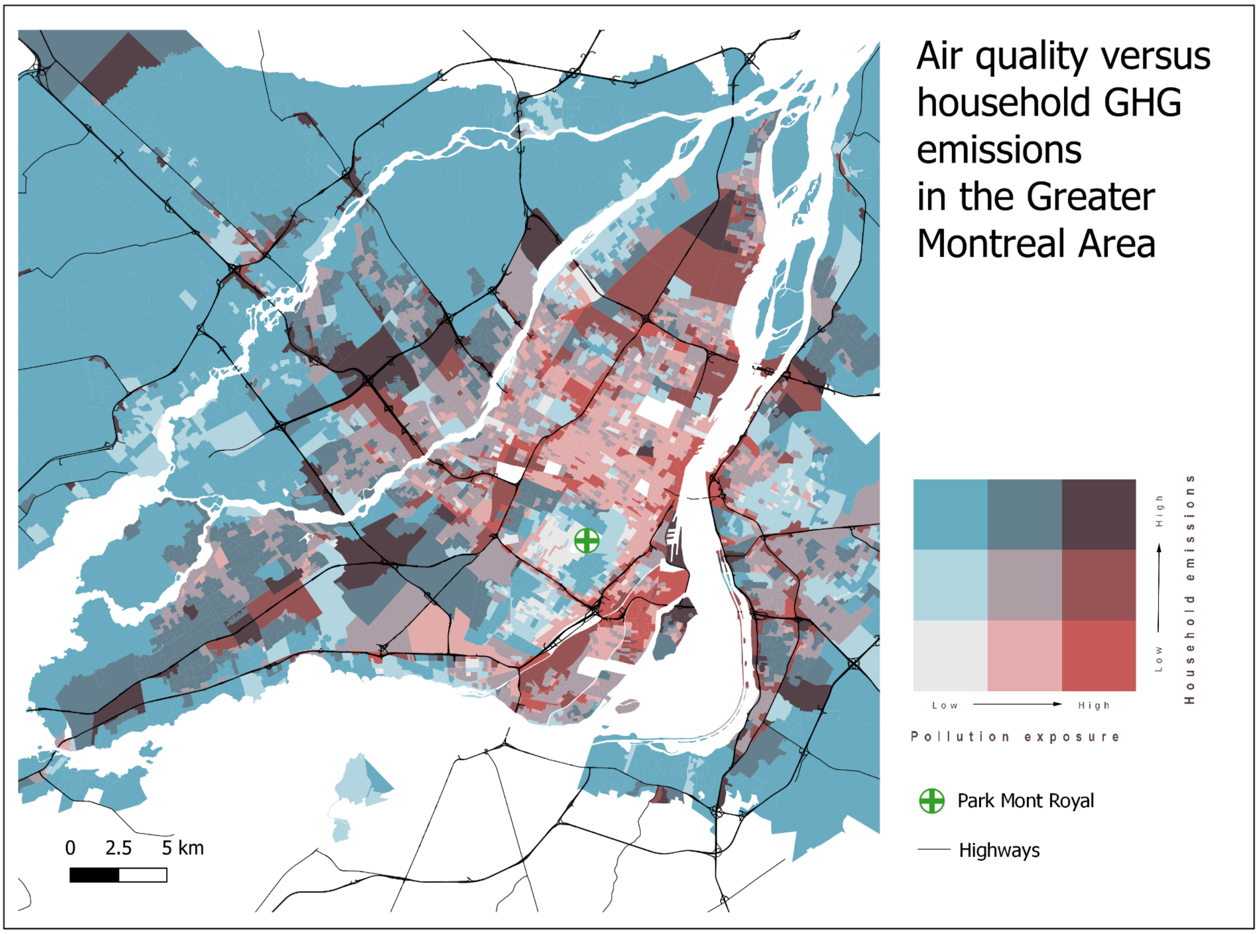

Figure 3. Final bivariate map of the Greater Montreal area showing pollution exposure and household GHG emissions household.

Limitations

Several limitations exist in our research. Some of those are specific to the GHG or air quality variables, while others are general limitations. General limitations include the following:

- Scale of our bivariate data was limited to the DA.
- The reclassifications and overlays were subjective.

