Application of the Distributed Lag Models for Examining Associations Between the Built Environment and Obesity Risk in Children (QUALITY cohort)

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ABSTRACT

Features of the neighbourhood environment are associated with physical activity and nutrition habits in children and may be a key determinant for obesity risk. Studies commonly use a fixed, pre-specified buffer size for the spatial scale to construct environment measures and apply traditional methods of linear regression to calculate risk estimates. However, incorrect spatial scales can introduce biases. Whether the spatial scale changes depending on a person's age and sex is largely unknown. Distributed lag models (DLM) were recently proposed as an alternative methodology to fixed, pre-specified buffers. The DLM coefficients follow a smooth association over distance, and a pre-specification of buffer size is not required. Therefore, the DLMs may provide a more accurate estimation of association strength, as well as the point in which the association disappears or is no longer clinically meaningful.

Using a subsample of the QUALITY cohort (an ongoing longitudinal investigation of the natural history of obesity in Quebec youth, N=281, M_{age}=9.6 at baseline), we aimed to apply the DLM to determine whether the association between the residential neighbourhood built environment (BE) and obesity risk in children differed depending on age and sex. A second objective aimed to compare the DLM model with that of a linear regression model (which used pre-specified circular buffer sizes).

Different distances of association between the Retail Food Environment and BMI z-score were obtained for 1st and 2nd follow-ups, which also varies by sex. No significant association between the Recreational Facilities Environment and MVPA were detected.

Keywords

Children, body mass index, physical activity, neighbourhoods, built environment, food environment, recreational facilities, Geographic Information System (GIS), QUALITY cohort, distributed lag models.

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LIST OF ABBREVIATIONS

AIC	Akaike Information Criterion
BMI	Body mass index
CDC	Centers for Disease Control and Protection
CI	Confidence interval
CMA	Census Metropolitan Area
DA	Dissemination Area
DEXA	Dual-energy X-ray Absorptiometry
DLM	Distributed Lag Model
GIS	Geographic Information System
MVPA	Moderate and Vigorous Physical Activity
MAUP	Modifiable Area Unit Problem
OB	Obesity
OW	Overweight
PA	Physical Activity
QUALITY	**QU**ebec **A**dipose and **L**ifestyle **I**nves**T**igation in **Y**outh
RFE	Retail Food Environment
SES	Socioeconomic Status
SSB	Sugar-Sweetened Beverage
WHO	World Health Organisation

1. Introduction

1.1 Childhood obesity: prevalence, determinants and consequences

1.1.1 Prevalence and consequences of childhood obesity

Obesity and excess weight in all age groups are among the key risk factors for chronic health conditions and remain at alarming high levels in Canada (Barton, 2012). Obesity is associated with a number of health conditions and co-morbidities, including asthma, type 2 diabetes, osteoarthritis, chronic back pain, particular types of cancers and major types of cardiovascular disease (hypertension, stroke, and coronary artery disease) (Segula, 2014).

According to Statistics Canada (StatCan, 2015), 62% of Canadian adults and 31% of children and youth (5-17 years) have excess weight or obesity. Teens 12-17 years of age are also at high risk, as 27.9% of them have overweight or obesity (StatCan, 2017). The prevalence of overweight and obesity has more than doubled among youth aged 12 to 17 over the past 25 years (Shields, 2006). Despite an encouraging initial decline (from 31% to 27%) between 2004 and 2013 (Rodd & Sharma, 2017), the prevalence of overweight and obesity appears have plateaued and remains high among teens. According to the report of the World Obesity Federation (WOF), more than 10 million or 34 per cent of Canadian adults (over 18 years) will live with obesity by 2025.

Children with obesity show elevated rates of factors predictive of chronic disease such as obstructive sleep apnea, mental health problems, and cardiovascular risk factors (Dietz, 1998). As childhood obesity contributes to the early development of cardiovascular disease (Barton, 2012; Raitakari et al., 2005), the one-quarter of Canadian children with overweight or obesity are screened for cardiometabolic risk factors such as triglycerides, and high-density lipoprotein cholesterol (Daniels & Greer, 2008; Dehghan et al., 2005; Rao et al., 2016). In particular, because obesity tracks from childhood/adolescence into adulthood, childhood obesity may significantly accelerate the progression of chronic diseases such as cardiovascular disease and type 2 diabetes mellitus (Thompson et al., 1999).

Projected costs vary, but the overall forecast remains alarming with an approximate range of 2.2% to 12.0% of total health expenditures in Canada attributable to obesity-related problems (Tran et al., 2013). The health problems caused by the excessive weight will cost the country about C$33.7 billion each year in direct and indirect costs. According to the Canadian Obesity Network, the current estimation of the annual direct healthcare cost of obesity varies between $4.6 billion and $7.1 billion and is projected to rise to $8.8 billion by 2021 (Canadian Obesity Network Inc., 2017). For Quebec, in 2011 the overweight and obesity associated economic costs reached almost $3 billion ("Obesity and Overweight," 2016).

1.1.2 Determinants of obesity

There are numerous factors that could possibly explain the growth in obesity prevalence. The following four categories of potential obesity determinants are commonly considered by researchers: individual, social, behavioural/lifestyle, and environmental factors (Robiraille, 2009) although this list could be expanded to multiple other components such as biological, psychological, technological, economic and cultural (PHN Annual Reports, 2017).

Physical activity (PA) plays an important role in maintaining health in Canadian populations, increases wellbeing, and quality of life. Numerous studies have demonstrated that PA has a strong negative correlation with excessive weight (Rossi et al., 2018; Saelens et al., 2018; Wolch et al., 2011). PA is a well-established protective factor associated with numerous health benefits that can potentially prevent many health conditions, including cardiovascular disease, type 2 diabetes, overweight/obesity (Henderson et al., 2016; "World Health Organization. Global Report on Diabetes.," 2016). Importantly, PA is essential for healthy growth and children's mental and physical development. PA maintenance is associated with lower metabolic risk in adolescents (Silva et al., 2018) and can influence health indicators and decrease metabolic risk in later life through direct and indirect pathways (Werneck et al., 2018). PA during adolescence can develop the foundation for lifelong healthy habits and predicts PA in adulthood (Bélanger et al., 2015).

Regular and diverse activity develops cardiovascular fitness, bone density, and helps to prevent chronic heart disease in adult life. The benefits also include better weight control and school performance (Kino-Québec, 2000). For children daily PA can be undertaken in many different ways, including free play, games, sports, transportation (walking, cycling), and active forms of recreation. Access to facilities and programs and time spent outdoors were found to be positively and consistently related to children's PA (Sallis et al., 2000).

However, despite a lot of benefits, the majority of the world population of all age categories is insufficiently active. According to the World Health Organization, an estimated 23% of adults and 81% of adolescents failed to achieve recommended PA levels ("World Health Organization. Physical activity fact sheet, 2018"). Levels of PA in Canada also remain low. Data from the 2007-2015 Canadian Health Measures Survey indicate that only 7% of Canadian children and youth meet the requirements of a minimum of 60 minutes of Moderate and Vigorous Physical Activity (MVPA) on at least 6 out of 7 days according to the Canadian 24-Hour Movement Guidelines (Colley et al., 2017). Important sex differences have been noted: young boys of 6-11 years old are more active than girls (average 72 minutes of MVPA per day versus 46 minutes). For adolescents 12-17 years of age, boys accumulated an average 55 minutes, while girls accumulated 40 minutes of daily MVPA.

Public awareness campaigns, national strategies on diet, PA and health and many other preventive measures have been proposed by international organizations and national health services, for example WHO *Global action plan on physical activity 2018–2030: more active people for a healthier world.* In Quebec a number of programs committed to prevent obesity were implemented over the last few decades, with the main focus on further promotion of healthy diet and PA. About 166 interventions rolled out between 2006 and 2014, such as the action plan "Investing for the Future" (2006-2012) (Le Bodo et al., 2017). Nevertheless overconsumption of nutrient-poor foods and a lack of PA remain the main behavioural risk factors for obesity (Mihrshahi et al., 2018). While individuals' lifestyles vary, the consumption of unhealthy food is common on the population level (Nardocci et al., 2019).

For children, both dietary behaviour and PA is highly conditioned by the environment. For example, children living in neighbourhoods with greater access to fast food outlets and convenience stores had a higher likelihood of eating- and snacking- out (Van Hulst et al., 2012). In addition, children interact with their neighbourhood environments differently based on their age (Engler-Stringer et al., 2014). Young children are more likely to follow their parents' diet and food choices (Engler-Stringer et al., 2014; Muhajarine N., 2012). Older children are more independent and have greater mobility (by foot or bicycle).

