The Spatial and Social Inequities of Urban Transportation-Related Health Pathways in Montréal

by

Fiona M. McClave

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Department of Geography
McGill University
Montréal (Québec) Canada

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

The causal linkage between transportation and health has entered the realm of popular discourse. Transportation can be a mitigating or exacerbating component of the urban system on public health, with the potential to create health inequalities for already vulnerable urban sub-populations. Using a holistic framework outlined by Widener and Hatzopoulou (2016), I create four distinct pathways in which transportation has the power to affect urban health. By indexing relevant indicators for each pathway and employing hotspot analysis as well as descriptive statistics, this study examines the spatial and social patterns of transportation-related health within the city of Montreal. I find a contrast with the center of the Island and the East and West extremities for all pathways, with either health promoting or health undermining features concentrating around the downtown core depending. Significant differences concerning transportation-related health exist for visible minority, Black, and immigrant populations. These results should urge planners to rethink how transportation policy inequitably affects urban minorities' health.

CHAPTER 1: INTRODUCTION

The main objective of this research project is to understand the role urban transportation systems play in public health and to understand how inequities in transportation systems exacerbate the burden placed on already vulnerable population groups based on income, race, ethnicity, and immigrant status. The causal linkage between transportation and health outcomes has been well documented in recent decades, but the longer urban planners and policymakers fail to recognize the diverse ways transportation may adversely and disproportionately affect certain groups, the worse the problem will become. The expansion of transportation infrastructure and facilities has not benefited everyone equally, and indeed has the power to make certain groups worse off (Forkenbrock & Schweitzer, 1999). Using Michael Marmot's (2005) perspective of the social determinants of health, or non-medical factors that influence health outcomes, transportation can be a mitigating or exacerbating component of the impact of the urban system on public health.

By comparing spatial incidence of transportation effects and exposure with the locations of vulnerable populations, as seen by Forkenbrock and Schweitzer (1999) in their study of transportation-related environmental disparities on low-income groups, my goal is to explore spatial and social patterns of transportation-related health in the context of the city of Montreal. I believe that my research is relevant and important because health becomes ever more pertinent to consider alongside the environment when assessing sustainable transport policy or development (Cohen, Boniface & Watkins, 2014). Research on the health and social implications of transportation has the power to inform policy which may in turn enact real change by improving public health and reducing inequalities.

My overall interest in this study is to shed light on both the spatial and social patterns of transportation related health in the context of the city of Montreal. To accomplish this aim, I will answer the following two research questions:

RQ1: How are transportation-related health measures distributed across the island of Montreal? Where do potential sites of deprivation exist?

I will further subdivide this question to better examine the specific pathways that exist between transport systems and health, drawing principally from the framework outlined by

Widener & Hatzopoulou (2016). These pathways are identified as follows: Environment pathway, Proximity pathway, Crash pathway, Infrastructure pathway.

It is important to examine each pathway as each has distinct health implications, as described in chapter 2. Inequitable exposure to the outlined transport measures can have important mental and physical health implications for exposed populations. Therefore, it is critical to identify trends in association between socio demographics of the population of Montreal, and whether where the population lives can be deemed “healthy” or not. This brings me to my second research question:

RQ2: Are sites of potential health deprivation and sites of potential health promotion representative of the island of Montreal? Do associations exist between socio demographic subgroups and transport related health measures?

This question will address the second half of my conceptual framework, examining transportation justice and identifying groups whose health may disproportionately suffer due to the urban transportation systems that exist in Montreal. I plan to answer these questions using a combination of GIS hotspot analysis to address RQ1, and descriptive statistics using relevant census variables to address RQ2.

Through this research, I hope to address health inequalities as they pertain to urban transportation systems. I also hope to disseminate my findings effectively to inform policymakers in the Montreal transportation department in order to enact change, specifically to attenuate the health inequalities of vulnerable socio demographic groups.

This paper is structured as follows. In chapter 2, I present an in depth discussion of the central framework of my research, drawing principally from the Widener & Hatzopoulou (2016) paper, “Contextualizing research on transportation and health: A systems perspective” which outlines the main research trajectories by which transportation impacts health. I also review the existing literature on these trajectories and their specific implications for human health, as well as the disparities in these pathways among socio-demographic groups. In chapter 3, I describe the various datasets I utilize in the research, including the description and (when required) justification of measurements for each indicator, as well as a description of census variables to be used in the analysis. This section details the limitations of the data, and the important manipulations used in the software R to address such limitations. In chapter 4 I describe the analysis methodology and delve more into the exploratory analysis, utilizing both spatial analysis with the GIS application Getis-Ord Gi*, more commonly known as hotspot analysis, as well as descriptive statistics. In chapter 5 I reveal the overall trends of the resultant distributions and discuss the spatial patterns of each pathway. Chapter 5 also describes the correlation between socio demographic variables and transit-related health. In chapter 6, I conclude the study, stating important takeaways from the analysis and how the outcomes may inform local transit policymakers. This chapter also outlines areas of future research.

CHAPTER 2: CONCEPTUAL FRAMEWORK

My broad objective for this research is to explore the distribution of transportation-related health measures across the island of Montreal in order to understand the public health implications of these measures, and the implications of any observed inequitable distributions. To look at health from a transportation systems perspective broadly is quite overwhelming. Past conceptualizations of transportation and health literature have taken several forms. Cohen, Boniface, and Watkins (2014) divided the literature based on the specific health implications of transport policy. The authors determined four ways in which transportation is linked to health: by causing or preventing physical ill-health, causing mental illness and stress, causing or exacerbating problems of inequality which shapes health outcomes, and by causing or impeding a safe road environment (Cohen, Boniface, & Watkins, 2014). Meanwhile, Khreis, May, and Nieuwenhuijsen (2017) posed a framework organized by transport policy measures, of which they identify eight (8) specific measures. These measures include motor vehicle crashes, air pollution, noise, heat islands, lack of green space and biodiversity loss, physical inactivity, social exclusion, community severance and climate change, alongside their associated health effects. Both frameworks emphasize important concepts including the need to consider health alongside the environment when assessing transport policy or development, as well as the impact of these policies on vulnerable populations. However, these frameworks lack a holistic viewpoint linking all the ways transportation systems may impact health.

Thus, I instead draw from a framework laid out by Widener and Hatzopoulou (2016), in which the authors group research pertaining to transportation and health into five broad arenas. The paper describes five potential pathways urban transportation may affect health. The first is the “direct impact of transportation on the physical environment”, which I will refer to as the ‘Environment pathway’. Next is the “direct impact of transportation on access to healthy spaces and facilities”, referred to as the ‘Proximity pathway’. The third pathway outlined by Widener and Hatzopoulou (2016) is the “indirect and direct impacts on morbidity and mortality caused by transportation”, or ‘Crash pathway’. Next is “the indirect impact of transportation infrastructure on healthy behaviors”, known in this paper as ‘Infrastructure pathway’. The last pathway by which transportation affects health described by the authors is the “indirect impact of disease spread through transportation networks”. The last pathway will not be used in my research because it is too difficult to operationalize disease spread given the scope of the project.

Under this framework, the effects of urban transportation systems can be split into two parts: 1) the urban health effects transportation creates through each indicator of each pathway (which is further explained in chapter 3); and 2) how each pathway disproportionately affects certain urban sub-populations and consequently exacerbates existing health inequalities. This latter concept can broadly be summed up by "transportation justice", explained more thoroughly below.

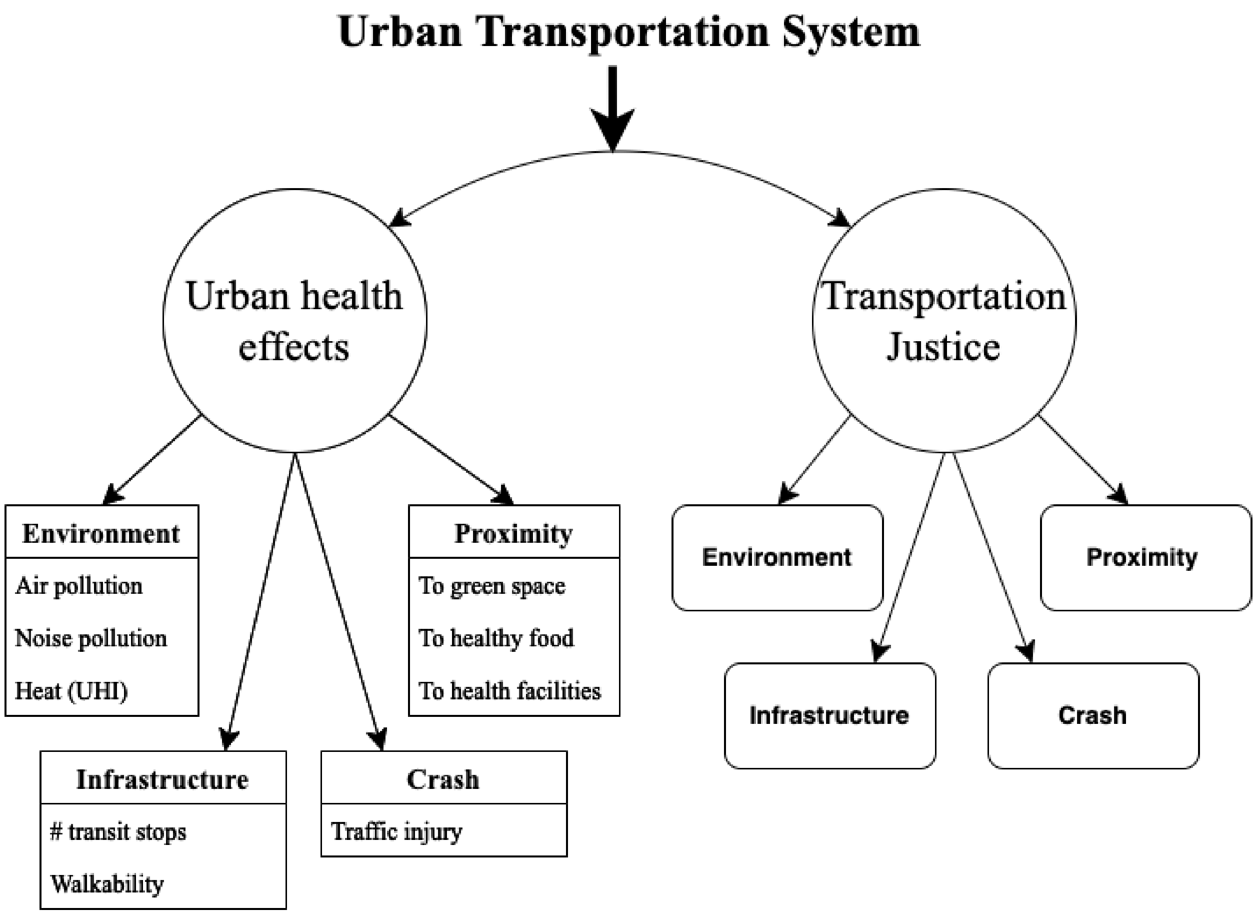

Figure 2.1 - Conceptual Framework

2.1 Urban Health effects

The outlined four pathways have the power to affect public health in a multitude of ways.

2.1.1 Environment

There are several indicators that measure the impact transportation plays on the environment, which consequently affects human health. First, vehicles are largely dependent on fossil fuels and produce air pollutants. Traffic-related emissions can affect ambient air quality from local roadsides to urban scales, and potentially across even broader areas. Traffic-related air pollution can cause a plethora of adverse health conditions among those consistently exposed. According to a Special Report conducted by the Health Effects Institute (HEI) in 2010, vehicle emissions cause an estimated 91,000 annual deaths globally from ischemic heart disease, 59,000 deaths from stroke, and 34,000 deaths from lower respiratory infections, chronic obstructive pulmonary disease, and lung cancer (Health Effects Institute, 2010). According to Kramer et al., traffic-related air pollution is associated with incident type 2 diabetes among elderly women (2010). Traffic pollution is also positively associated with increasing BMI in children aged 5-11 (Jerrett et al., 2014). Additionally, transportation requires the replacement of soil and vegetation with paved roads which contributes to the environmental phenomenon referred to as Urban Heat Islands, or UHI. The UHI effect is exacerbated by increased buildings and pavements, as well as the lack of green space and creates an urban localized climate that is on average 2 degrees higher throughout the year than its rural surroundings (Gago, Pacheco-Torres, Ordonez, 2013). While this phenomenon is often overlooked, increased urban heat can contribute to heat-related deaths and illnesses including respiratory difficulties, heat exhaustion, non-fatal heat stroke and general discomfort (Environmental Protection Agency: online). The UHI effect can also exacerbate health impacts by increasing the risk of flooding in urban areas and decreasing water quality (Hester & Bauman, 2013), as well as interacting with worsening air pollution (Xu, Yin, & Xie, 2014). Transportation is also a major contributor to noise pollution through engine revving, beeping and general traffic noise. Environmental noise can adversely affect health through annoyance, cognitive impairment in children, sleep disturbance, and tinnitus (World Health Organization, 2011). A review conducted in 2012 determined road traffic noise was positively and significantly associated with hypertension (van Kempen & Babisch, 2012). The same authors also concluded that populations exposed to transportation noise have an increased risk of cardiovascular disease. Thus, urban transportation systems have the ability to transform the natural and built environment, which in turn may negatively affect the health of residents within such systems.

2.1.2 Proximity

The next pathway by which transportation affects health is the proximity pathway, as outlined in the conceptual framework. Urban transportation systems facilitate mobility and can greatly affect spatial access to healthy spaces and facilities. Transportation can aid human health by helping individuals move through their surroundings to places that encourage healthy lifestyles. Important destinations include grocery stores, hospitals, and parks or urban green space. Lack of access to such resources may in turn adversely affect individual health. For example, areas which lack grocery stores, also known as food deserts, detrimentally affects health. Healthy foods provide nutrients essential for the human body. Living in areas where such foods are inaccessible will thereby lower nutrient intakes, and subsequently increase the risk for birth defects, anemia, cognitive problems, obesity and diabetes (Gundersen & Ziliak, 2015). A study by Kelli et al. (2019) revealed that living in a food desert is associated with a higher risk of adverse cardiovascular events for those with preexisting conditions. Health facilities are also accessed via transportation infrastructure, which promotes and maintains human health by providing health services. In emergency situations, close proximity to hospitals may greatly affect the probability of survival (Bertoli & Grembi, 2017). Last, transportation may allow greater access to urban green space which can promote mental and physical health by reducing exposure to pollution, releasing stress, and promoting social cohesion (World Health Organization, 2017). The positive effects of proximity to green space are well documented. For example, a 2018 literature review (Kondo et al., 2018) found that urban green space exposure was consistently negatively associated with mortality, and positively associated with increased attention and improved mood. Neighborhoods with increased proximity to and greater proportion of park area have also been associated with greater physical activity, especially in children (Roemmich et al., 2006). Urban transportation systems thus have the ability to increase accessibility to critical resources necessary for the maintenance of health.

2.1.3 Crash

The pathway between transportation and health can also be quite direct, demonstrated through the third pathway in the conceptual framework: Crash. Injuries and fatalities may occur as the result of transportation, such as vehicular crashes into pedestrians and cyclists. In fact, the World Health Organization reports that road traffic crashes are a leading cause of death globally and can cause mortality, injury, PTSD and perceived unsafety (World Health Organization, 2015). While primarily of importance in the developing world, Canada as a country reported 1,745 vehicular fatalities and 101,572 traffic related injuries in 2020 (Government of Canada: online), making this health hazard still quite prevalent. There are also lasting effects of traffic injury, with significant PTSD prevalence in traffic-injured children (de Vries et al., 1999).

2.1.4 Infrastructure

Finally, transportation infrastructure itself can influence healthy behaviors. Transportation infrastructure includes the built street environment which describes how well the local environment encourages residents to be active, and can be operationalized with the Active Living Environment (ALE) index. This index combines three measures of the built environment: three-way intersection density of roads and footpaths, weighted dwelling density, and points of interest (Herrmann, Ross, et al., 2019) to determine favorable active living environments. A neighborhood's walkability influences physical activity, and increased neighborhood walkability has been associated with higher levels of cardiorespiratory fitness and lower BMI (Hoehner et al., 2011). Infrastructure also includes access to transit, or the number of transit stops which again affects accessibility to critical spaces, facilities, and opportunities.