Air Quality Limitations

- In order to create the road network raster to combine with the others for air quality, we functioned under the assumptions that air pollution is spatially autocorrelated and that PM2.5 decreases at a specific rate moving away from its source (Beckerman et al, 2008; Hitchins, Morawska, Wolff & Gilbert, 2000).
- Although it is known that traffic volume has a strong correlation to pollution levels and air quality (Ryan & LeMasters, 2007), the data was unable to be acquired for the study and was therefore not used.
- Air pollutant monitoring stations were few in number and sparsely distributed around the study area, reducing the accuracy of the resulting interpolation of pollution exposure risk.

GHG Limitations

- We only looked at workers who are drivers, and not passengers. This assumption was supported by the following finding: Statistics Canada Household and Environment Survey (2006) showed that over 75% of households use their personal vehicle to commute to work and about 80% travel alone. The number only varies about 10–12% between colder and warmer months of the year (Statistics Canada, 2012).
- The data did not include different vehicle types. If a DA had more high polluting cars than another, our study was not able to take this variable in consideration.

Recommendations

Several recommendations emerge from our findings. One, the City of Montreal should consider improving air quality monitoring. This is currently a major limitation to pollution equity research. With improved measures of air quality across the urban surface, researchers could also consider whether low emitters burdened by pollution are also racialized, a question that was beyond the scope of our study.

Despite the limitations of our study, we also suggest that the City consider measures to address pollution equity now. This could mean researching what policies and programs would get higher-income households to reduce the activities that contribute to their local emissions footprint, such as driving private vehicles. City planning measures, including land-use zoning policies, infrastructure development planning and building code revisions, should also be assessed for their potential to reduce risk of air pollution exposure, particularly as they affect the high risk zones identified in our analysis.

Group Work

Table 3. Action plan devised in Phase 1 of the project, outlining and delegating tasks.

Categories	Tasks	Group Members
GHG emissions	Research on GIS methods for mapping GHG emission	Christiana & Margo
	Develop a weighted index to combine income & main mode of transportation.	
	Create ordinal categories to attribute an index that represents emissions high, medium, and low per dissemination area.	
	Calculate and map average carbon footprint per dissemination area	
Air quality	Research on GIS methods for mapping air quality.	Whitney, Vincenzo & Avery
	Data collection and spatial interpolation of air pollution involving the combination of selected relevant variables (PM2.5 concentration, road networks, temperature, and land use).	
Final Bivariate Map	Create a bivariate map to display the air quality and GHG emissions.	Whitney & Vincenzo

In order to accomplish the goals set out for the project, the team was separated into two groups. The first handled the collection and formatting of data for greenhouse gas emissions, and the second air quality. The benefit of this delegation of tasks was that it allowed the team to function in smaller groups, avoid schedule conflicts, and allowed members to focus on fewer topics at a time.

At the same time, this arrangement precluded each group member getting hands on experience of each step. For example, only two members of our group worked on the final bivariate map. However, debriefing sessions enabled everyone to understand the tools and processes used.

File transfer among group members posed another difficulty. In one instance, a process had to be redone because the file used was not the most up to date. If we had to work on a similar project again, we would organize an online file-sharing system.