Similarly, the observed increase in sedentary behaviour in adults and children is partly responsible for the current development of the obesity epidemic and is found to be associated with some neighbourhood BE attributes (Bejarano et al., 2019). PA was strongly mediated by family and peer support as well as accessibility to recreational and sport facilities in the neighbourhood (Eime et al., 2013). The number of recreational and sports facilities was also found to be associated with a reduction in excess weight among adolescents (Gordon-Larsen et al., 2006) and children's participation in PA was positively associated with publicly provided recreational infrastructure (Davison & Lawson, 2006).

1.2 Built Environment (BE) and health outcomes

Neighbourhood environment factors can be associated with nutrition habits and PA (French et al., 2001; Saelens et al., 2012). As obesity is the result of an energy imbalance (Hill et al., 2012), the influence of the neighbourhood's built environment (BE), such as food and sport / fitness / recreational related facilities on diet and PA may be important determinants of the obesity epidemic. As children are particularly vulnerable to obesity promoting environments, this issue is of greater importance for children as compared to adults (Oenema et al., 2006).

The BE can be considered as a space, modified and/or created by people for daily living and acting, which includes a wide range of objects, from buildings, service points and road networks to natural parks and recreational areas. Different Geographic Information System (GIS) methodologies were proposed to create environmental metrics in order to identify neighbourhoods as supportive and unsupportive for PA and healthy eating (Frank et al., 2012). For instance, walkability and the presence of parks were suggested for the evaluation of the PA environment, while the presence and density of retail food establishments and convenience stores were suggested for the evaluation of the nutrition environment (Saelens et al., 2012). The findings of many health-related studies suggest statistically significant associations between different aspects of the BE and obesity risk (Arcaya et al., 2016; Casey, 2014; Ding & Gebel, 2012; Frank et al., 2012). Children living in less environmentally supportive neighbourhoods had significantly less favorable BMI z-score changes and higher overweight or obesity rates compared with children in the most environmentally supportive neighbourhoods (Saelens et al., 2018).

As a powerful tool in health studies, modern GIS software can visualise the data and provide aggregated information for different spatial scales - traditionally using administratively defined areas (such as census tracts or dissemination areas), as well as predefined geometric forms. Common geometric forms include circular (circle shaped geographic area with radius of pre-specified size) or network (following roads and walking paths for a given pre-specified distance) buffers of different sizes. The spatial scale for evaluation of the accessibility and availability of BE features is oftentimes defined based on the study design and research question, as well as findings from previous studies. Due to the lack of consistency in defining the neighbourhood, researchers utilize different approaches and various spatial scales, resulting in significant variations in findings (Bancroft et al., 2015; Casey, 2014; Gamba et al., 2015).

This inconsistency of measuring and quantifying the BE features across studies is the primary challenge in accurately estimating the impact of the BE on obesity, especially across different age categories of the population (Papas et al., 2007). A recent systematic review by Arcaya and colleagues (2016) of the neighbourhood effects on 256 health studies' characteristics suggested that the methodology is not robust: studies differed in how neighbourhood was defined, and results were heavily affected by the choice of the spatial scale (Arcaya et al., 2016).

The incorrect selection of the geographic scale can lead to biased or even misleading estimation, known as the Modifiable Area Unit Problem (Openshaw, 1984). Thus for environmental variables and neighbourhood level characteristics (such as density of population) different spatial scale selection algorithms were introduced in order to identify the best scale for each buffer-based or area-level covariate (Grant et al., 2015). However, the question of what is the best spatial scale for BE variables in order to best explain the association with the variables of interest in a particular study remains unclear.

In addition, the association between the neighbourhood PA environments and adiposity may vary depending on age and spatial scale, often demonstrating inconsistent results (Kowaleski-Jones et al., 2017; Timperio et al., 2010). Ding and colleagues (2011) in the review of 103 studies showed access/proximity to parks and recreation facilities among the strongest correlates for PA in children, however the results were "inconsistent" – less than half of the results detected associations in the expected direction between PA and recreational facilities. Another review by Timperio et al. evaluated 88 studies where the spatial range included street blocks, census blocks, school attendance boundaries and a quarter-mile (400 m) route. Only 9 out of 32 tests of associations between parks and recreation facilities and PA obtained were in the expected direction (Timperio et al., 2015).

These results suggest that the appropriate buffer size may vary by the BE feature and constraints of the target population. In other words, people are able to walk for different distances (which depends on their age as well as on the purpose of activity – recreational walking, shopping, school/work commuting). While accurate neighbourhood measures should capture BE features and resources within the relevant area, theoretic or empirical guidance for correct neighbourhood definition is lacking.

Indeed, several researchers have aimed to improve the way the neighbourhood is operationally defined by evaluating the impact of the buffer size on the strength of the relationship. Seliske et al. (2012) compared six different network buffers ranging from 500 m to 5000 m and selected 1000 m to be the best buffer size based on Akaike Information Criterion (AIC) fit statistics (Seliske et al., 2012). Van Loon (2013) considered 200, 400, 800 and 1600 m buffers and found that MVPA in 8-11 year old Canadian children was best predicted based on the number of parks within a 1600 m buffer (van Loon et al., 2014). In contrast, Mitchell (2015) reported that 800m and 500m buffers best explained MVPA in boys and girls respectively, suggesting the presence of sex differences in the association between PA and BE. Thus there is no consensus on the correct spatial scale in measuring the BE, and investigations are ongoing (Guo & Bhat, 2007; Spielman & Yoo, 2009; Strominger et al., 2016).

In order to address this problem, the Distributed Lag Models (DLM) were recently proposed by Baek et al. (2016) as an alternative to circular buffers for estimation of the correct spatial scale in detecting associations between the BE features and health outcomes. Originally DLM was a model for time series data, in which the effect occurs over time and the regression equation contains lagged (past period) values of the explanatory variable. Simulation studies performed by Baek (2016) suggest that application of this model for spatial data also provides valid results. The DLM coefficients follow a smooth association over distance, and the arbitrary pre-specification of buffer size is not required. Therefore, the DLMs may provide a more accurate estimation of association strength, as well as the point in which the association disappears or is no longer clinically meaningful. Baek et al. (2016) compared DLMs to circular buffers in the study focused on the school BE. He found that higher availability of convenience stores within 1 mile around the high schools was positively associated with students' BMI z-scores. However, as a child's home is arguably their primary environment, a better understanding of the utility in DLMs in detecting associations between the residential neighbourhood BE and health is needed. In addition, whether the comparisons are dependent on children's age/sex is also unknown.

1.3 Motivation

The neighbourhood environment can be associated with nutrition behaviour and PA, which are among the main risk factors for increasing obesity in children. However, the process of children's development brings significant lifestyle changes (such as a growing level of independence and mobility), depending on the person's age and sex. As a result, the effects of the BE features can vary at distinct spatial scales, as adolescents tend to behave differently based on where they are active (such as their home neighbourhood, school neighbourhood and in other places) compared to younger children (Borner et al., 2018).

Distributed Lag Models (DLM) were proposed by Baek et al. (2016) as an alternative to circular buffers for estimation of the correct spatial scale (Baek et al., 2016). The method does not require a pre-specification of buffer size; only the maximum possible distance of a hypothetical association needs to be defined. Therefore, the DLMs may provide a more accurate estimation of the point in which the association disappears or is no longer clinically meaningful. A child's home neighbourhood is undoubtedly one of their primary environments. For adolescents, nearly half of non-school moderate–vigorous PA occurred within 150 m of their home (Maddison et al., 2010). DLMs could be a good and more precise method to examine the correct spatial scale of the association between the home BE and health in youth. Within this approach, interactions could be tested in order to verify if the strength of association is dependent on children's sex.

As a motivational example, we performed statistical analysis on data collected from the QUALITY study, a longitudinal cohort of children in Quebec (Lambert et al., 2012). The analysis is focused on three timepoints in the cohort between 2005-2016: baseline (2005-2008, $Mean_{(Age)}$=9.6) and two follow-ups at 2009-2011 ($Mean_{(Age)}$=11.7) and 2015-2017 ($Mean_{(Age)}$=16.8). We restricted analyses to those who did not change residence (N=281). The outcomes included age- and sex-adjusted BMI z-scores, and daily minutes of Moderate to Vigorous Physical Activity (MVPA). BE features included (1) the Retail Food Environment: defined as (1a) the number of fast-food restaurants, cafes and bakeries, and (1b) the number of convenience stores, and (2) Recreational Facilities Environment: defined as the number of parks, sport fields, swimming pools or fitness facilities open for public use.