Overall, it is important to be aware of the distributions these pathways may take as they have specific health implications for urban residents.

2.2 Transportation Justice

There is also evidence that the pathways described above have spatial distributions that may contribute to transportation injustice by disproportionately burdening areas where already vulnerable populations live. Indeed, Forkenbrock and Schweitzer state "the expansion of transportation facilities have not benefited everyone; that, in fact, they have made some populations, often low-income or minority people, worse off" (Forkenbrock & Schweitzer, 1999: 96). These populations may be unequally exposed to transportation pollutants, and transport injury, as well as living in areas with insufficient access to healthy resources, spaces and infrastructure, leading to overall adverse health effects. As Khreis et al. explain, "transport policies have the potential to increase health inequalities, contributing further to the ill health of the most deprived groups, who exhibit a variety of other factors that makes them more vulnerable to environmental exposures (e.g. poor diet, suboptimal health care, stress violence, etc)" (Khreis, May, & Nieuwenhuijsen, 2017: 211). To exacerbate these disparities, vulnerable impacted communities often have the fewest resources to confront or prevent these threats (Golub et al. 2013). Oftentimes, many communities are not even aware of the current or proposed transport policy that may negatively affect them (Golub et al. 2013). Disparities in exposure between socio-demographic groups can be observed for each of the outlined pathways.

In terms of the Environment pathway, pollution exposure patterns target lower-income areas. Both low income and unemployment rates were significant predictors of air pollution exposure in Hamilton, Ontario shown by Jerrett et al. (2001). A study by Krieg and Faber (2004) supports this concept of environmental injustice by revealing that poor communities of color are most likely to bear a disproportionate burden of negative externalities such as proximity to waste sites, and poor ambient air quality. General noise pollution also seemed to follow this pattern in NYC. A study conducted by Ramphal et al. (2022) demonstrated that census tracts with a higher proportion of low-income residents reported more monthly noise complaints, however there is a possibility this was not traffic noise related.

Spatial accessibility via transportation systems towards healthy facilities has also been shown to be lacking in predominantly Black neighborhoods. A study by Dai (2011) shows that accessibility to green spaces in Atlanta, Georgia is not evenly distributed, with a higher concentration of African Americans having significantly poorer access to green spaces. Black communities in metropolitan Detroit have also been burdened by spatial accessibility in terms of healthy foods, where predominantly Black neighborhoods were on average 1.1 miles further from the nearest supermarket than white neighborhoods (Zenk et al. 2004).

In regards to the Crash pathway, it has been seen that "although incidence and mortality are expected to decrease globally, some [socio demographic index] categories and specific vulnerable age groups may require particular attention" (Khan et al., 2017: 1). Thus, traffic injuries may also be unequally distributed. John Saylor (2021) fortifies this claim, describing the disproportionate burden of vehicular-caused fatalities and injuries from large pickup trucks and SUVs (coined by the author "light trucks") placed on already vulnerable populations including women, people of color, and low-income people.

Finally, there is evidence of transportation related infrastructure lacking in certain lower-income communities. A study done by Marshall, Brauer, and Frank (2009) examined the correlation between nitrogen oxide (NO), ozone (O_3) (both markers for direct vehicle emissions), and neighborhood walkability at the postal code. The study concludes each variable exhibits a city center-extremities gradient with high walkability and high NO concentrations close to the city center. The authors reveal a phenomenon they term "sweet-spot" neighborhoods with high walkability and low air pollution. Such neighborhoods were generally located near but not at the city center, and were almost exclusively higher income (Marshall, Brauer & Frank, 2009).

Such studies exemplify the unequal impacts transportation may pose across socio demographics, often benefiting majority groups.

CHAPTER 3: METHODOLOGY

In this section, I describe my research methodology for the study. I first describe the various datasets I utilize in the research, data needed to measure each indicator. I then explain the various structures of the corresponding datasets, along with important implications of the data characteristics. I detail important manipulations I use in the software R, and describe the analysis methodology so as to generate meaningful results.

3.1 Indicator Data

To answer my two research questions, I first made an indexed map to display the distribution of each pathway across the island of Montreal. To do so, I gathered data for every indicator that comprised each pathway. The list of indicators are summarized in Table 3.1. The indicator data is composed of twelve different datasets, one dataset per indicator with the exception of the air pollution indicator which was composed of three datasets (one for each of its three sub-indicators).

Table 3.1 - List of indicators

Pathway	Indicator	Sub-Indicator
Environment	Air Pollution	Ozone (O_3)
		Nitrogen Dioxide (NO_2)
		Particulate Matter ($PM_{2.5}$)
	Noise Pollution	
	Heat	
Proximity	Green Space	
	Health Facility	
	Healthy Food	
Crash	Traffic Injury	
Infrastructure	Walkability	
	# of Transit Stops	

In general, the data used in this study was limited to free sources that were open to either the general public or university affiliations. The three main requirements for the usage of datasets were as follows: 1) the datasets must cover the entirety of the study area (the island of Montreal), 2) the data must be recent (collected within the past 10 years), and 3) the data must be at the dissemination area (DA) level or at a higher resolution which can then be aggregated up. A dissemination area is a "small area composed of one or more neighboring dissemination blocks" (Statistics Canada: online) and was chosen to be the unit of the analysis because it is the "smallest standard geographic area for which all census data are disseminated". Thus, the data can be analyzed at the highest resolution possible, without losing any valuable information.

3.1.1 Environmental Pathway

First, I located data needed to measure the environmental pathway. My study measures traffic-related air pollution using three sub-indicators: atmospheric nitrogen dioxide (NO_2), particulate matter less than 2.5 μm in diameter (PM2.5), and atmospheric ozone (O_3). To justify my measurement of air pollution, I turn to past measurements of traffic-related air pollution. One study conducted in 2011 (Weichenthal et al., 2011) measures traffic-related air pollution by ultrafine particles, particulate matter 2.5, black carbon, volatile organic compounds, ambient NO_2, and O_3. Another study uses nitric oxide (NO) and O_3 as markers for direct vehicle emissions in their study of the built environment's role in exposure to air pollution and promotion of physical activity (Marshall, Brauer, & Frank, 2009). Additionally, the Government of Canada deems traffic-related air pollution as: nitrogen oxides, carbon monoxide, fine particulate matter (including PM2.5) and volatile organic compounds (Government of Canada: online). Out of the preceding, the most common markers of traffic-related pollution included NO_2, O_3 and $PM_{2.5}$, which combined I claim create a comprehensive measure of ambient traffic-related air pollution.

To measure these sub-indicators, three separate datasets were each taken from the Canadian Urban Environmental Health Research Consortium (CANUE) data portal. All data taken from this source covers the entirety of Canada, most at the postal code level. Ground level measurements of these pollutants are virtually impossible to attain at the dissemination area level across the entirety of the country, so estimation methods were used for the three sub-indicators. The ozone dataset measures the annual average ground-level parts per billion (ppb) O_3 concentration in 2015 using the Global Environmental Multi-scale Modelling Air Quality and Chemistry (GEM-MACH) model to estimate such concentrations for all of Canada. The nitrogen dioxide dataset measures the average ppb NO_2 concentration in 2016 estimated by a Land Use

Regression model. Last, the PM2.5 dataset measures the annual average concentration in μg/m³ and is estimated by a combination of Aerosol Optical Depth retrievals and the GEOS-CHEM chemical transport model.

Next, noise pollution can be much more directly measured via estimated noise levels, again taken from the CANUE data portal. Such estimates were calculated by CANUE most recently in 2019, using the Random Forest model, which used geographic predictors around monitoring locations to help predict the measured level of noise at each postal code.

The last indicator comprising the environmental pathway is annual average temperature, as a proxy to the environmental phenomenon of urban heat islands. Temperature data was taken once again from the CANUE data portal, which has taken base data from the Canadian Forest Service of Natural Resources Canada and interpolated such data for all of Canada at the postal code level. The most recent temperature dataset comes from 2015.

3.1.2 Proximity Pathway

To measure the proximity pathway, I found data for proximity to health facilities, to healthy food, and to green space. Proximity to health facilities was measured directly through a dataset from the CANUE data portal, originally developed by Statistics Canada and the Canadian Mortgage and Housing Corporation. In this data source, health facilities are considered businesses with codes 6211, 6212, 6213, 621494, and 622 under the North American Industry Classification System (NAICS). Proximity to these facilities are measured based on a simple gravity model that accounts for distance between the centroid of a given dissemination block (DB) and the centroids of all DBs where the facility is located. The distances are then normalized as an index value, with each DB given a score from 0 to 1 with 0 indicating the lowest proximity, and 1 the highest in Canada.

Proximity to healthy foods (proxied by grocery store proximity), was measured in the same fashion from the same CANUE dataset. Healthy foods (again, substituted by grocery stores) were classified as business code 4551 in the NAICS registrar.

Finally, data for proximity to green space was also taken from the CANUE database. This measure is a normalized value for each dissemination block in Canada proximity to parks. It measures the closeness of a neighborhood park within 1km walking distance. To derive this, CANUE has taken park data from authoritative open data sources and OpenStreetMap. All available CANUE proximity data is from the year 2019.

3.1.3 Crash Pathway

Data was then needed for the Crash pathway, specifically to measure traffic injury. Traffic injury was measured via the road collisions dataset from Montreal's Open Data Portal. The dataset was formatted as a point data shapefile, with each crash as one point. It contains collision point data from 2012 to 2019, and describes the type of injury as well as the victim (e.g. cyclist, motorist, pedestrian, vehicular). For the scope of this research aim, the data was focused on only pedestrian and cyclist victims, and injuries and mortalities were weighted equally. Additionally, due to the variability in DA size, crash point data was also weighted by area of DA, for a more even assessment.

3.1.4 Infrastructure Pathway

Lastly, data was collected for the infrastructure pathway, including measures of walkability and of transit stops. Data was found for both indicators in the Canadian Active Living Environment (CanALE) database, created by the Nancy Ross Research Group in 2016. The database covers all of the Montreal Census Metropolitan Area at the dissemination area level. Here, Active Living Environments are calculated by summing normalized z-scores for intersection density, dwelling density, and points of interest per dissemination area. DA walkability scores were then normalized to create an index. The second indicator, transit stops, is a more direct measure, calculated by a simple count of public transit stops/stations in the buffer around the DA centroid. These scores are again normalized by the data source.

In order to clip all of my data to the study area, and to convert resolutions to the unit of analysis, I needed a shapefile of the island of Montreal at the Dissemination Area level. I was able to obtain this shapefile from the Statistics Canada website which had boundary files covering the country of Canada at the DA level during the 2016 census year. I clipped this file in ArcMap to the boundary of Montreal.

3.1.5 Data Structure and Limitations

There is a clear variability in the format of many of the datasets. The variability includes the type of file (.shp or .csv), as well as the spatial resolution (postal code or DA or DB). Table 3.2 addresses such relevant data characteristics. The research methodology requires each dataset to be in .csv format in order to easily join multiple indicators to one geography. The spatial resolution must also consistently be at the dissemination area as it is the unit of analysis. To address these limitations, each dataset was entered into the programming software R to be organized and reformatted into usable data.

Table 3.2 - Description of Data

Pathway	Indicator	Sub-Indicator	Definition	Data Source	Year	Format	Spatial Resolution
Environment	Air Pollution	Ozone (O_3)	Annual average parts per billion (ppb) O_3 concentration	CANUE	2015	CSV	Postal Code
		Nitrogen Dioxide (NO_2)	Annual average ppb NO_2 concentration	CANUE	2016	CSV	Postal Code
		Particulate Matter ($PM_{2.5}$)	Annual average $PM_{2.5}$ concentration µg/m³	CANUE	2018	CSV	Postal Code
	Noise Pollution		Estimated level of noise	CANUE	2019	CSV	Postal Code
	Heat		Annual average temperature in C°	CANUE	2015	CSV	Postal Code
Proximity	Green Space		Proximity of a Dissmenation Block (DB) to any DB with a neighborhood park within 1km	CANUE	2019	CSV	DB
	Health Facility		Proximity of a DB to any DB with a health care facility within 3km	CANUE	2019	CSV	DB
	Healthy Food		Proximity of a DB to any DB with a grocery store within walking distance 1km	CANUE	2019	CSV	DB
Crash	Traffic Injuiry		victims + total number of cyclist crash victims	Montreal Open Data Portal	2012-2019	CSV	N/A (point)
Infrastructure	Walkability		dwelling density, and points of interest measures	CAN-ALE	2016	CSV	DA
	# of Transit Stops		stops/stations in buffer around DA centroid	CAN-ALE	2016	CSV	DA
Montreal Shapefile				Statistics Canada	2016	Shapefile	DA

3.2 Data Preparation Methodology

After collecting all necessary data, I then began the primary methodology, which was the creation of indexed maps of Montreal for each of the four pathways. To begin, I loaded each dataset into the software program R. I then deleted extraneous or N/A values found in the .csv tables. As acknowledged in section 4.1.5, variability exists within the datasets so to create an index I needed to address the irregularity in spatial resolution of datasets. So I reprojected all data to the World Geodetic System 1984 (WGS84) projection using the given latitude and longitude values. I then used a spatial join to join each indicator dataset with the Montreal shapefile I described in section 4.1. I then grouped each dataset by dissemination area and got the average for all values that fell within the DA, with the exception of the crash point data where I got a count for the number of crashes that fell within each DA.

The next step was to normalize each dataset using z-score normalization. Z-score normalization works by taking each value in the data, subtracting it from the mean of the set, and dividing by the standard deviation (see Figure 3.1). It is also important to note that while some pathways undermine health, such as exposure to environmental pollutants, other pathways promote health such as higher walkability and increased transit stops. To account for the differing positive and negative impacts of each pathway, I multiplied the resultant z-score by -1 if the impact of the pathway was negative, such that each index would correlate higher z-scores to overall better health. The pathways and their impacts are illustrated by Figure 3.2.

$$\mathbf{Z = [x - \mu] / \sigma}$$

Figure 3.1 - Z-score formula (where Z is the standard score, x is the observed value, μ is the mean of the sample, and σ is the standard deviation of the sample)

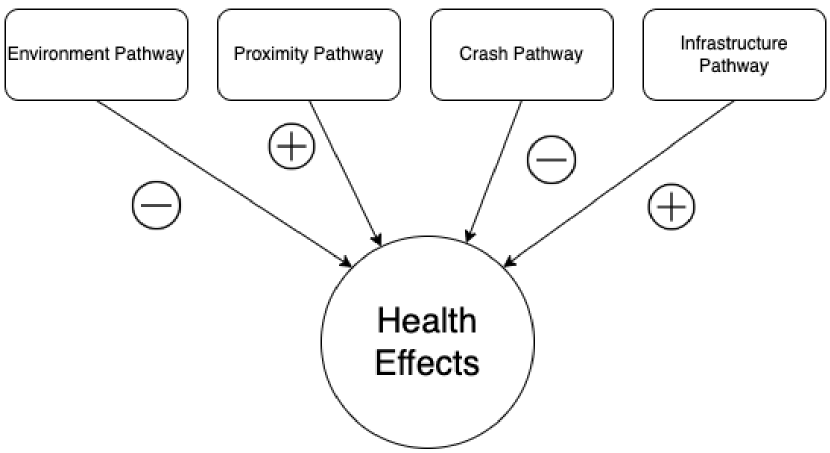

Figure 3.2 - Normalization conceptualization

Last, I summed the z-scores for indicators in each category together and renormalized to create indices of the four pathways. I also summed the z-scores for all indicators together and renormalized to create a composite index. I joined the files back to the shapefile geometry and mapped each pathway, as well as the composite index using the ggplot R function.
For the sake of reproducibility, I have attached the R code in appendix A.