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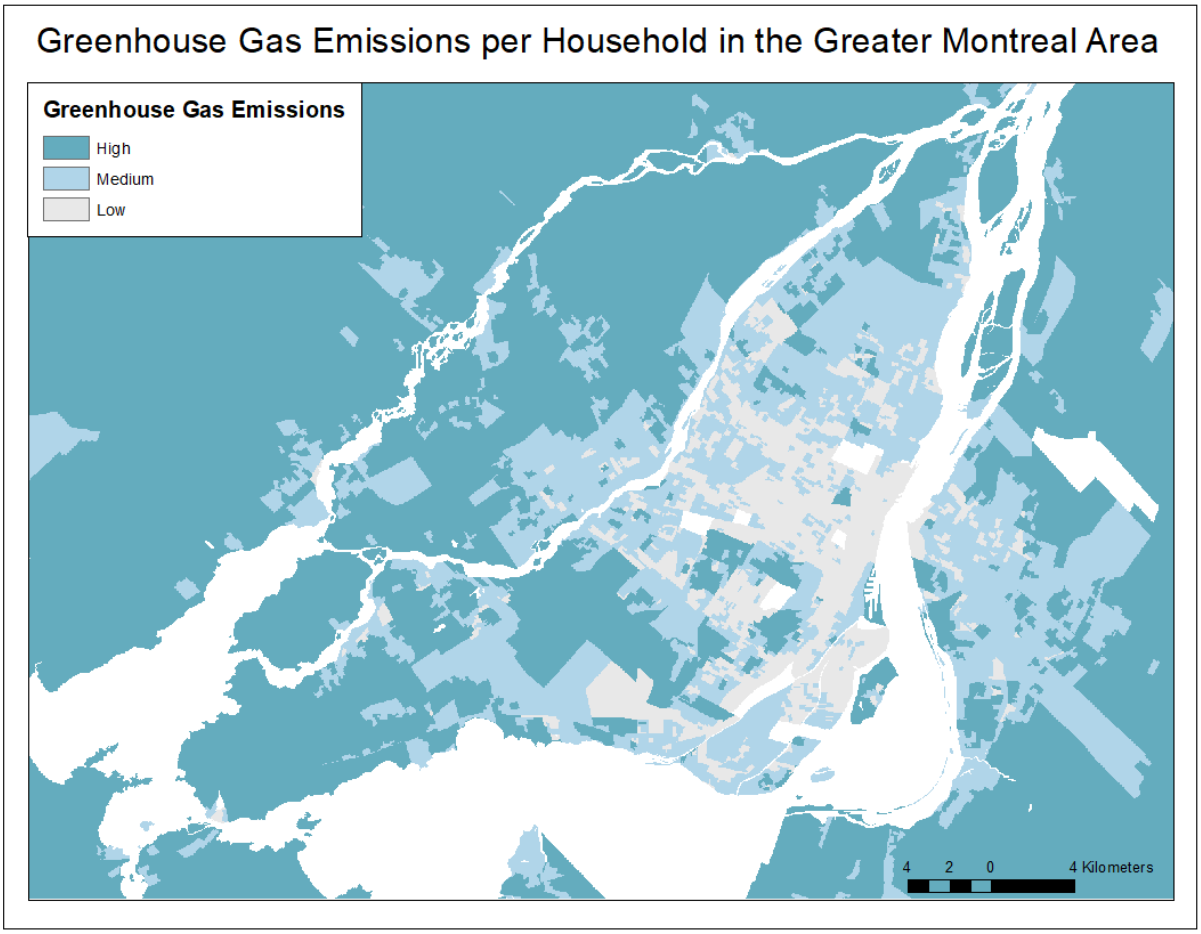
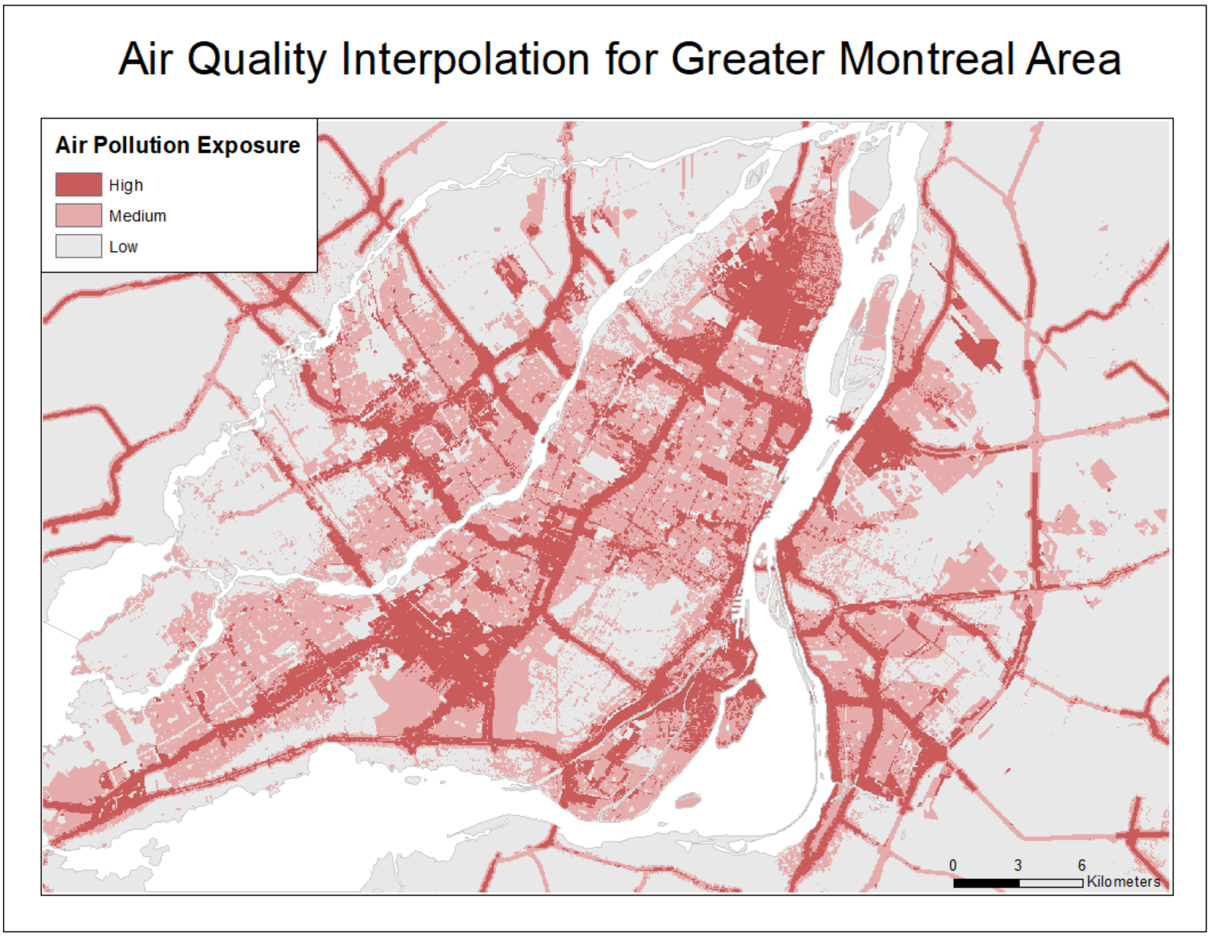
Appendix