Objectives

I. To apply the DLM to examine the association between the BE and obesity risk in children as a function of distance, and to examine if and how the BE spatial scale changes at different ages and by sex;

II. A secondary objective assessed comparison of DLM and linear regression model results to choose best model fit.

Hypotheses

Based on the literature available to date, we hypothesized that DLM provides better model fit than linear regression model to define:

I. the spatial scale for the association between (a) the Retail Food Environment features and BMI z-score and (b) the Recreational Facilities Environment and level of MVPA;

II. the sex-stratified spatial scale for the association between (a) the Retail Food Environment features and BMI z-score and (b) between Recreational Facilities Environment and level of MVPA.

1.4 Outline

The remainder of this thesis will be organised in the following order: (I) literature overview of main theoretical methods and approaches developed and practiced by researchers for the study of the associations between the BE and obesity-related health outcomes; (II) summary of previous studies on the retail food environment accessibility and its association with BMI z-score as well as fitness facilities accessibility and its associations with the level of MVPA in children; (III) methods including data collection and selection of the variables for data analysis; (IV) results and (V) discussion and conclusion as well as strength and limitations of findings.

2 Literature overview

"The built environment provides the framework for how daily lives are conducted, influences health across life spans, and represents important pathways through which individuals come into contact with many health risks." (Lopez, 2012)

2.1 Neighbourhood environment: methods of assessment

2.1.1 Methodological challenges: defining neighbourhoods

The term 'Environment' is widely used and has different meanings depending on the discipline. R. Lopez in his book *The Built Environment and Public Health* (2012) suggests three broad domains: physical, social, and Built Environment (BE), where the last one consists of, 'all the many features that have been constructed and modified by humanity'. Alternatively the BE has been defined as, 'the human-made space in which people live, work, and recreate on a day-to-day basis' (Roof & Oleru, 2008). For research purposes the BE should be observed and examined in the context of the area, commonly called 'neighbourhood', where the subjects live and perform activity on a daily basis.

However, many definitions of 'neighbourhood' exist in the literature as the concept of the neighbourhood is not precise and also an issue of methodological challenge. In health research the term neighbourhood is commonly used to refer to, 'a person's immediate residential environment' (Diez Roux, 2001) or, 'generally defined spatially as a specific geographic area and functionally as a set of social networks' (Schck & Rosenbaum, 2000). The extensive discussions about the conception and operational definition of 'neighbourhood' can be found in the publication *On the Nature of Neighbourhood* (Galster, 2001). The definition of neighbourhood mainly depends on the research question, as neighbourhood characteristics and outcomes may vary.

The discussions that some environments are healthier than others were raised back in ancient times (Lopez, 2012). For example, Marcus Vetruvius, the famous Roman architect, in his treatise on architecture *De architectura*, approximately 30 A.D., suggested the complex approach: not only to examine food and water to learn whether a site is naturally healthy when choosing the places for cities to be founded, but also to provide the convenient placing of public facilities (markets, theatres, baths and roads). The important questions about the association between the BE and health were raised during the last two centuries, especially in growing European cities with sizable populations, like Paris and London (Snow, 1849), however this sphere of research is relatively new and was intensively investigated in modern epidemiology within the past few decades.

2.1.2 Spatial scale in health-related studies

In order to better define the neighbourhood attributes, the concept of geographical indicator was described by Robitaille et al (2009). Two main approaches to define the geographical indicators are: thematic and spatial. Thematic indicators demonstrate the association of values with the geographical objects, for example number of sport fields within a buffer. The spatial indicator is defined by spatial position of the object, for example, distance to the nearest sport field.

Nowadays sophisticated GIS provide advanced tools to visualize and analyze the data. Significant development of technologies linked to the GIS (such as connecting data from many databases) creates new opportunities for assessment of the BE. The point-based maps (created using geographical coordinates), are convenient tools for spatial analysis where data can be aggregated to differing areal units. However, attempts at this level of precision raises the concern of the Modifiable Area Unit Problem (MAUP) (Openshaw, 1984), such that an incorrect selection of the geographic scale can lead to biased estimation. For environmental variables and neighbourhood level characteristics different spatial scale selection algorithms were introduced in order to identify the best spatial scale for each covariate (Grant et al., 2015). In the case of the BE features, researchers usually choose the spatial scale in an ad hoc manner, based on findings in previous studies and reasonable assumptions related to the research question, for example assuming that on average, a person can walk to the point of interest (food outlet, park) for an average of 10 minutes and can cover ½ mile during this time.

The initial research question for a BE-related project could be defined as the following: which BE features at what spatial scale can have an affect on health? The most common pathway that the majority of researchers follow in their studies on BE attributes and health outcomes is (1) to suggest the relevant spatial scale (buffer, administrative boundary) in the context of the study and to define neighbourhood based on the chosen scale; (2) to define the set of BE features, which could be associated with health outcomes of interest within this spatial scale.

The main methods of constructing the neighbourhood limits are: (1) based on administrative boundaries (census tracts or dissemination areas) or (2) ego-centered study locations (such as residential addresses, postal codes, etc.). Administrative boundaries like census tracts and dissemination areas are the predominant method used. The popularity of this technique can be easily explained by its convenience: national and regional statistical bureaus regularly provide aggregated data for these administrative areas. However, this method is not without its limitations: the relative location of the subject of interest within an administrative boundary could infer bias. In other words, if the participant's residential address is located close to the border between two administrative boundaries, the true SES (Socioeconomic Status) and BE characteristics of the neighbourhood potentially can be missed. In addition all BE characteristics are examined within the same spatial scale, while their influence on health outcomes could be "spatially-sensitive" (Coffee et al., 2013).

Ego-centered areas include two main types of buffers: circular/straight-line, and network/street buffers. Both are centered at the point of location. The circular buffers are defined as a circle shaped geographic area with radius of pre-specified size. Circular buffers by definition ignore the design of the environment or land use, and as a result can capture environmental exposure inaccurately, as some BE features within the buffer may be inaccessible because of poor street connectivity. If the total measure of BE features within the buffer significantly differs compared to what is accessible, the overestimation bias could affect the results. In addition, circular buffers cannot account for the possible spatial clustering of BE features. For example, a 1000 m circular buffer would result in the similar geographical indicators and the same statistical results for a respondent with 5 fast food restaurants located next door to the study location, with that of another respondent with 5 fast food restaurants located close to the border of the buffer, at a distance almost 1000 m away.

Network buffers are created by following roads and walking paths for a given pre-specified distance, thereby addressing the circular buffers' limitation of inaccessibility. Thus network buffers may provide a more fair estimation of BE exposure. Oliver et al. (2007) compared network vs circular buffers and demonstrated that while circular buffers detected no associations, network-based buffers detected significant association between the BE and outcome. Nevertheless, common to both of these methods is the problem of choosing the correct size of the buffer. This is one of the main challenges in BE studies as associations between different BE features and health behaviours or outcomes may vary significantly for different geographic scales (Institute of Medicine, 2005).

For those studies where the GPS trip points are available, standard deviational (SD) ellipse buffers can be calculated for further analysis. This method is widely recognized as a good proxy of the spatial patterns, however because of the complexity of data collection from the GPS devices and other potential limitations (such as signal loss and imprecise recording due to interference of buildings, battery lifetime and position accuracy), this approach is not widely applied (Madsen et al., 2014).

2.1.3 Measurement of BE characteristics

The precise measurements and quality of data are crucial factors for performing statistical analysis that is minimized in error and bias. In order to better understand and analyse how BE features can be associated with population health and wellbeing, these characteristics should be measured precisely and impartially. The three main methodological approaches should be noted (Brownson et al., 2009). The first one is based on perception by the individual – the participants are asked to provide their estimation of BE characteristics, as well as some measurements (for example, individuals could be asked about the approximate distance to the nearest park in minutes) via questionnaires. Another method is a neighbourhood audit – an independent observer provides the assessment of the neighbourhood based on a pre-specified validated set of questions. The advantage of this method is its higher level of consistency and less variation caused by personal differences. However, such methods have been shown to be more reliable for items that are less subjective in nature (such as the presence or absence of street-level micro items), but demonstrates poor reliability for items that are more subjective in nature (such as the assessment of safety, general atmosphere, aesthetic appeal etc). The third approach is an assessment based on GIS data (such as the presence or absence of BE features), which can be collected and visualized using special GIS software, such as ArcGIS or QGIS. The databases of different points of interest (for example grocery stores and gas stations) are available from commercial and state agencies. The addresses can be geocoded and used for further spatial analysis. For instance, the total number of BE features of different types, or the distance to the nearest BE feature can be calculated for each predefined spatial scale, administrative area or buffer. While most geospatial databases are not without errors, their use has become more accessible due to the recent development in technologies, which has increased the convenience, objectivity, and ease of use of this method. For the purposes of this thesis, GIS data will exclusively be used.