3.3 Positionality

When introducing my methodology, it is important to, in the spirit of self-reflectivity, acknowledge my positionality in order to situate my research in context, as well as to address potential limitations. While my study is internal, meaning I will not be interacting with outside participants, and thus not need to factor in the implications of my perception, my positionality may still impact the outcomes of this study. For my background, I did not grow up in an urban core, and was never aware of the positive or negative impacts that transportation could have. After living on the island of Montreal for four years, I am more conscious towards the localized effects of transportation, specifically on this island. I am also presently a student in the McGill University Geography department, which has been quite influential in the formation of my interests and ideas, as well as potential methodologies. More towards my positionality, based on my conceptual framework and courses I have taken, I have adopted the assumption that I will indeed find significance in my distributions, which may potentially influence how my methodology is conducted or the prevailing results. As I will be going through this research more or less solely in the semi-narrow lens of my conceptual framework, I may ignore important nuances of my results. It is also crucial to note that this study should not be taken out of the Montreal context, as any specific spatial distributions or results I may find may not be transferable.

CHAPTER 4: ANALYSIS

My analysis takes the distributions created in the primary methodology, and utilizes two different analysis techniques to answer the two posed research questions. To address RQ1, determining spatial trends and identifying sites of deprivation within the island of Montreal, I use Getis-Ord Gi*, commonly known as Hotspot Analysis, through ArcGIS software. Next, to answer RQ2, revealing patterns of unequal exposure to transportation-related health measures among different socio demographic groups, I use variables from the 2016 Canadian census to determine significant association between the pathways using descriptive statistics and scatter plots.

4.1 Census Data

To conduct the analysis for this research, census variables were needed to analyze socio demographics of residents to see if there were any social implications of transportation-related health. Such data also needed to be at a dissemination area level or lower so to aggregate the data. A suitable data source was found via the University of Toronto's CHASS data center which provides data from the 2016 Canadian census in units as small as dissemination areas. The relevant socio demographic variables I chose to include in my analysis were total visible minority population, total black population, average age of the population (both sexes), and total immigrant population. Additionally, to measure low-income, I used the prevalence of low income cut-offs after tax measure (LICO-AT). The LICO is an income threshold that estimates an income threshold at which families are expected to spend 20% or more of their income than the average family does on food, shelter and clothing. (Statistics Canada, 2015: online) Such purchases of necessities are made with after-tax dollars, thus I will be using the LICO after-tax measure to determine low economic well-being (Statistics Canada, 2015: online). Census population counts were also needed for later analysis. The format of this data was given as a comma-separated values (.csv) file.

4.2 Getis-Ord Gi*

To address my research question on where sites of transit related health deprivation occur, I used GIS to apply the Getis-Ord Gi* statistical method. The Getis-Ord Gi* technique looks at each feature within the context of neighboring features to determine where features with low or high values cluster spatially (Esri:online). This spatial association method was developed by J.K. Ord and Arthur Getis in 1992 (Getis & Ord, 1992) and remodified in 1995 (Ord & Getis, 1995). This method was chosen for my analysis of determining hotspots of health promoting and health undermining areas because the Gi* statistics allow the user to detect local pockets of dependence that would not be detectable when using global statistics (Getis & Ord, 1992). The method takes as input my index values, and returns z-scores and p-values. In the case of hotspot analysis, a high positive z-score and a small p-value indicates a spatial clustering of high values, while a low negative z-score and small p-value indicates a spatial clustering of low values (Esri: online). To be considered statistically significant, the p-value of the z-score must equal 0.01 or below. To better understand the application of this analysis technique, I looked at examples of the technique being used in the mapping of road accidents in the city of Kuala Lumpur (Manap et al., 2019) and in the mapping of environmental pollutants (Lin, Chu, Chang, et al. 2010) which are both relevant indicators in my study and were beneficial sources of learning to apply the Getis-Ord Gi* technique.

To apply this technique, I first needed to export shapefiles of each pathway from R. To do so I used the "st_write" function in R to export each pathway's shapefile into my working directory. Next, I loaded each shapefile into ArcMap. The Getis-Ord Gi* method allows for a range of the Conceptualization of Spatial Relationships parameter, which reflects the inherent relationships among the features you analyze (Esri: online). I decided on the fixed distance band conceptualization as it uses a critical distance to determine the neighbors, and disregards the variability of polygon size that my dataset includes. The fixed distance band conceptualization requires an input of a distance threshold, so I used Global Moran's I to determine an appropriate threshold.

It is important to use the two features in conjunction in order to identify characteristics of patterns not revealed by the global statistic alone (Getis & Ord, 1992). The Global Moran's I measures global spatial autocorrelation based on feature locations and feature values simultaneously (Esri: online) This method is useful when testing for the existence of spatial dependence in the data (Wulder et al., 2007). The statistic is a weighted correlation coefficient given a null hypothesis of randomness (Wulder et al., 2007) and returns a z-score based on the spatial autocorrelation given a certain distance threshold (Esri: online). To determine a distance threshold, I inputted different distance thresholds at intervals of 100m, starting at 100m and ending at 2000m using the Global Moran's I tool. According to Esri (n.d.), an appropriate process to pick a threshold given my shapefile characteristics is by choosing the threshold where you see the first dip in the Global Moran's I z-score. This dip was found around 300m, and so the distance threshold was determined for subsequent hotspot analysis. I input my shapefile, and field of interest (index z-score) into the Getis-Ord Gi* method and set the distance to 300m, as previously determined. This method adds two columns to the attribute table: a z-score and a p-value. As mentioned above, very high positive z-scores represent hotspots, and very high negative z-scores represent coldspots. I selected all rows in the attribute table with a p-value lower than 0.01 so I would only include statistically significant hotspots and coldspots. I then created a shapefile for the hotspots (high positive z-score) and a shapefile for the coldspots (high negative z-score) for each pathway. In some pathways, exclusively only coldspots or hotspots were found.

4.3 Hotspot Descriptive Statistics

To answer my research question of *who* is living in these health promoting/undermining areas via the Montreal transport system, I then took the shapefiles of the hotspots and coldspots for each pathway (when applicable). I joined the census variables .csv file to the Montreal Dissemination Area shapefile, and then clipped this shapefile to the geometries of each of the hotspot and coldspot shapefiles. I exported the clipped shapefiles from ArcMap and imported them back into the R software to create descriptive statistics about the demographics in each hotspot coldspot using sum() and mean() functions for each variable. I then used the same census data, but clipped to the entire island of Montreal and ran the same statistics as before, so to compare the hotspots and coldspots to demographics of the island as a whole.

The basic formulation of this part of the analysis comes from Chakraborty (2006), wherein the author details an index that represents a quotient between the percentages inside a buffer zone and the percentages in the rest of the study area. If the proportion of the studied group (e.g. visible minorities) exceeds their respective proportion in the area outside, the value of the idex will be greater than one and suggests a disproportionate effect on the sub-group being examined (Chakraborty, 2006: p. 318). To determine whether any of this study's subgroups were being disportionately represented in any of the pathways' hotspots or coldspots, I found the prevalence for each group by taking the total number of individuals residing in the DAs that made up the respective hotspots and coldspots, and divided by the population within that area. I then found corresponding demographic statistics, again from the University of Toronto's CHASS data center, for the total island of Montreal, and compared using the Area Comparison index

(ACI) formula taken from Chakraborty (2006) to determine whether areas with extreme health undermining or promoting transit measures were demographically representative of the entire study area or if disparities exist. This formula was used for each studied variable: immigrant population, Black population, visible minority population, and low-income (LICO-AT) population.

I then determined the statistical significance of the difference between prevalence within the impacted area and prevalence outside the area using a t-test for each variable. The resultant p-value of each t-test was then used to determine if the difference was significant (p-value<0.01) or not significant (p-value>0.01).

$$\mathrm{ACI}_{\mathrm{Race}} = \frac{\text{Number of Non-Whites inside impacted area/Total population inside impacted area}}{\text{Number of Non-Whites outside impacted area/Total population outside impacted area}}$$

Figure 4.1 - Representation formula *Source: Chakraborty, 2006*

4.4 Plotted Trends

To determine if there were any overall associations between each census variable and the pathway indices, I used a two-way scatter plot. This is a graphical method used to explore the relationship between two continuous variables. Each socio demographic variable (percentage of visible minorities, percentage of immigrants, Black population percentage, and low-income percentage) is used as the independent variable, plotted against each pathway's z-score index, which is the dependent variable. The scatter plots were created in the R program, as well as a trend line for each plot. The trend line shows the fitted regression line and displays the linear relationship between each socio demographic variable and the z-score index for each of the four pathways. In total, 16 scatter plots were created in R using this methodology.

CHAPTER 5: RESULTS & DISCUSSION

This section presents the results and interpretations from my analyses and addresses my research questions RQ1: How are transportation-related health measures distributed across the island of Montreal? Where do potential sites of deprivation exist? and RQ2: Are sites of potential health deprivation and sites of potential health promotion representative of the island of Montreal? Do there exist associations between socio demographic subgroups and transportation-related health measures?

In conducting my analysis, I find significant spatial and social differences within each pathway's distribution. The results of such are organized by pathway, starting with the Environmental pathway, then Proximity, Crash, and finally Infrastructure. Studying these pathways illustrates the variability in transportation-related health measures and the social and health implications associated with each distribution.

5.1 Environment Pathway

To reiterate, the purpose of this research is twofold - to expose both spatial and social differences within each pathway. Applied to the Environment pathway, I look first for spatial trends in how traffic related environmental exposure is distributed across the island of Montreal. I then determine where hotspots and coldspots of environmental exposure are clustered.

To answer the first component of RQ1 I have implemented my primary methodology, described in chapter 3 which indexes the three environmental indicators: air pollution exposure, noise pollution exposure, and average temperature. The resultant choropleth map of the normalized index score is shown in Figure 5.1. Figure 5.1 provides a *relative* distribution of transport related environmental exposure, thus I justify using quintiles to display, which divides the index values into 5 equal bins. A lower score is associated with more health promoting features, so for this pathway a lower z-score corresponds to decreased environmental exposure. A higher score then corresponds to more health undermining features, so increased environmental exposure. The lowest z-scores are presented in blue, while the highest are red. In general, this distribution translates to "positive health" displayed in the blue and cooler colors, and "negative health" displayed in red and warmer colors. The average value of the index across disseminations areas (DAs) correlates to a z-score of 0, which in Figure 5.1 would be the yellow quintile.

The most visually salient component of Figure 5.1 is the increased environmental exposure in DAs by major road arteries, and sites of commerce or heavy industry. Evidence of this spatial patterning can be seen by the high z-scores of Montreal downtown (Ville-Marie borough), the Montreal Trudeau airport in Dorval, and around the Lachine Canal (le Sud-Ouest borough) which has historically been a site of industrial development (Desloges & Kelly, 2002). Relatively high environmental exposure exists west of Mount Royal, around the Lachine Canal (le Sud-Ouest borough), and in the downtown center. Additionally, there is far less environmental exposure at and nearby Mount Royal, as well as Île Bizard. Île Bizard is composed primarily of a nature park and two golf courses, so both locations are primarily green space. It would thus make sense that there would be decreased air pollution, noise pollution, and decreased heat in such areas due to the shading, unpaved soil, and vegetation urban green space provides (Heidt & Neef, 2008, p.85). There is also less environmental exposure around the boroughs of Westmount, and Rosemont.

The second component of RQ1 looks for sites of deprivation, or “hotspots" of health undermining features. According to the framework, hotspots under the Environment pathway would be areas with the most exposure to air pollution, noise pollution, and heat, and subsequently refer to adverse health. Coldspots on the other hand, would correlate to sites with the least environment exposure, and would correlate to health promotion. Hotspots exist around the Central Business District (CBD) and le Sud-Ouest borough, while coldspots exist mainly around Mount Royal spreading into le Plateau and Outremont.

As previously stated, the spatial distribution of this pathway is completely relative. Thus, there are no determinate conclusions one can make from this distribution about true health, as there is no threshold of pollutant and heat exposure that would determine if an environment is “healthy” to live in or not. However, it is interesting to note the clear spatial variability in environmental exposure, with low exposure around areas of green space, and high exposure around more industrial and commercial land uses.

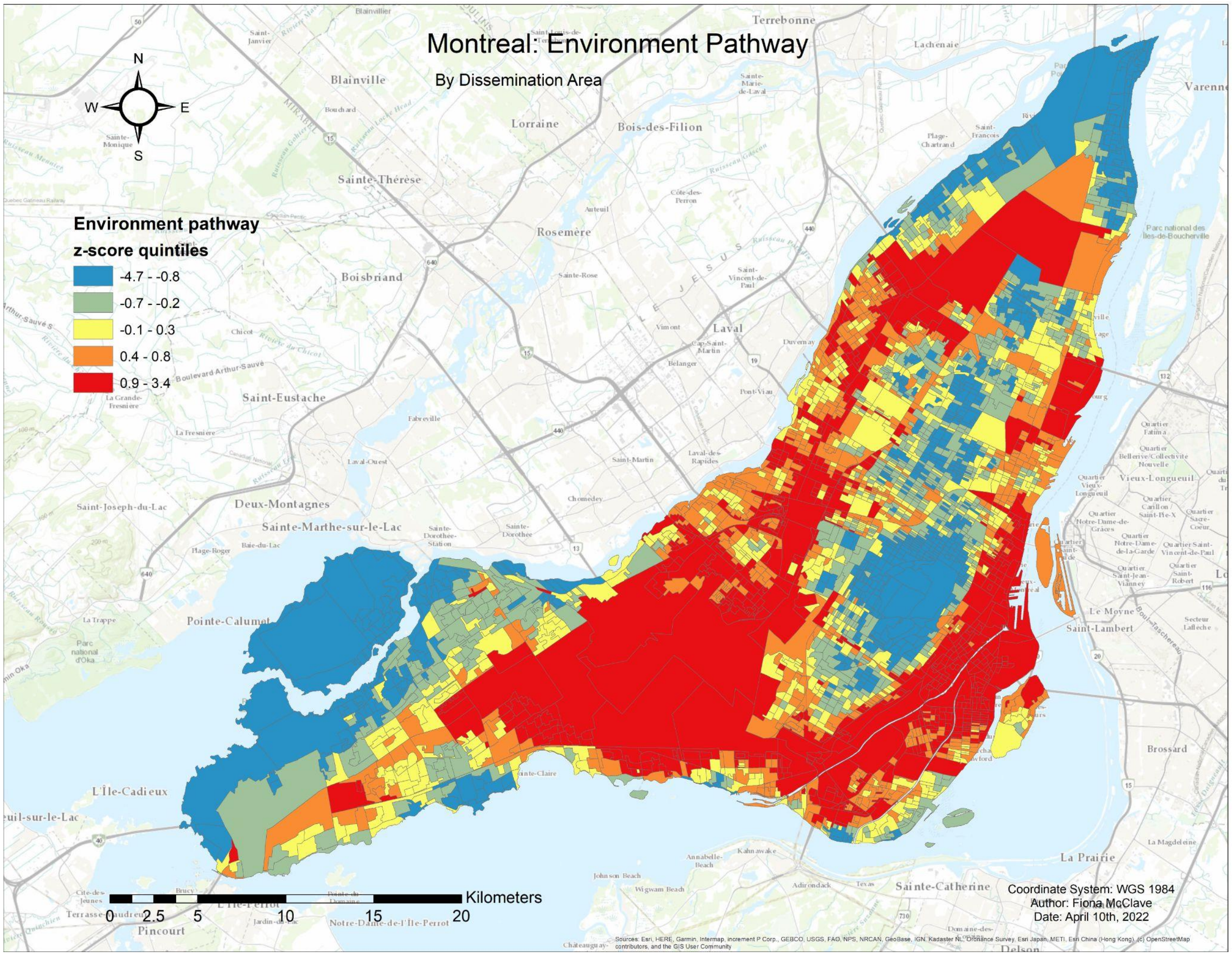

Figure 5.1 - Choropleth Map of Environment pathway z-score index. Z-score distribution divided into quintiles. Generated in ArcMap 10.8.2. *Source: CANUE 2019*