Appendix A. Maps

Map 1. Greenhouse Gas Emissions per Household in the Greater Montreal Area.



Map 2. Air Quality Interpolation for Greater Montreal Area.



Appendix B. Tables

Appendix B.1. GHG Indexes & Classification.

GHG Indicator	How was it obtained ?	Category	Category Score	Score range	Weight
Median after-tax income of households in 2015 (in CAD, $)	- Carbon footprint can be estimated by income deciles. As income increases, GHG emissions increase. (Kuzyk, 2011; Mackenzie, et al., 2008; Stats Canada)	($)0 - 10300	0	0 - 10	60%
		10300.1 - 23700	1		
		23700.1 - 33700	2		
		33700.1 - 43400	3		
		43400.1 - 54500	4		
		54500.1 - 66800	5		
		66800.1 - 81600	6		
		81600.1 - 99600	7		
		99600.1 - 125700	8		
		125700.1 - 200400	9		
		200400.1 - 283904	10		
Main mode of commuting for the employed labour force aged 15 years and over in private households with a usual place of work or no fixed workplace address	- The Statistics Canada Household and Environment Survey (2006) showed that over 75% of households use their personal vehicle to commute to work and about 80% travel alone. The number only varies about 10–12% between colder and warmer months of the year. - Therefore we only took into consideration the drivers (not the car passengers) - I used equal intervals : this way it is easy to compare each DA : a dissemination area under 20% has half as many people driving as a DA with 40% of drivers	0 - 20%	1	1 - 8	40%
		20 - 40%	2		
		40 - 60%	4		
		60 - 80 %	6		
		80 - 100 %	8		

Appendix B.2. Air quality, land use reclassification.

Land use category (broad)	**Land use categories (narrow)**	**Category score (0 = no pollution risk, 10 = high risk)**
Commercial	commercial, office	10
Industrial	industry, public utility, rail, airport, parking	9
Residential	all types of residential	5
Institutional	institutional, economic institution, non-economic institution	4
Ecological	park, empty, golf, agriculture, water	0

Appendix B.3. Surface temperature, reclassification.

Standardized pollution-risk ranking	**Original category**
0	coolest (1,2)
1	less cool (3, 4)
3	no specific qualifier (5)
4	no specific qualifier (6)
5	no specific qualifier (7)
9	heat island (9)
10	serious heat island (10)