2.1.4 BE characteristics in neighbourhood-related studies

Currently three key methods based on GIS data are used to measure the accessibility and availability of BE features of different domains (for example Retail Food Environment, Fitness Facilities, etc.) in health-related studies (Robiraille, 2009).

- Accessibility: Represented by the total distance (in miles or km) to the nearest point of interest. Usually the shortest path along the road network from a participant's residential location is calculated (most popular variations include Euclidean "straight-line" distance and Manhattan "rectilinear" or "city block" distance);
- Availability: Represented by the number of BE features in the neighbourhood area and is calculated in a circle or network-based buffer centered in the residential location. The common practice is to pre-specify the buffer size depending on study characteristics;
- Combination of accessibility/availability: Represented by the density of BE features (number per square area unit). It is calculated by the kernel density estimation method, with different techniques for the optimal bandwidth selection (Carlos, Shi, Sargent, Tanski, & Berke, 2010).

All three methods require careful consideration as an inadequately chosen spatial scale can lead to biased estimation and even misleading results (Spielman & Yoo, 2009).

2.1.5 Methods to select the appropriate boundary size

Many studies compared the use of different spatial scales (such as various administrative boundaries, or circular compared with network-based buffers of multiple sizes), primarily by using different types of complex indices (for example land-use mix index, walkability index or regional accessibility).

As a demonstration of the variability in approaches being used, Davison & Lawson reported in their review that out of 33 studies, only 6 used GIS-based methodologies attributes in order to examine if the BE influences children's PA, while the rest of the studies used the perceived environment measurements or neighbourhood audit (Davison & Lawson, 2006). A literature review by Leal and Chaix (2011) on the relationship between geographic environments and cardiometabolic risk factors revealed that about 20% of studies used buffers as a spatial scale, radial in 2 out of 3 cases (with radius varying from 100 to 4800 m and network buffers varying between 640 and 2000 m). Out of 131 studies, 73% used only pre-defined administrative area subdivisions (Leal & Chaix, 2011).

A recent review performed within the ELIANE research project (Casey, 2014) reported that weight was positively associated with the presence of convenience stores in 3 out of 6 publications and negatively associated with accessibility to recreational facilities in 4 out of 9 publications. In 14 out of 25 publications, the neighbourhood was estimated based on a buffer (ranging from 400 m to 5 km), while the rest of the publications used administrative boundaries. In a comprehensive simulation study, Spielman (2009) concluded that if the same study design is applied with different methods (such as buffer size, or administrative boundary), neighbourhood effect estimates can differ and model fit in most situations fails to select the appropriate spatial scale (Spielman & Yoo, 2009).

Results of a study in San Francisco Bay Area suggested that the network band definition was marginally superior to circular buffer and census units (Guo & Bhat, 2007). While all models were found to be consistent in the signs of the parameter estimates, the variables were significant at different spatial scales. According to the findings from the Children's Environmental Health Initiative study, the impact of BE on health outcomes vary significantly depending on the spatial scale chosen for neighbourhood construction (Strominger et al., 2016), and in context of high density of BE features (e.g. in urban areas with high level of population) the correct and suitable spatial scale of measures is crucial for the analysis (Sun et al., 2018).

For instance, Caughy (2013) examined the association between the BE and behaviour problems in US school age children comparing the neighbourhood boundaries of different scales. Although circular buffers ranging from 50 m to 1000 m were tested, only neighbourhood condition in the 400 – 800 meter circles were statistically significant (Caughy et al., 2013). Spatial scales using network buffers demonstrated the same uncertainty. PA measures were calculated for network-distances from 500 m up to 2 km for the IDEFICS study. Using a kernel approach, the stronger effects were found for larger scales. Also a strong variation in the association between the BE and PA of children based on the network-distance were reported (Buck et al., 2015).

Thus, as the results depend on the study design and the choice of spatial scale, some studies found no scale-dependent differences (Lamichhane et al., 2012). In terms of spatial analysis, due to the arbitrarily defined boundaries of different scales while measuring BE attributes, this uncertainty appear as a result of MAUP (Openshaw, 1984). Thus when examining the areas with high density of BE features, the correct and suitable selection of the spatial scales are crucial (Sun et al., 2018).

Seliske et al. (2012) used Akaike Information Criteria to select the best spatial scale among six different network buffers ranging from 500 m to 5000 m and concluded that a 1000 m buffer provided the best model fit (Seliske et al., 2012). Van Loon (2013) assessed model fit with marginal R^2 values while comparing 200, 400, 800 and 1600 m buffers and the larger buffer was found to be the best scale for association between number of parks and MVPA in 8-11 year old Canadian children (van Loon et al., 2014). Spielman et al (2013) used the simulation study and found that neighbourhood effect estimates were strongly influenced by the definition of neighbourhoods and particularly by the size of area used to approximate a person's neighbourhood, while a misspecified spatial scale led to systematic bias in estimates of neighbourhood effects (Spielman et al., 2013).

2.2 Statistical models in neighbourhood-related studies

2.2.1 Common methods of statistical analysis

Depending on the research question and the overall characteristics of the study, different statistical analysis methods have been applied in neighbourhood related projects. The main statistical approaches in the health research domain include variations of (1) a linear regression model; (2) generalized estimating equations; (3) multilevel generalized linear model or (4) analysis of covariance (Cerin, 2011; Diez Roux, 2001). While examining neighbourhood effects on health, the common practice is to simultaneously include individual- and neighbourhood-level independent variables in regression equations. This approach enables the epidemiologists to examine the area effects while adjusting for individual confounders (Diez Roux, 2001).

2.2.2 Distributed lag models

The idea of applying mathematical models from other domains opens a lot of additional interesting avenues to explore in BE related studies. As a novel method of statistical analysis, the DLM models were initially introduced by Shirley Almon in 1965 for predicting quarterly capital expenditures in manufacturing industries. DLM is a widely applied model in time series analysis; it helps to predict Y_t - current values of a dependent variable using both the current values and the lagged values for the past periods of an explanatory variable X_t (Zanobetti et al., 2000) and has had wide application in econometrics.

The general form of a linear infinite DLM model is:

$$Y_t = \sum_{i=0}^{\infty} \beta_i X_{t-i} + \varepsilon_t, \qquad t = 1, \ldots, T.$$

In the situation when after k periods of time, changes in X_t do not affect $E[Y_t]$ (in other words all beta coefficients after a particular time point vanish), the model reduces to a finite distributed lag with upper limit of the summations sign and has a form:

$$Y_t = \beta_0 + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \cdots + \beta_n X_{t-n} + \varepsilon_t. \qquad (1)$$

However, the successive lags of the variable of interest are likely to be highly correlated and can result in severe multicollinearity. In order to solve this problem, Shirley Almon suggested to apply the Weierstrass's Approximation Theorem which allowed the restriction of the coefficients to be a low-degree polynomial. Originally Lagrangian interpolation polynomials were proposed. During the last few decades, many publications on numerical methods suggested that, with respect to interpolation, spline functions are superior to Lagrangian polynomial fit. The advantages of splines are higher accuracy combined with more computational efficiency and easily implemented algorithms. The cubic splines lead to a smooth interpolation and are commonly used now for DLM.

Following this approach, the values of regression coefficients could be set as:

$$\beta_i = g(i) = a_0 + a_1 i + a_2 i^2 + \cdots + a_p i^p, \qquad i = 1, \ldots, n; \qquad (2)$$

approximated using polynomial of order P, which typically takes small values of 2, 3 or 4 (Smith & Giles, 1976). The Bayesian approach was proposed and implemented in econometrics later (Giles, 1977; Wells et al., 2016).