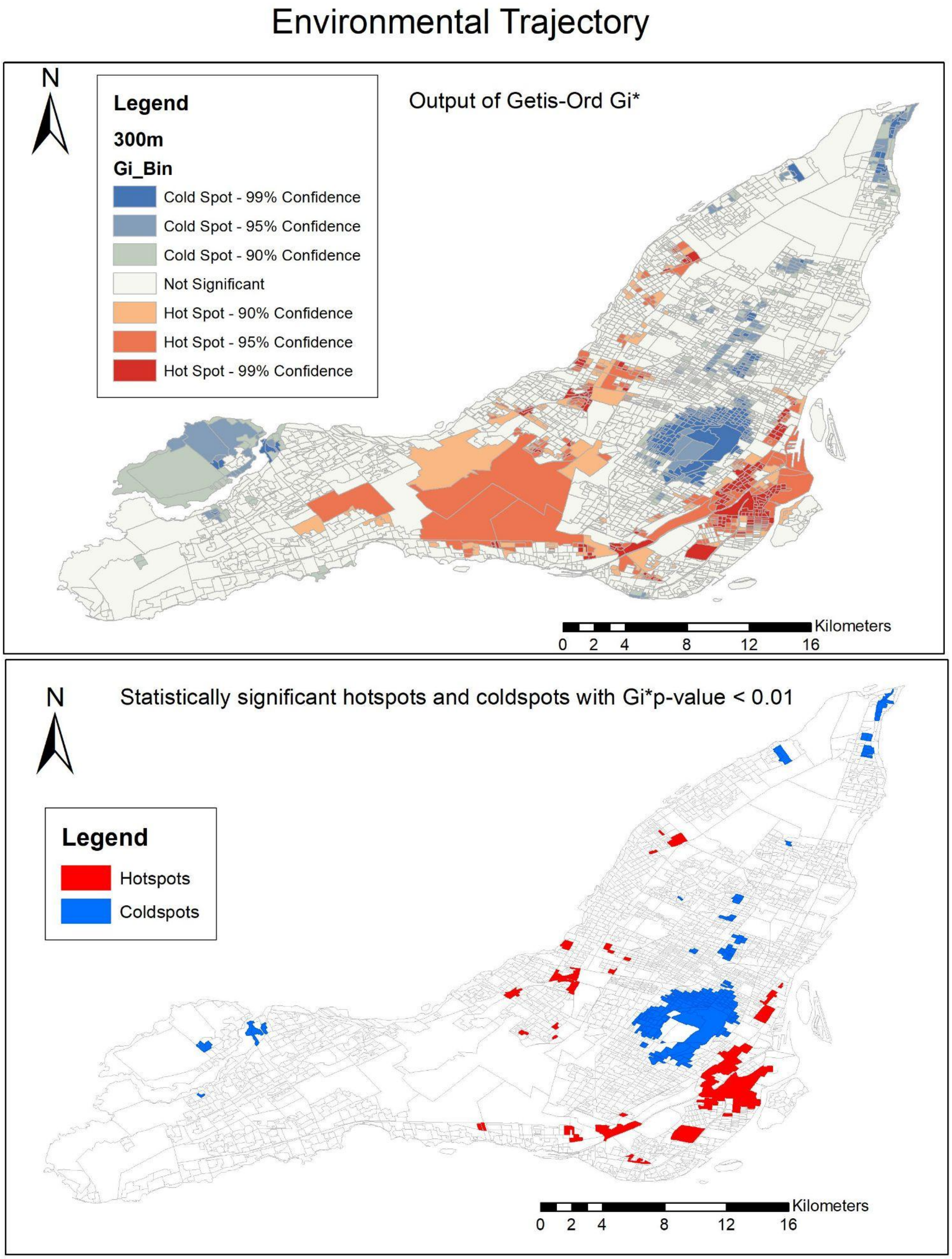

Figure 5.2 - Output of Getis-Ord Gi* Analysis Map for Environment pathway with associated Map of Hotspots and Coldspots with Gi* p-value < 0.01. Generated in ArcMap 10.8.2. *Source: CANUE 2019*

Next I look at the social component of the analysis to answer RQ2. RQ2 first asks whether the hotspots and coldspots of environmental exposure are representative of the rest of the island of Montreal, using the Chakraborty (2006) Area Comparison Index (ACI) statistic as described in section 4.3. This statistic determines if a minority group (visible minority, Black, immigrant, low-income populations) is overrepresented or underrepresented in an impacted area. To interpret the ACI statistic, a value greater than 1 represents an overrepresentation of a sub-population living in a hotspot/coldspot, while a value less than 1 represents an underrepresentation of that group compared to the rest of Montreal. Additionally, to determine if these differences are statistically significant, I used t-tests for each variable. The statistically significant ACI values (t-test with p-value <0.01) are emphasized in bold in Table 5.1.

Using this technique, I found that all vulnerable socio demographic groups I tested for were overrepresented in areas with the most environmental exposure. However, the only statistically significant finding I discovered was that the proportion of low-income populations living in extreme environmental exposure was 1.4272 times greater than the rest of Montreal. On the other hand, in "coldspot" areas, or areas with the least environmental exposure, visible minority populations, Black populations, and immigrant populations were significantly underrepresented. Proportionally, they were 0.7056, 0.6040, and 0.8772 less likely respectively to live in health promoting areas compared to the rest of Montreal. Low-income populations were overrepresented in coldspots, but not significantly.

The main salient finding is that in general, visible minority populations, Black populations, and immigrant populations were overrepresented in areas with health undermining features, while each respective group was *under*represented in areas with health promoting features. There was however, no identifiable pattern with the low-income variable, as low-income populations were overrepresented in both health promoting and health undermining areas within the Environment pathway.

In terms of the second component of RQ2: Do there exist associations between socio demographic subgroups and transportation-related health measures?, using 2-way scatterplots to graphically represent the association, I find there is a slightly positive association between the z-score index and each socio demographic variable. The results of this analysis can be seen in Figure 5.3, with the trend line shown in blue. To restate, a higher z-score represents greater environmental exposure, thus there is a slightly positive association between being a visible minority, Black, an immigrant, or person with low-income and living in areas with worse environmental health.

Overall, one can cautiously conclude that there is indeed a correlation between higher percentage of vulnerable minority groups, and living in areas with worse environmental exposure. These findings correlate with Krieg and Faber (2004) who find that communities of color are more likely to bear a disproportionate burden of exposure to poor ambient air quality. However, my findings do not reveal any support for an association between low-income and environmental exposure.

Table 5.1 - Descriptive statistics for dissemination areas with Gi* p-value < 0.01, compared to island of Montreal demographics. For significance of ACI, refer to Figure 4.1. **Bold** values represent statistically significant statistic with p-value < 0.01

Environmental Hotspots

Demographic	**Total**	**Montreal Total**	**ACI statistic**
Population	105068	1942044	*N/A*
Average Age	38.63	40.46 yrs	*N/A*
Visible minority population	37670	623875	1.1235
Black population	10440	180565	1.0729
Immigrant population	35160	644845	1.0082
Low-income (LICO-AT)	25545	338490	**1.4272**

Environmental Coldspots

Demographic	**Total**	**Montreal Total**	**ACI statistic**
Population	121810	1942044	*N/A*
Average Age	38.20	40.46 yrs	*N/A*
Visible minority population	28130	623875	**0.7056**
Black population	7015	180565	**0.6040**
Immigrant population	35755	644845	**0.8772**
Low-income (LICO-AT)	25220	338490	1.2030

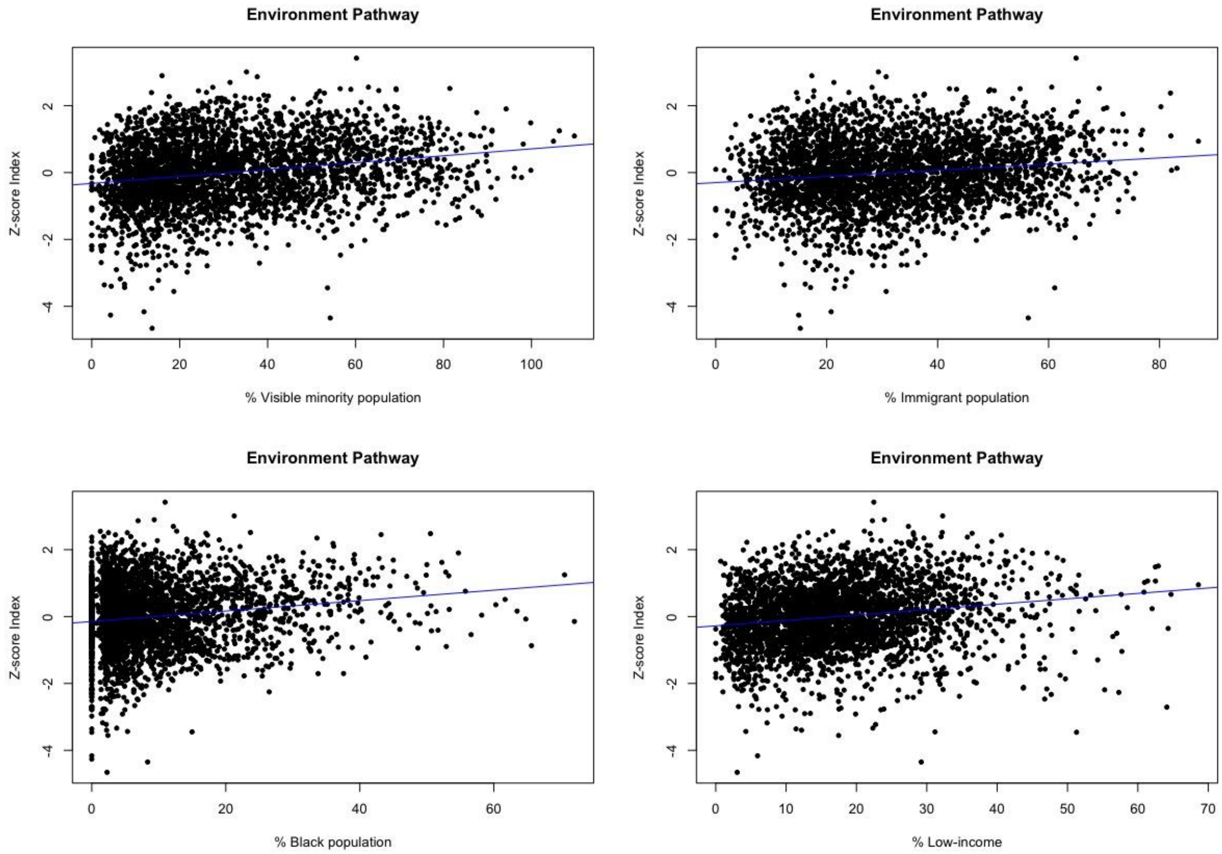

Figure 5.3 - 2-way scatter plot indicating linear association between the z-score index of the Environment pathway and the percentage of visible minorities, immigrants, Black population, low-income respectively, by dissemination area. Generated in R. *Source: Canadian Census 2016, CANUE 2019*

5.2 Proximity Pathway

To apply my research aim to the Proximity Pathway, I look first for spatial trends of where healthy spaces and facilities are distributed across the island of Montreal. I then determine where areas of extremely poor accessibility and extremely rich accessibility are located.

To answer the first component of RQ1, I have implemented my primary methodology, described in chapter 3 which indexes the three proximity indicators: proximity to grocery stores, proximity to health facilities, and proximity to green space. The resultant choropleth map of the normalized index score is shown in Figure 5.4. Again, Figure 5.4 provides a *relative* distribution of proximity measures and is displayed using quintiles which breaks the index values into five (5) equal sized bins. A lower score is associated with more health promoting features, so for this pathway a lower score would correspond to increased proximity to healthy spaces and facilities. A higher score is then associated with more health undermining features, or decreased proximity. The lowest z-scores quintile is presented in blue, while the highest is in red. Consistent with the Environment distribution, this distribution translates to “positive health” displayed in the blue and cooler colors, and “negative health” displayed in red and warmer colors. The average value of the index across disseminations areas (DAs) correlates to a z-score of 0, which in Map 5.3 would be between the green and yellow quintiles.

The island of Montreal was broadly characterized by a difference between the center of the island and the West and East extremities, wherein the closer to the downtown core, the better proximity there is to grocery stores, health facilities, and green space. There is a gradual decrease in proximity to such resources as one travels farther from the city center, understandably so as the downtown has often been the site of points of interest (Hartman, 1950). The closest proximity to such resources exist in the boroughs of Ville-Marie, le Plateau, and Notre-Dame-de-Grâce (NDG), while the most healthy space/facility deprived areas seem to be concentrated in northern Montreal as well as western Saint-Laurent into Dorval and Pointe-Claire. This area is mostly runways for the airport and for the Bombardier airplane factory, so one would not expect many amenities there.

The second component of RQ1 looks for sites of deprivation, or “hotspots" of health undermining features. According to the framework, hotspots under the Proximity pathway would be areas with the furthest proximity to grocery stores, health facilities, and urban green space. Coldspots on the other hand, would correlate to sites with the closest proximity to such resources, and would correlate to health promotion. It is important to note that the Getis-Ord Gi* analysis determined there were no statistically significant hotspots within the Proximity pathway. This means there were no places with extremely limited access and thus no sites of deprivation. Coldspots, however, were found in the Plateau neighborhood, NDG, and the Montreal Downtown, seen in Figure 5.5.

Again, while I can draw no conclusions on the actual health of residents, the noticeable differences in proximity to important healthy spaces and facilities is compelling. There is an apparent difference between the Island center and its extremities, with the most accessibility to resources concentrating in the Montreal downtown and Plateau neighborhoods. The further outward from this area, there is a decreased availability of such resources.

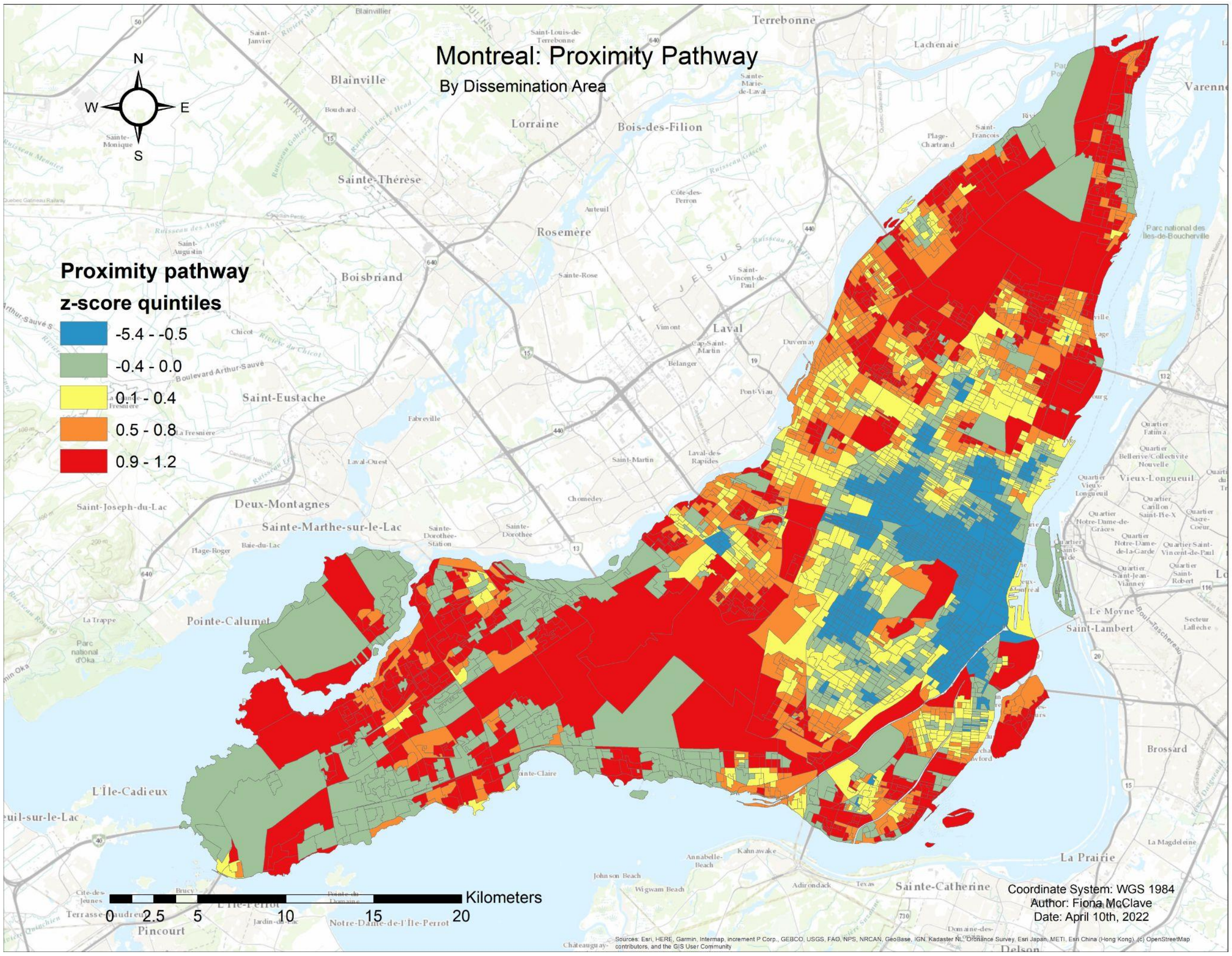

Figure 5.4 - Choropleth Map of Proximity pathway z-score index. Z-score distribution divided into quintiles. Generated in ArcMap 10.8.2. *Source: CANUE 2019*

Proximity Trajectory

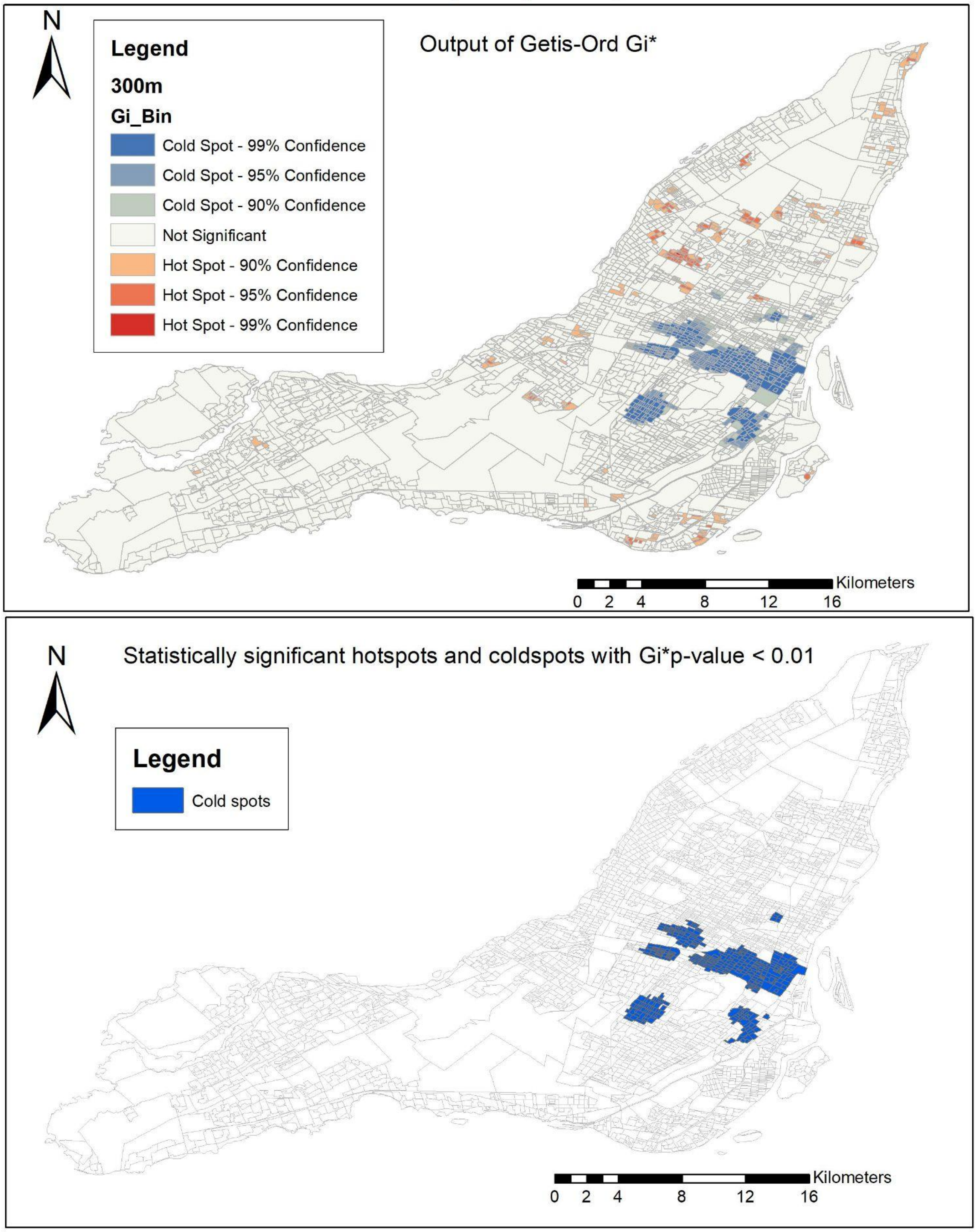

Figure 5.5 - Output of Getis-Ord Gi* Analysis Map for Proximity pathway with associated Map of Coldspots (no Hotspots) with Gi* p-value < 0.01. Generated in ArcMap 10.8.2. *Source: CANUE 2019*

Next, I look at the social component of the analysis to answer RQ2. RQ2 first asks whether the hotspots and coldspots of accessibility to healthy resources are representative of the rest of the island of Montreal, using the Chakraborty (2006) Area Comparison Index (ACI) statistic as described in section 4.3. Additionally, to determine if these differences are statistically significant, I used t-tests for each variable. The statistically significant ACI values (t-test with p-value <0.01) are emphasized in bold in Table 5.2.

Noticeably, there were no "hotspots" of proximity, meaning no areas with extremely poor accessibility to healthy spaces and facilities. This has positive health implications, as the lack of proximity hotspots means no group is especially worse in terms of accessing health resources. Using the ACI technique on the areas of extreme accessibility, it appears that Black populations are significantly underrepresented, as they are proportionally 0.5628 less likely to live in such health promoting areas. Meanwhile, low-income populations are proportionately 1.0911 overrepresented in these areas. This result is similar to the environment exposure hotspots and coldspots. There was no significant difference between visible minority and immigrant populations living in areas of extreme accessibility compared to the rest of Montreal. The most interesting finding from this analysis is the negative correlation between being Black in Montreal and being close to important resources including grocery stores, health facilities, and urban green space.

In terms of the second component of RQ2 which seeks to determine overall associations between socio demographic subgroups and proximity to health resources, using 2-way scatterplots to graphically represent the association. The findings here are diverse. The results of this analysis can be seen in Figure 5.6, with the trend line shown in blue. First, there is virtually no association between percentage of visible minority populations and the proximity distribution, nor is there an association between percentage of immigrants and the proximity distribution. There is, however, a slight positive association between the percentage of Black population and the z-score index. Meaning, the higher the z-score, or the less proximity to healthy resources, the greater the percentage of Black populations living in such areas. Most intriguing is the association between low-income and proximity to healthy resources. The trendline of the 2-way scatter plot between percentage of low-income and the proximity index is fairly obviously negative.

Overall, the absence of areas with extremely low accessibility indicates positive health implications. However, Black populations seem to be underrepresented in areas with the highest proximity to healthy resources and are in general negatively associated with high proximity. This finding supports studies conducted by both Dai (2011) and Zenk et al. (2004) who, as mentioned previously, found racial disparities for access to green space and access to grocery stores respectively. Surprisingly, low-income populations are overrepresented in areas with the highest proximity to healthy resources and are in general positively associated with high proximity.

Table 5.2 - Descriptive statistics for dissemination areas with Gi* p-value < 0.01, compared to island of Montreal demographics. For significance of ACI, refer to Figure 4.1. **Bold** values represent statistically significant statistic with p-value < 0.01

Proximity Coldspots

Demographic	**Total**	**Montreal Total**	**ACI statistic**
Population	210872	1942044	*N/A*
Average Age	37.87	40.46 yrs	*N/A*
Visible minority population	74715	623875	1.1169
Black population	11585	180565	**0.5628**
Immigrant population	72175	644845	1.0347
Low-income (LICO-AT)	59515	338490	**1.0911**

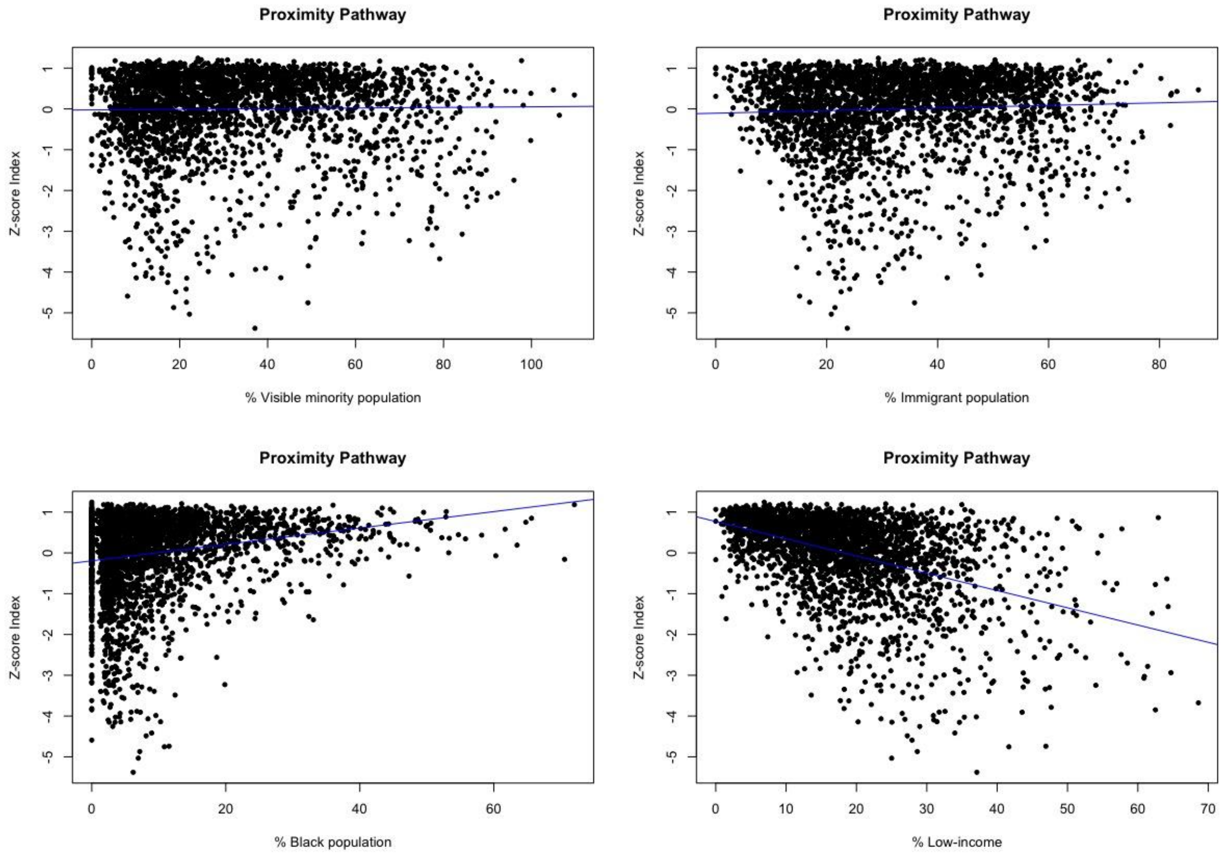

Figure 5.6 - 2-way scatter plot indicating linear association between the z-score index of the Proximity pathway and the percentage of visible minorities, immigrants, Black population, low-income respectively, by dissemination area. Generated in R. *Source: Canadian Census 2016, CANUE 2019*

5.3 Crash Pathway

To apply my first research question to the Crash Pathway, I look first for spatial trends in how vehicular crashes are distributed across the island of Montreal. I then determine where hotspots and coldspots of crashes are clustered.

To answer the first component of RQ1, I have implemented my primary methodology, described in chapter 3 which normalizes the number of vehicular crashes with pedestrian or cyclist victims per DA and weights the value by area. The resultant choropleth map of the normalized index score is shown in Figure 5.7, which is similarly formatted to the previous Figure 5.1 and Figure 5.4, as well as the relative scaling and meaning of the z-score index. To reiterate, a lower score (blue) is associated with less vehicular injury, and a higher score (red) is then associated with increased vehicular injury.

An important point to emphasize is that the number of crashes per DA has been weighted by area. This process has slightly skewed the resultant z-score distribution. In general, there were only a handful of recorded crashes per dissemination area, if any. This shifted the distribution of z-scores, so there were very few spots of “extremely” limited exposure, as many DAs had no recorded crashes to begin with. Overall, the Crash distribution was patterned such that there is increased exposure to traffic injury closer to the Montreal downtown, spreading into the peripheral downtown neighborhoods such as le Plateau and the Mile End. When considering where motorists are likely to share the road with pedestrians and cyclists, this downtown, residential patterning makes plausible sense.

The second component of RQ1 looks for sites of deprivation, or “hotspots" of health undermining features. According to the framework, hotspots under the Crash pathway would be areas with the most recorded vehicular crashes. It is important to note that the Getis-Ord Gi* analysis determined there were no statistically significant coldspots within the Crash pathway, as the baseline for normalization was close to 0. The hotspot analysis did, however, uncover several hotspots. Vehicular crash hotspots were primarily concentrated in the Plateau neighborhood, extending south of rue Sherbrooke into Ville-Marie. Considering the residential, and populated nature of street infrastructure in the Plateau, this clustering makes reasonable sense. Additionally, a study conducted in 2015 revealed living in the Plateau borough had a reducing effect of 33% for household car ownership (Anowar, Eluru & Miranda-Moreno, 2015, p.19), meaning Plateau residents are more likely to walk or bike than ride a car compared to other neighborhoods. This would subsequently put Plateau residents more at risk of traffic injury.

Overall, incidence of traffic injury seems to follow a clear contrast between the center of the island and the West and East extremities, with most of the vehicular crashes into pedestrians and cyclists occurring near and around the downtown core. This patterning is similar to the Proximity distribution, but has reversed health implications for downtown residents. In general, residents of downtown areas with closer proximity to healthy spaces and facilities, also incur the increased risk of traffic morbidity and mortality.