Substituting (2) into (1) and rearranging in order to gather up terms:

$$Y_t = a_0 Z_{0t} + a_1 Z_{1t} + a_2 Z_{2t} + \cdots + a_p Z_{pt} + \varepsilon_t,$$

where

$$Z_{it} = X_{t-i} + 2^i X_{t-1} + 3^i X_{t-1} + \cdots + n^i X_{t-n}, \qquad i = 1, \ldots, p.$$

Finally using constructed Z variables, coefficients a_i can be estimated by applying ordinary least squares (OLS) and thus the estimates could be used to reconstruct original β coefficients (Smith & Giles, 1976).

The use of a spline function was proposed as an attractive option to increase flexibility in modeling the coefficients. Subsequently, the combination of spline-based DLM with the generalized additive model was proposed, which allowed researchers to incorporate additional covariate information (Zanobetti et al., 2000a).

2.2.3 DLM and environmental studies in epidemiology

Since the 2000s this approach was applied in epidemiological studies to investigate associations between air pollution and health outcomes (Heaton & Peng, 2012; Schwartz, 2000; Zanobetti et al., 2000b), with further extension to incorporate other covariate information, e.g., generalized additive DLM (Schwartz, 2000) and hypothesized interactions between lagged predictors (Heaton & Peng, 2014). Welty (2005) used two flexible versions of DLM for sensitivity analysis in the US National Morbidity, Mortality and Air Pollution Study (Welty & Zeger, 2005) and then demonstrated the application of Bayesian DLM in estimation of the effect of air pollution on daily mortality (Welty et al., 2009). As a further extension of the model, distributed lag non-linear models (DLNMs), a new methodology for examining lagged relationships in environmental epidemiology and medicine was recently introduced (Gasparrini, 2014; Gasparrini & Armstrong, 2013; Gasparrini et al., 2010).

2.2.4 DLM and BE studies

The DLM was recently proposed by Baek et al. (2016) as a novel viable alternative to existing methods of evaluation of the association between BE features and health outcomes. For these BE related studies Baek (2016) suggested to define the lagged exposure as the amount of a BE features measured between two radii, $r_{\ell-1}$ and r_ℓ from study locations, $\ell = 1, \dots, L$, $r_0 = 0$. And the model can be expressed as:

$$Y_i = \beta_0 + \sum_{\ell=1}^{L} \beta(r_{\ell-1}; r_\ell) X_i(r_{\ell-1}; r_\ell) + \varepsilon_i, \quad (3)$$

where Y_i represents a continuous outcome at location *i,* β_0 is the intercept, $X_i(r_{\ell-1}; r_\ell)$ is the number of BE features measured within area between relevant radii, $\beta(r_{\ell-1}; r_\ell)$ is the association of the BE features measured between relevant radii and the outcome, and $\varepsilon_i \sim N(0, \tau^2)$. For the purpose of consistency, we'll follow notations from Baek (2016) in this thesis.

It was demonstrated that using a radial basis function to model the association coefficients $\beta(r_{\ell-1}; r_\ell)$ helps to avoid possible complications that may appear in cases in which many lags have zero values:

$$\beta(r_{\ell-1}; r_\ell) = \alpha_0 + \alpha_1 r_\ell + \sum_{k=1}^{L} \tilde{\alpha}_k |r_\ell - r_k|^3. \tag{4}$$

Function $\beta(r_{\ell-1}; r_\ell)$ is a piecewise polynomial of degree 3. As the estimation of the coefficients via linear regression model can result in too wriggly function, Zanobetti (2000) suggested to solve this problem through the penalized spline smoothing strategy: to restrict the size of α_k by adding a penalty term $\lambda \sum_{k=1}^{K} \tilde{\alpha}_k^2$ to the least squares criterion, where $\boldsymbol{\lambda}$ is the smoothing parameter. The detailed decomposition procedure can be found at Baek et al., 2016 publication.

The estimates of the standard errors of the β_i could be obtained as the following:

$$\widehat{\mathrm{SE}}\left(\widehat{\beta_\ell}\right) = \sqrt{\ell_{\mathrm{th}} \text{ diagonal entry of} \left(\mathrm{U} \operatorname{cov}\left(\widehat{\theta_{\mathrm{r}}}\right)_{\mathrm{lag}} \mathrm{U}^{\mathrm{T}}\right)}, \tag{5}$$

where θ is vector of parameters estimates and $cov\left(\widehat{\theta_r}\right)_{lag}$ is the block of $cov\left(\widehat{\theta_r}\right)$ which corresponds to distributed lag terms.

Using this methodology, Baek et al (2016) compared DLMs to linear regression with circular buffers of different sizes using a few types of simulated datasets with various spatial structures. Baek (2016) demonstrated superiority of the DLM method over the traditional fixed-size buffer approach. The findings demonstrated that the DLM provided good inference in all considered scenarios where a smooth function was used to model the association, and its estimates demonstrated correct inference over all radii. Results suggested DLM have better coverage rate, smaller bias and deviance information criteria (DIC, a hierarchical modeling generalization of the AIC). With enough power (i.e. 6000 schools were sampled), DIC selected the DLM, but when power to detect the effect was low (i.e. 1000 schools were sampled), the DLM and linear models performed equivalently.

Additionally, the DLM method was applied to publicly available data to investigate the convenience stores availability near schools in California as a determinant of obesity in high school students (Baek et al., 2016). The results showed that availability of convenience stores was associated with higher BMI z-score when they were within a distance of approximately 1 mile from schools. Comparison of averaged estimated association within fixed buffers of ¼, ½, ¾ and 1 mile showed 4 times larger in the coefficient estimated by linear regression model than by the DLM model, where the latter provided smaller estimates and SE.

However, as a child's home is arguably their primary environment, a better understanding of the utility in DLMs in detecting associations between the residential neighbourhood BE and health is needed. Thus we aim to apply the DLM method to examine the association between the presence of different BE features in a child's home neighbourhood with their health outcomes. Because of the study design (locations within 75 km from Quebec main urban areas) and unique urban environment of the Montreal island, the neighbourhoods potentially could significantly vary in their characteristics, with possible spatial autocorrelation for particular BE features. This will create a good case to demonstrate the ability of the DLM model to provide the adequate estimation of association in the potential presence of spatial clustering

Because of the Montreal island size and presence of the naturally occurring boundaries of the island, the main challenges are to define the appropriate maximum distance and lag size for DLM.

3 Methods

3.1 QUALITY cohort profile

The data for this thesis stem from the QUALITY (QUebec Adipose and Lifestyle InvesTigation in Youth) cohort, an ongoing longitudinal investigation of the natural history of obesity and cardiovascular risk in Quebec youth (Lambert et al., 2012). Because of the growth in the prevalence of paediatric obesity observed during the last few decades, this cohort study was designed by an interdisciplinary team of researchers in order to investigate the possible determinants of childhood obesity and its metabolic and cardiovascular consequences.

Potential participants located within 75 km of either of Montreal, Quebec City, or Sherbrooke (Quebec, Canada) were targeted with a school-based sampling strategy. Children aged 8 – 10 years at recruitment with at least one obese biological parent were eligible to participate in this study. Parent's obesity was defined based on self-reported measurements of weight, height and waist circumference (BMI $\geq$ 30 kg/m^2 and/or waist circumference > 102 cm in men and > 88 cm in women). The sample was limited to Caucasian children of Western European ancestry in order to avoid genetic admixture. Families were not eligible to participate if the family had pending plans to move out of the province.

Ethical approval for the QUALITY study was obtained from the Research Ethics Committee of the Centre de recherche du Centre Hospitalier Universitaire Sainte-Justine. All parents provided informed consent, and study participants provided assent before baseline assessments.