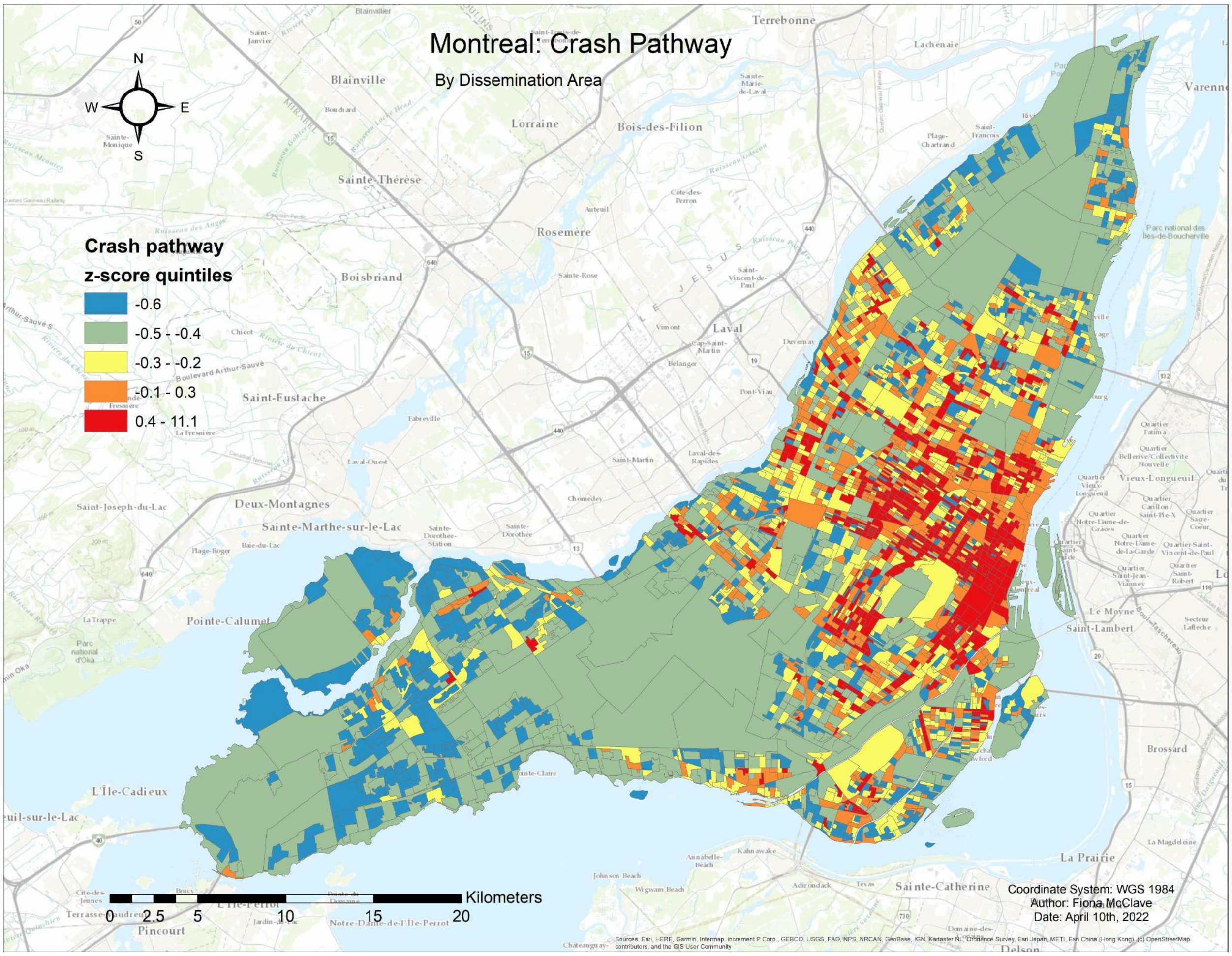

Figure 5.7 - Choropleth Map of Crash pathway z-score index. Z-score distribution divided into quintiles. Generated in ArcMap 10.8.2. *Source: Montreal Open Data Portal 2019*

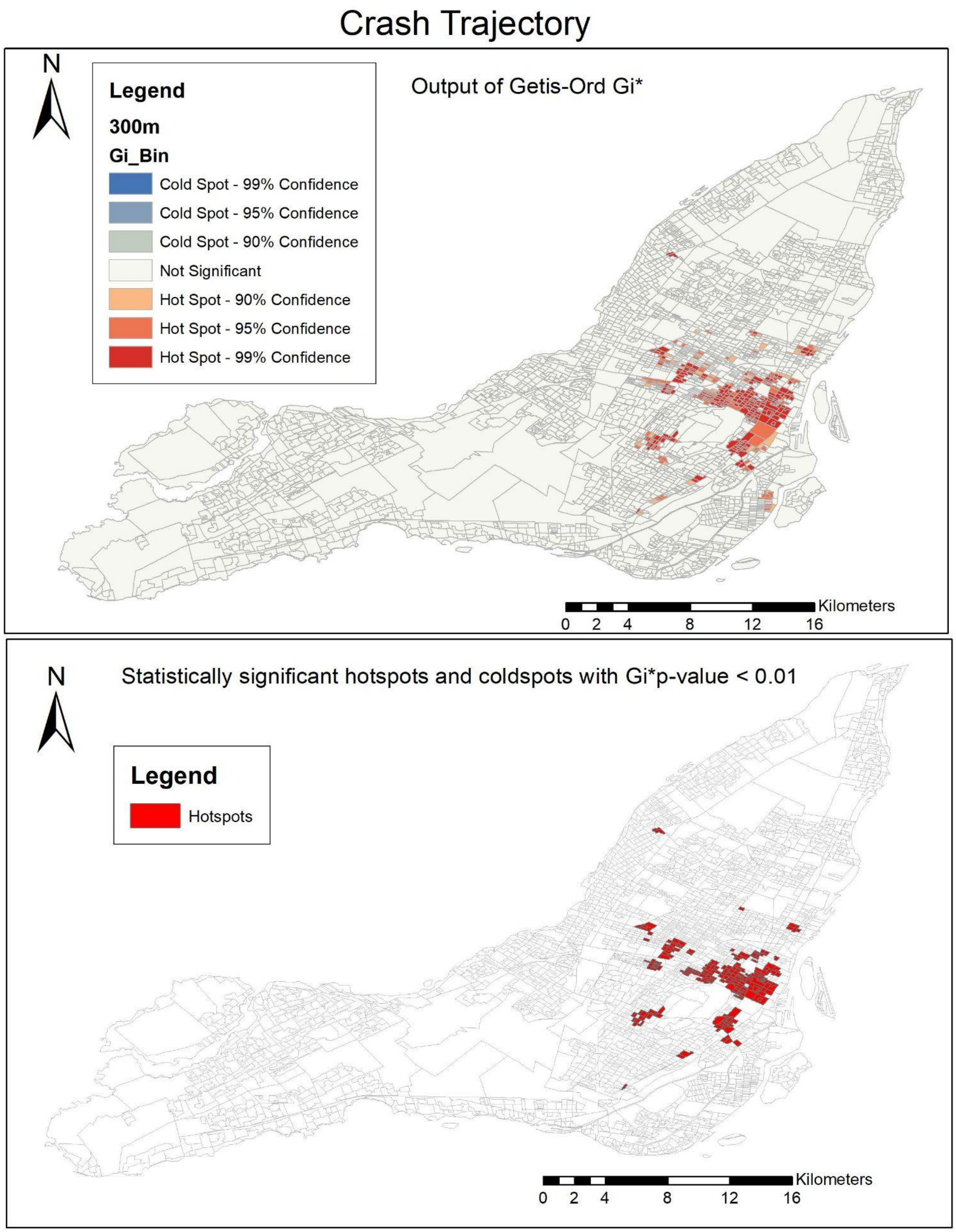

Figure 5.8 - Output of Getis-Ord Gi* Analysis Map for Crash pathway with associated Map of Hotspots (no Coldspots) with Gi* p-value < 0.01. Generated in ArcMap 10.8.2. *Source: Montreal Open Data Portal 2019*

Next, I look at the social component of the analysis to answer RQ2. RQ2 first asks whether the hotspots and coldspots of traffic injury are representative of the rest of the island of Montreal, using the Chakraborty (2006) Area Comparison Index (ACI) statistic as described in section 4.3. Additionally, to determine if these differences are statistically significant, I used t-tests for each variable. The statistically significant ACI values (t-test with p-value <0.01) are emphasized in bold in Table 5.3.

Noticeably, there were no "coldspots" of traffic injury, meaning no areas with extremely low recorded traffic injury comparatively. Using the ACI technique on the disseminations areas with the most injuries, it appears that Black populations are significantly underrepresented, as they are proportionately 0.5509 less represented in such health undermining areas. Meanwhile, low-income populations are proportionately 1.8488 times overrepresented in these areas. While similar to the proximity coldspots, the health implications for these groups are reversed. Instead, Black populations are less likely to live in health undermining DAs, while low-income populations are more likely. There was again no significant difference found between visible minority and immigrant populations living in areas of extreme traffic injury occurrence.

In terms of the second component of RQ2 which seeks to determine overall associations between socio demographic subgroups and incidence of traffic injury, I use 2-way scatterplots to graphically represent the association. The results of this analysis can be seen in Figure 5.9, with the trend line shown in blue. Overall, there was virtually no correlation between percentage of visible minority populations, immigrant populations, or Black populations and traffic injury incidence. There is, however, a slight positive association between the percentage of low-income populations and the z-score index. Meaning, the higher the z-score, or the greater incidence of pedestrian and cyclist traffic injury, the greater the percentage of low-income populations living in such areas. This was supported by the overrepresentation of low-income populations in DAs with the highest incidence of recorded crashes.

Overall, the most significant finding would be the positive association between being low-income and living in dissemination areas with high incidence of traffic injury. While this does not necessarily mean low-income individuals are more likely to be hit, their living environment does pose more of a risk to traffic injury than what is average on the island of Montreal.

Table 5.3 - Descriptive statistics for dissemination areas with Gi* p-value < 0.01, compared to island of Montreal demographics. For significance of ACI, refer to Figure 4.1. **Bold** values represent statistically significant statistic with p-value < 0.01

Crash Hotspots

Demographic	Total	Montreal Total	ACI statistic
Population	136239	1942044	*N/A*
Average Age	38.52	40.46 yrs	*N/A*
Visible minority population	45080	623875	1.0324
Black population	7205	180565	**0.5509**
Immigrant population	43450	644845	0.9576
Low-income (LICO-AT)	41435	338490	**1.8488**

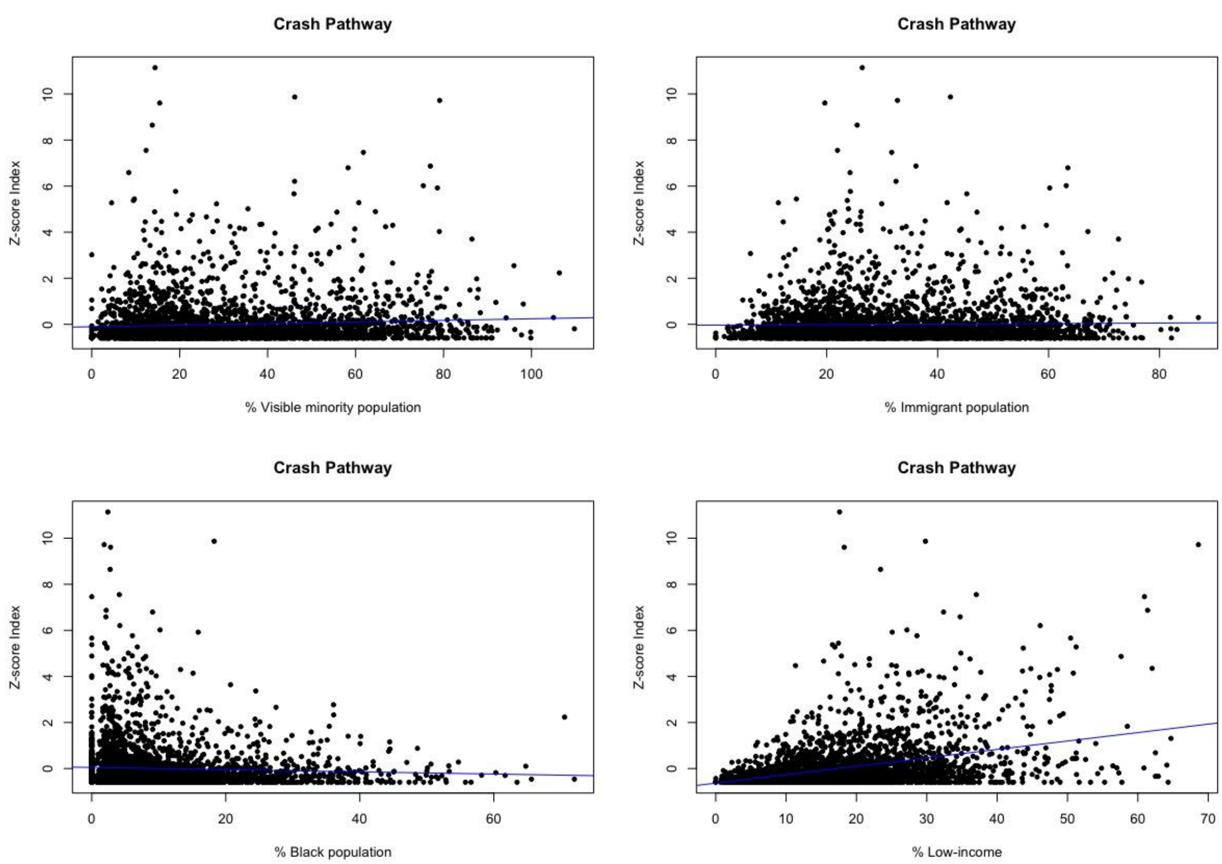

Figure 5.9 - 2-way scatter plot indicating linear association between the z-score index of the Crash pathway and the percentage of visible minorities, immigrants, Black population,

low-income respectively, by dissemination area. Generated in R. *Source: Canadian Census 2016, Montreal Open Data Portal 2019*

5.4 Infrastructure Pathway

To apply my first research question to the Infrastructure pathway, I look first for spatial trends in how active transportation infrastructure is distributed across the island of Montreal. I then determine where hotspots and coldspots of active transportation infrastructure are clustered.

To answer the first component of RQ1, I have implemented my primary methodology, described in chapter 3 which indexes together values of the Active Living Environment index and the number of transit stops accessible from a DA within a certain radius. The resultant choropleth map of the normalized index score is shown in Figure 5.10, which is similarly formatted to the previous choropleths Figure 5.1, Figure 5.4, and Figure 5.7 as well as the relative scaling and meaning of the z-score index. To reiterate, a lower score (blue) is associated with better active transportation infrastructure, that better promotes active living and increases access to transit, while a higher score (red) is then associated with worse active transportation infrastructure.

The island of Montreal is characterized by a concentration of better infrastructure in the downtown, with a gradual decline of active transportation infrastructure outwards towards the periphery dissemination areas. This patterning is quite similar to the center/extremities gradient seen in the Proximity pathway. I observe better transport infrastructure around Mount Royal, specifically in the Ville-Marie, le Plateau, and Mile End borough.

The other spatial question this project seeks to address is where sites of deprivation, or “hotspots" of health undermining features exist on the island. According to the framework, hotspots under the Infrastructure pathway would be areas with the worst active transportation infrastructure. Coldspots, on the other hand, would represent areas with the comparatively best active transportation infrastructure on the island. The results of the Getis-Ord Gi* hotspot analysis shows very few infrastructure hotspots. The two small hotspots, located at the Northern tip of Montreal and within the Park Extension borough, show no identifiable spatial trends. Considering the dense, urban nature of Montreal, one may infer most areas will score high in the Active Living Environment Index, and thus areas with extremely poor infrastructure would be rare. Coldspots, or dissemination areas with the best infrastructure, are clustered east and south of Mount Royal, covering the Ville-Marie, Plateau, and Mile End boroughs.

The virtual absence of infrastructure "hotspots" has positive implications for Montreal residents, as very few people are subject to areas with extremely poor active transportation infrastructure comparatively. The general distribution of this pathway once again follows a patterning quite similar to the Proximity distribution. One can find the best active transportation in the downtown and Plateau boroughs, extending out north towards the Mile End.