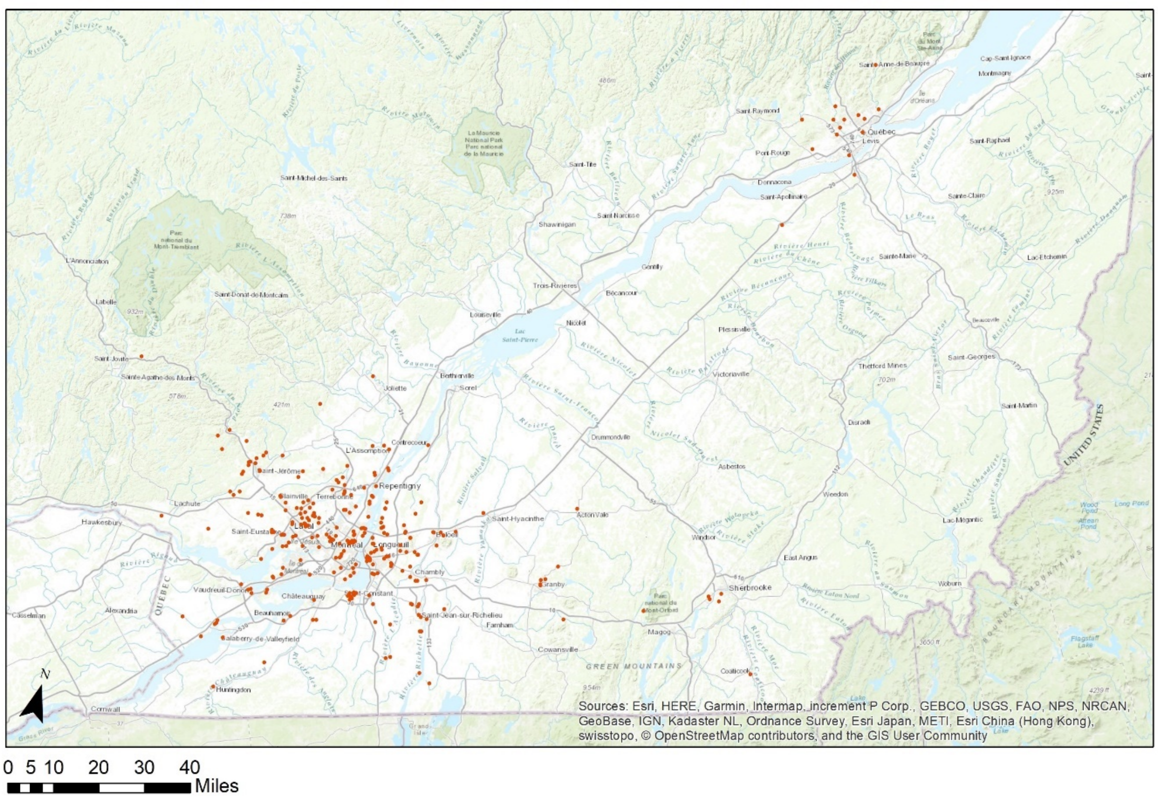
3.2 Data collection: baseline and follow-up

Baseline data, when youth were aged 8–10 years (Visit 1), were collected between July 2005 and December 2008 (n=630). The first follow-up assessment, when youth were aged 10–12 years (Visit 2) occurred between July 2007 and March 2011 (n=564). Second follow up (Visit 3) occurred between October 2012 and May 2016 when youth were aged 15–17 years (n=377). Data collection for baseline and follow-up assessments involved a full-day clinic visit which included questionnaires as well as biological and physiological measurements for both children and parents.

For this study the analyses were restricted to participants living at the same address (non-movers) and for which complete baseline data, 1st and 2nd follow-ups anthropometric and PA measurements were available (complete cases, n=281) (***Figure 1***). A detailed description of the study design and methods is available in Lambert et al., (2012).

Each young person's address was geocoded using ArcMap 10.6.

Figure 1: Map of the QUALITY study participants, non-movers (n=281)



3.3 Main outcomes and confounders

3.3.1 Anthropometric

At each study visit, anthropometric measurements were taken according to standardized protocols. Participants were dressed in light indoor clothing, without shoes, and height was measured with a stadiometer, and weight was measured with an electronic scale. Measurements were taken twice; when differences were 0.5 cm (height) or 0.2 kg (weight) or more, a third measurement was taken. The average of the two closest measurements was used for analysis.

Fat mass, fat-free mass, percent body fat, fat distribution (upper body, lower body and trunk fat masses) and bone mineral density were determined with Dual-energy X-ray absorptiometry (DEXA) (Prodigy Bone Densitometer System, DFþ14664, GE Lunar Corporation, Madison, WI, USA). Fat mass index (total fat mass in kilograms divided by height in meters squared) and percentage of body fat were used as a measure of adiposity.

3.3.2 BMI as a measure of adiposity

Obesity and overweight are two conditions characterised by an excess of body mass. While overweight denotes high weight from total body mass and is not recognized as a clinical term for high adiposity, the term 'obesity' provides a more accurate indication of body fat excess, and has more clear associations with serious health risks and abnormalities (Barlow & Expert Committee, 2007). Many paediatric researchers have aimed to identify the best easy-to-use anthropometric measures which could provide better analysis of the relationship between adiposity and cardiometabolic risk factors. However, their findings remain controversial in youth, as a number of measures, including Body Mass Index (BMI), waist-to-hip ratio, waist circumference and waist-to-height ratio were suggested as accurate predictors of cardiometabolic risk factors (Horan et al., 2015; Samouda et al., 2015). BMI, one of the popular anthropometric measures, is a measure of weight adjusted for height of the individual. BMI has become a practical and commonly accepted method for assessing body fat in epidemiological studies. Because BMI is a proxy measure of excess weight, its main limitation is its inaccuracy in assessing body fat in comparison to other methods such as computed tomography or DEXA (Freedman et al., 2017; Freedman et al., 2005).

However, BMI requires only simple measurements and calculations, is non-invasive, and inexpensive. Although imperfect, BMI has been validated as a measure of adiposity, and adiposity change in children (Boeke et al., 2013; Kakinami et al., 2014; Pietrobelli et al., 1998).

Availability of different growth curves and standard cut-offs helps health professionals to monitor adiposity on the population level. Although many different growth curves exist, the WHO growth curves are recommended for use in Canadian population. Publicly available programs were used to compute age-specific and sex-specific BMI centile and BMI z-score according to WHO reference curves (www.who.int/childgrowth/software). The WHO defines overweight as BMI ≥ 85th percentile, and obesity as BMI ≥ 97^{th} percentile (Kuczmarski et al., 2002; Secker, 2010). For this study having either overweight or obesity was defined as BMI ≥ 85th percentile.

3.3.3 Physical activity

Children's PA was measured using 7-day accelerometry measures (Actigraph LS 7164 activity monitor, Actigraph LLC, Pensacola, FL, USA) in the week following the clinic visit. Accelerometry data were used for analysis only if they met requirements according to the procedure described in the Canadian Health Measures Survey (a minimum of 4 days with accelerometer wear-time >10 hours per day) (Colley et al., 2010).

For this study, minutes of Moderate-to-Vigorous PA (MVPA) was computed by adding the total minutes spent in moderate PA and in vigorous PA daily, then this amount was averaged over the total number of valid days of accelerometer wear-time (available for the baseline and 1^{st} follow-up only).

Physical activity guidelines: According to the guidelines published by the World Health Organization, children were classified as meeting PA guidelines if they accumulated at least 60 minutes of MVPA per day when averaged across a week. This is consistent with the recently released Canadian 24-Hour Movement Guidelines for Children and Youth (2016), which suggests to classify children as adherent if their average daily MVPA is at least 60 minutes per day (Colley et al., 2017).

3.3.4 Modifiers

Sociodemographic variables used for this study were collected during the first visit. The child's age was computed in years using date of birth, child's sex was recorded by the interviewer.

3.4 Covariates

3.4.1 Household income

Parents were provided with questionnaires where they reported their age, highest level of education and annual household income (in $10,000 increments up to $140,000 or more). Income is a well-known determinant of childhood adiposity, level of PA, as well other physical and mental health outcomes (Shah et al., 1987). The protective effect of income against childhood obesity and related cardiovascular disease was recently reported in a study based on data from the National Survey of Children's Health (NSCH) (Assari, 2018). For the current study, the 'adjusting household income for household size' was calculated in accordance with the literature (Government of Canada, 2016), where the adjustment factor, also known as the equivalence scale, is the square root of the number of persons in the household:

$$\text{Adjusted income } = \frac{Total\ Household\ Income}{\sqrt{Number\ of\ people}}$$

As income was reported in bins, the midpoint value of each category was used. Because the investigation of the difference in association between BE features and health outcomes based on the different levels of household income was not the primary goal of the current study, income was kept continuous to prevent loss of power. For better interpretation of the beta coefficients income was expressed in ten thousand. In other words, per 10K difference in household income, the estimate of beta coefficient represents the mean change in the response variable while holding other predictors in the model constant.