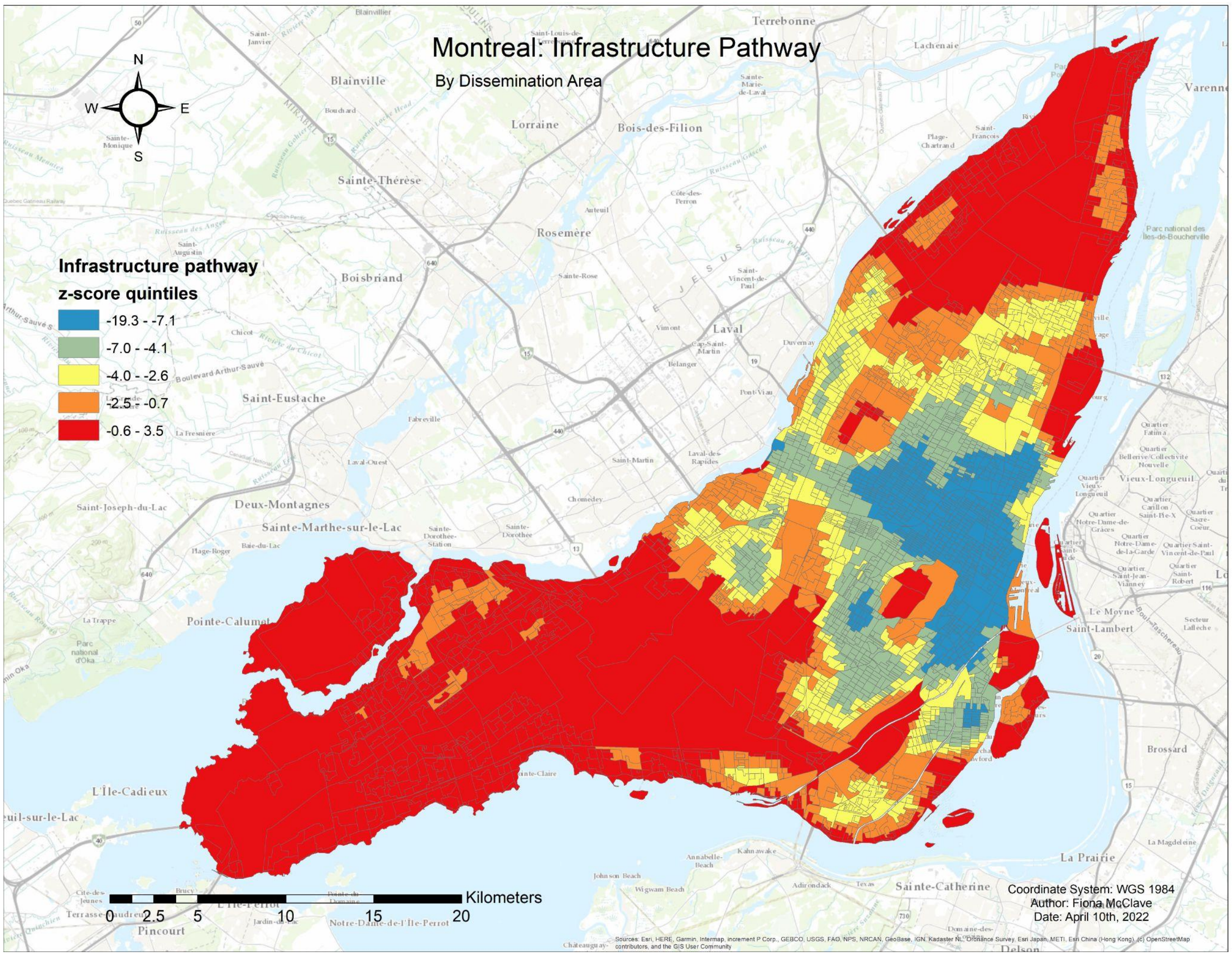

Figure 5.10 - Choropleth Map of Infrastructure pathway z-score index. Z-score distribution divided into quintiles. Generated in ArcMap 10.8.2. *Source: CanALE 2016*

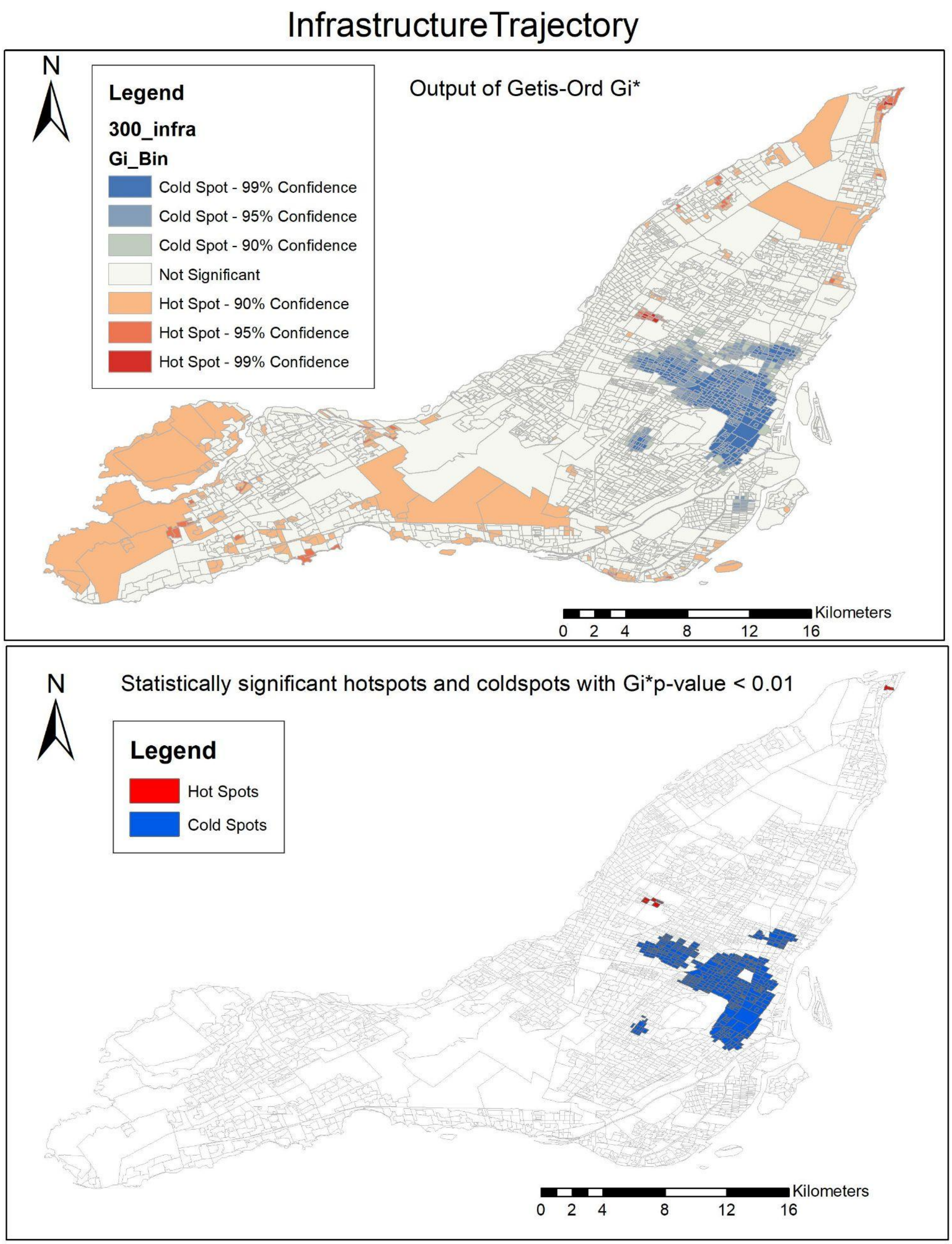

Figure 5.11 - Output of Getis-Ord Gi* Analysis Map for Infrastructure pathway with associated Map of Hotspots and Coldspots with Gi* p-value < 0.01. Generated in ArcMap 10.8.2. *Source: CanALE 2016*

Next, I look at the social component of the analysis to answer RQ2. RQ2 first asks whether the hotspots and coldspots of accessibility to healthy resources are representative of the rest of the island of Montreal, using the Chakraborty (2006) Area Comparison Index (ACI) statistic as described in section 4.3. Additionally, to determine if these differences are statistically significant, I used t-tests for each variable. The statistically significant ACI values (t-test with p-value <0.01) are emphasized in bold in Table 5.4.

Using this technique, I found that all vulnerable socio demographic groups I tested for were overrepresented in areas with the worst active transportation infrastructure, and most were significantly underrepresented in areas with the best active transportation infrastructure with the exception of low-income. However, no statistically significant conclusions could be made from the infrastructure "hotspots" (worst infrastructure), as the population count was quite low. For areas with the best active transportation infrastructure comparatively, I discovered visible minority populations are proportionately 0.7811 underrepresented, Black populations are proportionately 0.4292 underrepresented, and immigrant populations are proportionately 0.7884 times underrepresented. Meanwhile, low-income populations were proportionately 1.6770 times overrepresented in these areas. The main salient finding is that in general, visible minority populations, Black populations, and immigrant populations were significantly underrepresented in areas with health promoting features. There was however, no identifiable pattern with the low-income variable, as low-income populations were overrepresented in both health promoting and health undermining areas within the Infrastructure pathway.

In terms of the second component of RQ2 which seeks to determine overall associations between socio demographic subgroups and incidence of traffic injury, I use 2-way scatterplots to graphically represent the association. The results of this analysis can be seen in Figure 5.12, with the trend line shown in blue. In general, I do not find many statistical patterns within these plots. However, there does seem to be a generally positive association between percentage of low-income populations and a high z-score index. To restate, a higher z-score represents worse active transportation infrastructure, thus there seems to be a negative association between being low-income and living in areas with "good" active transportation infrastructure.

Overall, the infrastructure "hotspots" reveal very little due to the low population. We see ethnic minorities and immigrants underrepresented in areas with the best active transportation infrastructure, but no overwhelming patterns between socio demographic variables and active transport infrastructure in general. The low-income measure is still indeterminate.

Table 5.4 - Descriptive statistics for dissemination areas with Gi* p-value < 0.01, compared to island of Montreal demographics. For significance of ACI, refer to Figure 4.1. **Bold** values represent statistically significant statistic with p-value < 0.01

Infrastructure Hotspots

Demographic	Total	Montreal Total	ACI statistic
Population	3609	1942044	*N/A*
Average Age	38.07	40.46 yrs	*N/A*
Visible minority population	2420	623875	2.0916
Black population	885	180565	2.6455
Immigrant population	1805	644845	1.5077
Low-income (LICO-AT)	755	338490	1.2007

Infrastructure Coldspots

Demographic	Total	Montreal Total	ACI statistic
Population	246155	1942044	*N/A*
Average Age	38.11	40.46 yrs	*N/A*
Visible minority population	63530	623875	**0.7811**
Black population	10590	180565	**0.4292**
Immigrant population	66215	644845	**0.7884**
Low-income (LICO-AT)	66265	338490	**1.6770**

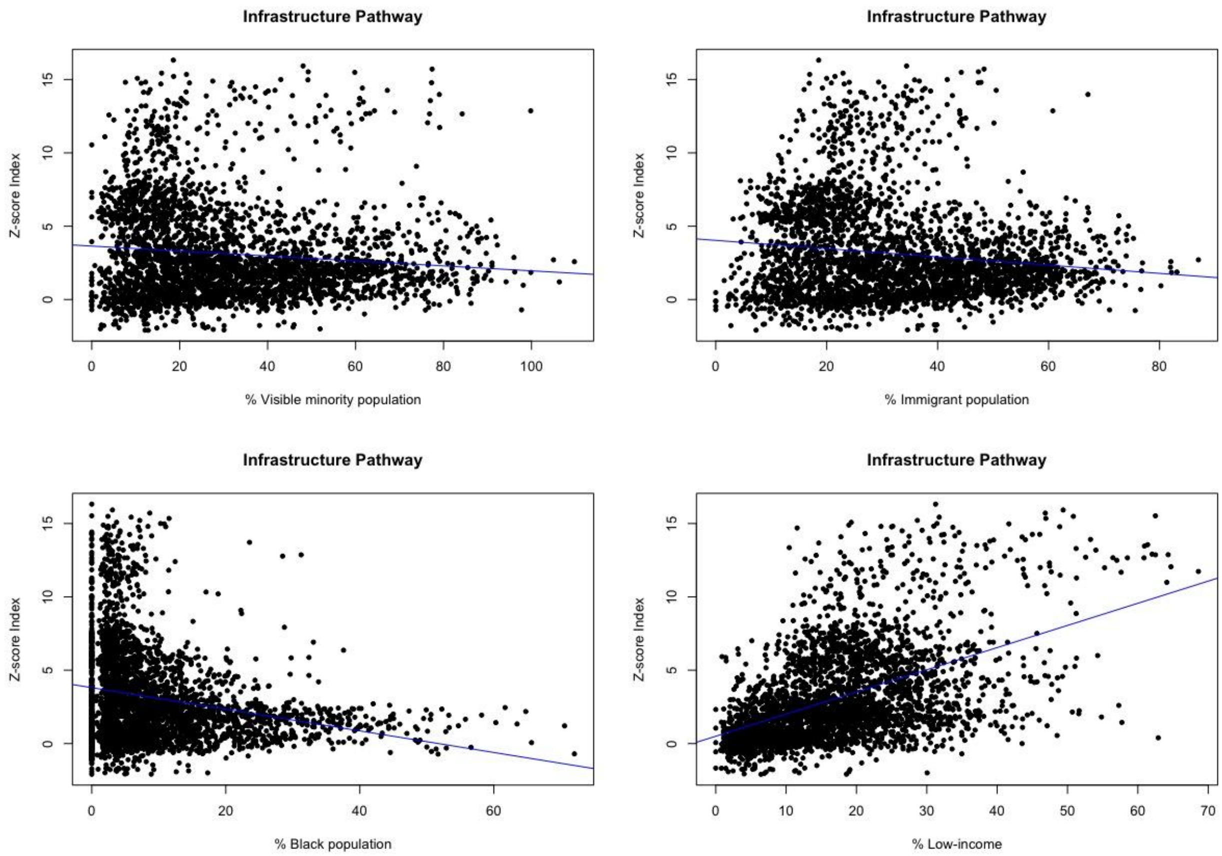

Figure 5.12 - 2-way scatter plot indicating linear association between the z-score index of the Infrastructure pathway and the percentage of visible minorities, immigrants, Black population, low-income respectively, by dissemination area. Generated in R. *Source: Canadian Census 2016, CanALE 2016*

CHAPTER 6: CONCLUSION

The purpose of this study was to investigate the spatial and social differences of transportation related health in Montreal. To view this topic holistically, I adapted the framework taken from Widener and Hatzopoulou (2016) and created four separate pathways based on how the effects of urban transportation systems and its infrastructure can affect the living environment for Montreal residents, and subsequently determine individual human health. Certain aspects of transportation can be health promoting, such as aiding in mobility and increasing accessibility of healthy spaces. Transportation infrastructure can also promote active, healthy behaviors by altering the built environment. Other aspects of urban transportation systems are health undermining. Transportation can deteriorate ambient air and noise quality, as well as increase city temperatures through the UHI phenomenon. Transportation also causes traffic morbidity and mortality when vehicles collide with pedestrians. Where in the city you live may affect how transportation promotes or undermines your health. Residence in the city can also be socially patterned and, depending on the transportation features within the local environment, can potentially exacerbate pre-existent health inequalities for vulnerable subpopulations on the island.

This study reveals several compelling takeaways. First, are the implications for the Montreal downtown and downtown peripheral neighborhoods. Each pathway had extreme exposure concentrated around the downtown core. The downtown had the best active transportation infrastructure as well as the best accessibility to healthy resources. However, it was also the site of some of the worst environmental exposure and the highest incidence of traffic injury. Additionally, there were significant differences found in who was living in health promoting v. undermining areas, with visible minority and immigrant populations being slightly overrepresented in areas with poor transit health or underrepresented in areas with good transit health. Black populations followed this trend as well, but to a more significant degree.

The main outlier of this study was the lack of significant conclusions regarding the association between the low-income (LICO-AT) measure and each of the pathways. It appeared that low-income populations for each pathway were overrepresented for both hotspots and coldspots. Perhaps this represents a potential issue with the census data, with an overestimation of the number of people living in each dissemination area compared to the overall Montreal demographics. To continue to address other potential limitations of the study, many of the datasets used to measure each indicator were formed using estimation or interpolation techniques, and most were not directly measured for each DA. Thus, some of the indicator values, for example air pollutant concentrations, may be slightly off from their actual value. Another limitation concerns the variability of urban movement. Cities are centers for constant movement and relocation. Thus, some of the socio demographic census data has been subject to change considering the data was taken 6 years ago during the most recent 2016 Canadian census. Many individuals have presumably moved into or out of certain DAs, which would alter the data and subsequent analysis. Census counts may not be entirely accurate either, as mentioned previously.