3.4.2 Parents' education

It is well-known that parental education plays an important role in children's health development. Better-educated parents can more accurately estimate their child's weight status, thus they are more likely to create healthier home environment and to take appropriate actions to prevent and/or correct their child's obesity (Bailey-Davis et al., 2017; Cullinan & Cawley, 2017). For this analysis parents' level of education at baseline was categorized as a binary variable as whether at least 1 parent had at least a university degree.

3.4.3 Seasonality

As there are strong seasonality effects in Quebec, the analysis was adjusted for season in order to account for the differences of reduced PA in the winter (Bélanger et al., 2009). The winter season was defined as November – March, while April – October was considered as the non-winter season (dichotomous variable).

3.5 Neighbourhood - level variables

Area-level socioeconomic characteristics traditionally play an important role in the research on BE and health because of potential confounding effects (Diez Roux, 2004). Numerous studies which examined the association between adiposity and SES reported that low SES on either the individual or neighbourhood level was positively (and independently) associated with adiposity (Hsieh et al., 2015; McCormack et al., 2018). In other words, families living in neighbourhoods with low SES are more likely to be overweight or obese, regardless of their individual SES level. (Côté-Lussier et al., 2019; Hrudey et al., 2015; Moffat et al., 2005; Shrewsbury & Wardle, 2008).

To address the neighbourhood-level socioeconomic measures for periods related to the 1st and 2nd follow-ups for the QUALITY cohort, the aggregated data for dissemination areas from Census 2006 and Census 2011 were used.

3.5.1 Density of population

Analysis of neighbourhoods naturally involve people and different things people use in everyday life. Thus, some BE features (such as retail outlets and food environments), have higher concentration in areas where more people live. As a result, the knowledge of local population distribution is crucial for the correct interpretation of the effects of the neighbourhood characteristics (Carlos et al., 2010). The data for all dissemination areas in Quebec were extracted using Canadian Census Analyser, Census 2006 and Census 2011. The weighted density of the population (centered at the participants' address locations) was calculated in accordance with the literature.

3.5.2 Connectivity

Walkability indices are among the most important connectivity confounders in studies of the BE and health (Merchant et al., 2007; Villeneuve et al., 2018). Higher scores promote active wellbeing, and have been associated with lower risk of having a number of unfavourable health conditions such as overweight, hypertension and diabetes (Loo et al., 2017; McCormack et al., 2018). Walking and high level of PA are protective factors against some chronic conditions such as obesity, asthma and diabetes (Simons et al, 2018). Residential density, street connectivity, and land-use are the most popular walkability variables considered by BE investigators. However, different methods to calculate walkability indices used in health research provide different results and may be misrepresentative of actual human behaviour (Shashank & Schuurman, 2019). In this study we focused on the street network as an important measure of proximity, accessibility and connectivity in the neighbourhood.

A recently published study demonstrated that increasing street connectivity levels were inversely associated with BMI in US adults (Leonardi et al., 2017), and a Canadian adult population (Glazier et al., 2014). However the positive influence of street connectivity on obesity can vary between urbanized areas (Wang et al., 2013). While street connectivity could be beneficial for adult active transportation, it could have controversial effects on children and youth. High connectivity (often observed in socially disadvantaged neighbourhoods) is related to higher population density, which could result in lower neighbourhood safety and higher traffic related accidents and crime rates.

According to the study based on the 2006 Health Behaviour in School-aged Children (HBSC) survey, street connectivity (measured in 5000 m circular buffer around schools), was negatively associated with PA in Canadian youth (Mecredy et al., 2011). Mixed results confirm that analysis of youth behaviour is a complex issue that is not easily understood, and which requires accounting of many factors of individual and local levels as well as correctly defined spatial scale for analysis.

Nevertheless, street connectivity was chosen for this study in order to adjust for network structure of the neighbourhood. Street connectivity was defined as intersection density and was calculated as the number of three-way or greater intersections per km^2. CanMap RouteLogistics [computer file] Markham: DMTI Spatial Inc., 2012 was used as a source.

3.5.3 Neighbourhood sociodemographic characteristics

An important confounder in our models is neighbourhood SES. In this study the sociodemographic characteristics of participants' neighbourhoods were assessed using the Pampalon Deprivation Index. Originally designed in 1990, the index is available at the dissemination area level and is a measure of neighbourhood deprivation (Pampalon et al., 2012). The index has two main components: the first combines indicators of education, employment and income (the material component), the second combines indicators related to marital status and family structure (the social component).

The index values (factor scores for material and social deprivation) were calculated as an optimally-weighted linear combination of the indicators using its factor loading, indicating the level of deprivation in every dissemination area. As a result, it is possible to classify all small areas with population-weighted quintiles (i.e., groups of 20%) ranging from the least deprived (first quintile or Q1) to the most deprived (fifth quintile or Q5). The 2006 and 2011 Pampalon Deprivation Indexes from the Institute National de Santé Publique du Québec (INSPQ) website were utilized for this study (INSPQ, 2011).

While 2006 Deprivation Index was calculated based on 2006 Canadian census data, the next edition of the Pampalon Deprivation Index available was based on the data collected through the National Household Survey (NHS), a voluntary measure which replaced the mandatory long-form census. This major change caused the increase in the global non-response rate, introducing risks of bias. However, according to Gamache and colleagues, (2017) their extensive validation process demonstrated that the 2011 deprivation is valid (Gamache et al., 2017). For the current analysis Pampalon Deprivation index 2006 was used for baseline and 1st follow-up, and Deprivation index 2011 was used for 2nd follow-up. A high degree of reliability was found between Deprivation Index 2006 and 2011. The average Intraclass correlation coefficient (ICC) was 0.85 (95% CI: 0.81- 0.88) for the Material component and 0.88 (95% CI: 0.85- 0.91) for the Social component.

The weighted Deprivation Index Material score was computed for 1000 m circular buffer using the population-weighted segments of dissemination areas overlapping 1000 m circular buffers centred on participants' residential locations. For the purposes of consistency, weighted Deprivation Index (1000 m circular buffer) was used for both the Linear Regression model and DLM model as a (I) continuous variable and as a (II) categorical variable via quantiles, for investigating possible difference between the least and most deprived neighbourhoods. No differences in the main results were noted between (I) and (II). For better understanding of the SES differences, socioeconomic characteristics of quantiles are presented in the Appendix **(Table *8*)**.

3.5.4 Retail Food Environment

The data about food retail stores were obtained from DMTI Spatial Inc. [computer file]. Enhanced Point of Interest [EPOI]. Markham: DMTI Spatial Inc., 2008 and 2012 in order to collect the data representative for 1st and 2nd follow-ups. The EPOI database had shown a moderate capacity to detect the presence of a food store, with an estimated representativity of 77.7%, with measures of sensitivity and positive predictive value (PPV) of 65.5% and 77.3% respectively (Clary & Kestens, 2013). In that study, a novel measure of representativity to compensate between false negatives (FNs) and false positives (FPs) within the same business category and area was introduced. To compile the Retail Food Environment data, the methodology developed by Clary & Kestens (2013) was followed. Two main categories of food establishments were considered: (1) the number of fast-food restaurants (including cafes, bakeries and pizza take-outs), and (2) the number of convenience stores. Fast food restaurants were defined as restaurants/food chains with limited or no wait staff where customers order food and pay for it at a counter prior to receiving food. The data were compiled using selected Standard Industrial Classification (SIC) codes, which included various Quebec fast food chains restaurants or franchises as well as convenience store chains.

For linear regression analysis Retail Food Environment exposure were expressed as a count of food stores within the circular buffers of fixed sizes 500 m, 750 m and 1000 m. These choices are conditioned by the buffer sizes defined by the QUALITY Neighbourhood Study, an adjunct to the QUALITY Cohort study (The QUALITY Residential Built Environment complementary study protocol, grant #PG-040291).

For the DLM method the number of food stores was counted for 100 m ring-shaped areas up to 3.5 km centered on the participants' addresses using ArcGIS 10.6 software (ESRI, Redlands, CA) following the approach described in ***Figure 2***. A lag of 100 m (roughly equal to the size of one block in Montreal island) was used.