In terms of the Environment pathway, sites of increased environmental exposure were found by sites of heavy industry and commercial land uses. Visible minorities, Black populations, immigrant populations, and low-income populations were overrepresented in these areas, though not significantly. Such findings supported the study by Krieg and Faber (2004) who found that poor communities of color were more likely to be disproportionately exposed to poorer ambient air quality. Such health consequences of living in these "hotspot" sites are well-documented and diverse. To name just a few, urban residents (especially the listed minority groups) may be at risk of heat-related deaths and illnesses, lower respiratory infections and lung cancer, and hypertension (EPA: online, HEI, 2010, van Kempen & Babisch, 2012). On the other hand, sites of low environmental exposure were found around areas of green space including Ile Bizard and Mount Royal. Visible minority, Black, and immigrant populations are less likely to benefit from living in areas of limited exposure, as these subpopulations were underrepresented in such DAs. Indeed, there was a slight positive association with each subpopulation and increased exposure.

Main takeaways from the Proximity pathway were for one, the contrast between Island center and its East/West extremities that characterized the spatial distribution of the pathway. Healthy amenities were concentrated in the downtown and into the Plateau neighborhood, as well as NDG. The further outward from this area, the less availability of health promoting resources. There were no sites of extreme deprivation within this pathway, however, noticeably, Black populations were underrepresented in sites with the best accessibility. There was also a positive association between percentage of Black population and decreased proximity measures in general for each DA. This finding adds to the growing body of literature demonstrating the racial disparities found for access to healthy spaces and facilities, specifically access to green space and to grocery stores (Dai, 2011, Zenk et al., 2004).

To address the Crash pathway, the distribution was patterned such that there was an increased incidence of traffic injury closer to the Montreal downtown, spreading into peripheral downtown neighborhoods. The most recorded traffic injuries occured in the Plateau neighborhood, with a cluster in the NDG neighborhood. Overall, this distribution also followed a gradient similar to the Proximity spatial distribution. However, the health implications here are reversed. While downtown residents may be advantaged by more healthy amenities, they also incur the increased risk of traffic morbidity and mortality. It is interesting to observe similarities between these pathways.

Lastly, the Infrastructure pathway followed quite similar trends to the two previous pathways, with the best infrastructure centered downtown and worsening infrastructure out towards the East and West extremities. There were very few areas with comparatively poor active transport infrastructure, however, in areas with comparatively good active transport infrastructure, visible minority, Black and immigrant populations were significantly underrepresented once again. However, health implications are the most detrimental for areas of deprivation, of which there were very few noted on the island.

This study is novel in that it is the first to apply the holistic framework outlined by Widener and Hatzopoulou (2016) to a physical urban context. This study has contributed to the understanding of the spatial and social distribution of Environment, Proximity, Crash, and Infrastructure transportation-related health indicators. I urge urban planners and policymakers to further look into these growing social inequalities to attenuate future disparities through improved transport policy.

While only four pathways of Widener and Hatzopoulou's (2016) were used, I implore future research to include the fifth pathway, "indirect impact of disease spread through transportation networks", alongside the other four pathways when applying the framework to other cities. While out of the scope of this project, the impact transportation has on disease spread would be a very relevant arena to research given the current COVID-19 pandemic.

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APPENDIX A: R-SCRIPT

```
#add libraries

library (tidyverse)
library (sf)
library(data.table)
library(readr)
library(ggplot2)
library(mapview)
library(dplyr)
library(cancensus)
library(scales)
library (raster)
library(heatmaply)
library(GGally)
library(mlbench)
library(caret)
library(RNHANES)
library(broom)
library(httr)
library(lwgeom)


#load category 1
noise_19 <- read.csv("nhnse_ava_19.csv")
heat <- read.csv("wthnrc_a_15.csv")
ozone <- read.csv("o3chg_a_15.csv")
no2 <- read.csv("no2lur_a_16.csv")
pm2.5 <- read.csv("pm25dalc_a_18.csv")

#get rid of extraneous values
```

```
noise_19[noise_19==-9999] <- NA
no2[no2==-9999] <- NA
pm2.5[pm2.5==-9999] <- NA
new_pm <- pm2.5[complete.cases(pm2.5),]
new_no2 <- no2[complete.cases(no2),]
new_noise <- noise_19[complete.cases(noise_19),]


#load category 2
park <- read.csv("prox_parks.csv")
prox <- read.csv("nhpmd_ann_19.csv")
prox[prox==-9999] <- NA
prox[prox==-1111] <- NA
park[park==-9999] <- NA
park[park==-1111] <- NA
proximity <- prox[complete.cases(prox),]
parks <- park[complete.cases(park),]


#load category 3
crash <- read.csv("collisions_routieres.csv")
crash1 <- crash[ c(33, 53, 59, 67, 68) ]
final_crash <- na.omit(crash1)
final_crash$victims_total <- final_crash$NB_VICTIMES_PIETON +
final_crash$NB_VICTIMES_VELO



#load category 4
walkability <- read.csv("CanALE_2016 (1).csv")
colnames(walkability)[1] <- "DAUID"
```

```
final_walk <- walkability[c(1,8,9,10,11,12,13) ]

#load sociodemographics
census <- read.csv("potential_sociodemos.csv")
colnames(census) <- c('GEOUID', 'DA_NAME', 'Pop', 'Vis_Min', 'Black', 'Age', 'Immigration',
'Mobility', 'LICO%', 'LICO#', 'LIM%', 'LIM#')


noise_points <- new_noise %>%
  st_as_sf(coords = c("longitude", "latitude")) %>%
  st_set_crs(4326)
heat_points <- heat %>%
  st_as_sf(coords = c("longitude", "latitude")) %>%
  st_set_crs(4326)
ozone_points <- ozone %>%
  st_as_sf(coords = c("longitude", "latitude")) %>%
  st_set_crs(4326)
no2_points <- new_no2 %>%
  st_as_sf (coords = c("longitude", "latitude")) %>%
  st_set_crs(4326)
pm_points <- new_pm %>%
  st_as_sf(coords = c("longitude", "latitude")) %>%
  st_set_crs (4326)
crash_points <- final_crash %>%
  st_as_sf(coords = c("LOC_LONG", "LOC_LAT")) %>%
  st_set_crs (4326)
prox_points <- proximity %>%
  st_as_sf(coords = c("longitude", "latitude")) %>%
  st_set_crs (4326)
parks_points <- parks %>%
  st_as_sf(coords = c("longitude", "latitude")) %>%
```

```
  st_set_crs (4326)

#mtl <- read_sf("montreal_final.shp")
mtl <- read_sf("montreal.shp")


sf::sf_use_s2(FALSE)
# find points within  - rename as appropriate
nse_points_polygon <- st_join(noise_points, mtl, join = st_within)
heat_points_polygon <- st_join(heat_points, mtl, join = st_within)
oz_points_polygon <- st_join (ozone_points, mtl, join = st_within)
no2_points_polygon <- st_join (no2_points, mtl, join = st_within)
pm_points_polygon <- st_join (pm_points, mtl, join = st_within)

crash_points_polygon <- st_join (crash_points, mtl, join = st_within)
prox_points_polygon <- st_join (prox_points, mtl, join = st_within)
parks_points_polygon <- st_join (parks_points, mtl, join = st_within)


# average of value (interpolation for NDVI etc.)
noise_DA <- nse_points_polygon %>%
  st_drop_geometry() %>%
  group_by(DAUID) %>%
  summarize(mean = mean(nhnse19_02))
heat_DA <- heat_points_polygon %>%
  st_drop_geometry() %>%
  group_by(DAUID) %>%
  summarize(mean = mean(wthnrc15_03))
ozone_DA <- oz_points_polygon %>%
  st_drop_geometry() %>%
  group_by (DAUID) %>%
```

```
  summarize(mean = mean(o3chg15_01))
no2_DA <- no2_points_polygon %>%
  st_drop_geometry() %>%
  group_by(DAUID) %>%
  summarize (mean = mean(no2lur16_02))
pm_DA <- pm_points_polygon %>%
  st_drop_geometry() %>%
  group_by (DAUID) %>%
  summarize (mean = mean(pm25dal18_01))
crash_DA <- crash_points_polygon %>%
  st_drop_geometry() %>%
  group_by (DAUID) %>%
  summarize (count =sum(victims_total))
grocery_DA <- prox_points_polygon %>%
  st_drop_geometry() %>%
  group_by(DAUID) %>%
  summarize(mean = mean(nhpmd19_11))
healthcare_DA <- prox_points_polygon %>%
  st_drop_geometry() %>%
  group_by(DAUID) %>%
  summarize(mean = mean(nhpmd19_09))
parks_DA <- parks_points_polygon %>%
  st_drop_geometry() %>%
  group_by(DAUID) %>%
  summarize(mean = mean(nhpmd19_19))


#z-score normalization
noise_DA$zscore <- (noise_DA$mean - mean(noise_DA$mean, na.rm = TRUE)) /
sd(noise_DA$mean, na.rm = TRUE)
```

```
heat_DA$zscore <- (heat_DA$mean - mean(heat_DA$mean, na.rm = TRUE)) /
sd(heat_DA$mean, na.rm = TRUE)
ozone_DA$zscore <- (ozone_DA$mean - mean(ozone_DA$mean, na.rm = TRUE)) /
sd(ozone_DA$mean, na.rm = TRUE)
no2_DA$zscore <- (no2_DA$mean - mean(no2_DA$mean, na.rm = TRUE)) /
sd(no2_DA$mean, na.rm = TRUE)
pm_DA$zscore <- (pm_DA$mean - mean(pm_DA$mean, na.rm = TRUE)) / sd(pm_DA$mean,
na.rm = TRUE)
heat_DA$zscore <- (heat_DA$mean - mean(heat_DA$mean, na.rm = TRUE)) /
sd(heat_DA$mean, na.rm = TRUE)
grocery_DA$zscore <- (grocery_DA$mean - mean(grocery_DA$mean, na.rm = TRUE)) /
sd(grocery_DA$mean, na.rm = TRUE)
healthcare_DA$zscore <- (healthcare_DA$mean - mean(healthcare_DA$mean, na.rm = TRUE))
/ sd(healthcare_DA$mean, na.rm = TRUE)
parks_DA$zscore <- (parks_DA$mean - mean(parks_DA$mean, na.rm = TRUE)) /
sd(parks_DA$mean, na.rm = TRUE)


#sum air pollution indicators and normalize for even weighting
testing <-
  left_join(ozone_DA, pm_DA, by = "DAUID")
testingg <-
  left_join(testing, no2_DA, by = "DAUID")
testingg$sum_scores <- testingg$zscore.x + testingg$zscore.y + testingg$zscore
testingg$final_score <- (testingg$sum_scores - mean(testingg$sum_scores, na.rm = TRUE)) /
sd(testingg$sum_scores, na.rm = TRUE)

#create index for environment category
environmen_index <-
  left_join(testingg, heat_DA, by = "DAUID")
environment_index <-
```

```
  left_join(environmen_index, noise_DA, by = "DAUID")
environment_index$index_sum <-
  environment_index$final_score + environment_index$zscore.y.y + environment_index$zscore
#normalize environment category
environment_index$index <- -1*(environment_index$index_sum -
mean(environment_index$index_sum, na.rm = TRUE)) / sd(environment_index$index_sum,
na.rm = TRUE)


#create index for proximity category
p <-left_join(grocery_DA, healthcare_DA, by = "DAUID")
prox_index <- left_join(p, parks_DA, by = "DAUID")
prox_index$sum_scores <- prox_index$mean + prox_index$mean.x + prox_index$mean.y
#normalize proximity category
prox_index$index <- (prox_index$sum_scores - mean(prox_index$sum_scores, na.rm =
TRUE))/ sd(prox_index$sum_scores, na.rm = TRUE)


#create index for walk category



# join to sf
oz_DA_join <-
  left_join(mtl, ozone_DA, by = "DAUID")
pm_DA_join <-
  left_join(mtl, pm_DA, by = "DAUID" )
no2_DA_join <-
  left_join(mtl, no2_DA, by = "DAUID")
nse_DA_join <-
  left_join(mtl, noise_DA, by = "DAUID")
heat_DA_join <-
```

```
  left_join(mtl, heat_DA, by = "DAUID")
crash_DA_join <-
  left_join (mtl, crash_DA, by = "DAUID")
airpoll_DA_join <-
  left_join (mtl, testingg, by = "DAUID")
environment_DA_join <-
  left_join(mtl, environment_index, by = "DAUID")
grocery_DA_join <-
  left_join(mtl, grocery_DA, by = "DAUID")
healthcare_DA_join <-
  left_join(mtl, healthcare_DA, by = "DAUID")
parks_DA_join <-
  left_join(mtl, parks_DA, by = "DAUID")
prox_index_DA_join <-
  left_join(mtl, prox_index, by = "DAUID")


census$DAUID <- census$GEOUID
census$DAUID <- as.character(census$DAUID)
census_DA_join <-
  left_join(mtl, census, by = "DAUID")

totalpop <- sum(census_DA_join$Pop)
avage <- mean(census_DA_join$Age, na.rm = TRUE)
vismin <- sum(census_DA_join$Vis_Min, na.rm = TRUE)
black<- sum(census_DA_join$Black, na.rm = TRUE)
immigrant <- sum(census_DA_join$Immigration, na.rm = TRUE)
lico <- sum(census_DA_join$`LICO#`, na.rm = TRUE)


#weight by area for crash
```

```
crash_DA_join$area <- st_area(crash_DA_join)

crash_DA_join$weighted_area <- 1000*(crash_DA_join$count/crash_DA_join$area)
crash_DA_join$zscore <- (crash_DA_join$weighted_area -
mean(crash_DA_join$weighted_area, na.rm = TRUE)) / sd(crash_DA_join$weighted_area,
na.rm = TRUE)

final_walk$DAUID <- as.character(final_walk$DAUID)

final_walk$ale_tranist <- as.numeric(final_walk$ale_tranist)
final_walk$ale_tranist <- -1*final_walk$ale_tranist
final_walk$ale_index <- as.numeric(final_walk$ale_index)
walk_DA_join <-
  left_join (mtl, final_walk, by = "DAUID")




#export
write.csv2(environment_index, "/Volumes/VERBATIM/trajectory1.csv")
write.csv2(prox_index_DA_join, "/Volumes/VERBATIM/trajectory2.csv")
write.csv2(crash_DA_join, "/Volumes/VERBATIM/trajectory3.csv")
write.csv2(walk_DA_join, "/Volumes/VERBATIM/trajectory4.csv")
st_write(environment_DA_join, "/Volumes/VERBATIM/traj1shp.shp")
st_write(prox_index_DA_join, "/Volumes/VERBATIM/traj2shp.shp")
st_write(environment_DA_join, "/Volumes/VERBATIM/environment.shp")
st_write(crash_DA_join, "/Volumes/VERBATIM/crash.shp")
st_write(walk_DA_join, "/Volumes/VERBATIM/infrastructure.shp")
st_write(census_DA_join, "/Volumes/VERBATIM/census.shp")

st_write(work, "/Volumes/VERBATIM/prox_reversed.shp")
st_write(work2, "/Volumes/VERBATIM/infra_reversed.shp")
```

```
work <- read_sf("traj2shp.shp")
work2 <- read_sf("infrastructure.shp")

work$index <- -1*work$index
work2$al_trns <- -1*work2$al_trns

#rename air pollution columns
#colnames (airpoll_DA_join)
#names(airpoll_DA_join)[names(airpoll_DA_join) == "mean.x"] <- "ozone_mean"
#names(airpoll_DA_join)[names(airpoll_DA_join) == "mean.y"] <- "no2_mean"
#names (airpoll_DA_join)[names(airpoll_DA_join) == "mean"] <- "pm_mean"

# map
ggplot() +
  geom_sf(data = environment_DA_join,
          aes(fill = cut_number(index_sum, 10)),
          alpha = 0.8,
          colour = 'transparent',
          size = 0.3) +
  scale_fill_brewer(palette = "RdYlGn",
                    name = "")
ggplot() +
  geom_sf(data = prox_index_DA_join,
          aes(fill = cut_number(norm, 10)),
          alpha = 0.8,
          colour = 'transparent',
          size = 0.9) +
  scale_fill_brewer(palette = "RdYlGn",
                    name = "")
```