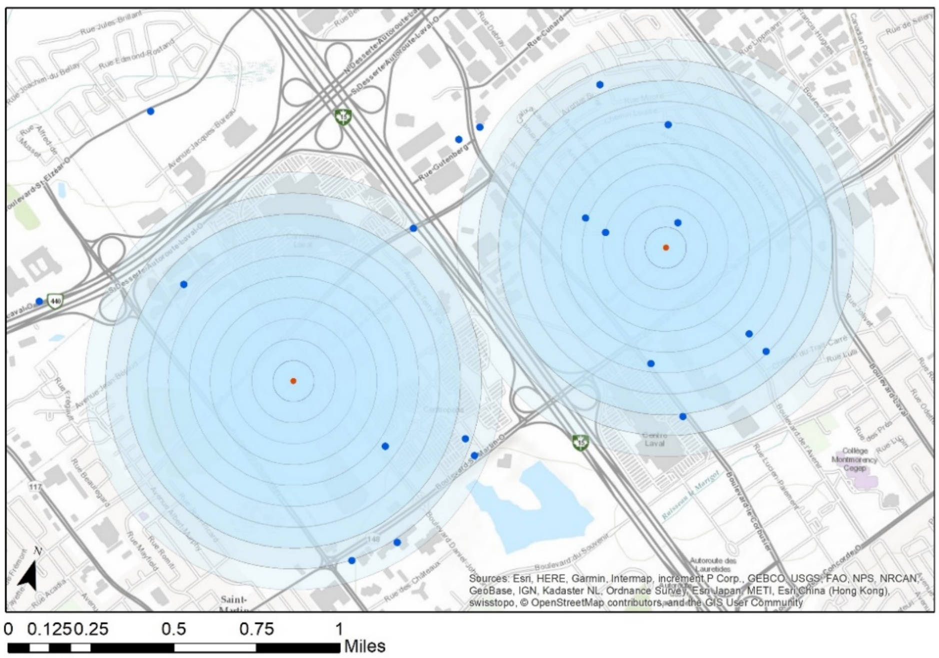
3.5.5 Recreational Facilities Environment

Land use and EPOI information used in this study were from CanMap Content Suite (DMTI Spatial Inc.). In order to measure the neighbourhood's BE characteristics related to PA, various measurements suggested in the literature included: population density and vehicular traffic, land-use mix, access to recreational facilities, lighting, street pattern and sidewalk coverage, greenness/vegetation etc. as well as a composite variables/index representing a combination of different measures (Brownson et al., 2009; Buck, Kneib, et al., 2015; Buck, Tkaczick, et al., 2015). The counts of recreational facilities (including parks, recreational areas, playgrounds, sport fields and stadiums, arenas, picnic areas and swimming pools, fitness and recreational sport centres, sport teams and clubs) were selected for this study based on previous findings suggesting that PA in children was positively associated with publicly provided recreational infrastructure (Davison & Lawson, 2006) .

For linear regression analysis and DLM the data was collected following the same procedure as for the Retail Food Environment.

The data were derived from buffer analysis using the ArcMap 10.6 Geographic Information System (ESRI Redlands, CA). These features were linked to child's BMI and MVPA data based on GIS coordinates of the participants' residential addresses.

Figure 2. Built Environment data collection for DLM. Circular ring-shaped areas with lag=100 m



3.6 Statistical models

3.6.1 Linear regression models

The traditional approach of using linear regression models with predefined fixed-size buffers were performed in order to examine the difference in association between the BE features and continuous health outcomes for circular buffers of 500 m, 750 m and 1000 m. We used the OLS method for estimating the unknown parameters in a linear regression model. The principle of least squares (minimizing the square of prediction error) was used to obtain the parameters for the model. For bivariate and multivariable analyses, we opted for a linear regression model using the BMI z-score or MVPA counts as the dependent variables. As the first step, we tested the bivariate association between these health outcomes and BE variables separately. Then, for multivariable analysis the linear regression models were adjusted for individual- and neighbourhood- level variables. As the primary objective of this study was to examine if the spatial scale for 1^{st} and 2^{nd} follow-up differed between one another, the statistical analysis was conducted on the cross-sectional data.

$$Y_i = \beta_0 + \beta_1 X_{i(0;r_k)} + Z_{\mathrm{i}}^T \delta_i + \varepsilon_i, \qquad i = 1, \ldots, n. \tag{6}$$

Where:

Y_i represents BMI z-score or daily MVPA counts of participant at location,

β_0 the intercept,

β_1 the estimated coefficient of association between the BE features measured in the fixed size buffer and the outcome,

$X_{i(0;r_k)}$ represents the measure of BE features within the fixed size buffer centered at location with the radius equal to r_k (in current study 500 m, 750 m and 1000 m),

Z_i represents vector of individual and neighbourhood characteristics of i^{th} participant,

δ_i coefficients of association of covariates and $\varepsilon_i \sim N(0, \tau^2)$.

Three fixed circular buffers (500 m, 750 m and 1000 m) were tested for each model. Using a circular buffer of 500 m as an example, the general model has the form:

$$BMIz = \beta_0 + \beta_1 FastFood_{500m} + \delta_1 Age + \delta_2 Sex_{female} + \delta_3 EDU_{parent} + \delta_4 Income_{parent} + \delta_5 Connectivity + \delta_6 Density + \delta_7 Deprivation + \varepsilon.$$

To test if the association differs by sex, a model with the following interaction term has the form:

$$\begin{aligned} BMIz = \beta_0 + \beta_1 FastFood_{500m} + \delta_1 Age + \delta_2\, Sex_{female} + \delta_3 FastFood_{500m} \times Sex_{female} \\ + \delta_4 EDU_{parent} + \delta_5 Income_{parent} + \delta_6 Connectivity + \delta_7 Density \\ + \delta_8 Deprivation + \varepsilon. \end{aligned}$$

To examine association between PA and presence of Fitness Facilities in the 500 m fixed buffer:

$$\begin{aligned} MVPA_{daily} = \beta_0 + \beta_1 Fitness_{500m} + \delta_1 Age + \delta_2 Sex_{female} + \delta_3 Overweight + \delta_4 EDU_{parent} \\ + \delta_5 Income_{parent} + \delta_6 Connectivity + \delta_7 Density + \delta_8 Deprivation \\ + \delta_9 Summer + \varepsilon. \end{aligned}$$

Following the previously described approach, to test if the association differs by sex, a model with the following interaction term has the form:

$$\begin{aligned} MVPA_{daily} = \beta_0 + \beta_1 Fitness_{500m} + \delta_1 Age + \delta_2 Sex_{female} + \delta_3 Overweight \\ + \delta_4 Fitness_{500m} \times Sex_{female} + \delta_5 EDU_{parent} + \delta_6 Income_{parent} \\ + \delta_7 Connectivity + \delta_8 Density + \delta_9 Deprivation + \delta_{10} Summer + \varepsilon. \end{aligned}$$

AIC and R^2 for all models were compared to identify the best circular buffer size among the linear regression models.

For the current data analysis, the statistical models were adjusted for neighbourhood-level covariates, defined as weighted values of relevant variable or count of BE features within 1 km circular buffer centered at participants' locations. For example, the weighted Pampalon Deprivation index, calculated proportionally to the population of parts of Dissemination areas within 1000 m buffer, or the number of the intersections within 1000 m buffer centered at participants' locations.

3.6.2 Distributed lag models

DLMs were used to describe the association between BE features and outcomes as a function of distance from the home locations. Following the approach described in a previous section (2.2.4) in our study, $X_i(r_{\ell-1}; r_\ell)$ represented the measure of BE features (e.g., number of fast foods, convenience stores or fitness facilities) within "ring" shaped areas around the participants' residential addresses. We modeled the associations between BMI z-score and individual-, neighbourhood-related independent variables and measure of BE features as a mixed-effect model:

$$Y_i = \beta_0 + \sum_{\ell=1}^{L} \beta(r_{\ell-1}; r_\ell) X_i(r_{\ell-1}; r_\ell) + Z_i^T \delta_i + \varepsilon_i. \quad (7)$$

With the main elements remaining the same, the data and coefficients for different lags were incorporated in this model. $X_i(r_{\ell-1}; r_\ell)$ represents the measure of BE features within the area between 2 radii, and $\beta(r_{\ell-1}; r_\ell)$ represents the estimated association between presence of one additional BE feature within this area and the outcome. Z_i represents the vector of individual and neighbourhood characteristics of i^{th} participant, δ_i represents the coefficients of association of covariates and $\varepsilon_i \sim N(0, \tau^2)$.

The DLM has the following form:

$$BMIz_i = \beta_0 + \sum_{\ell=1}^{L} \beta(r_{\ell-1}; r_\ell) X_i(r_{\ell-1}; r_\ell) + \delta_1 Age + \delta_2 Sex + \delta_3 EDU_{parent} + \delta_4 Income_{parent} + \delta_5 Connectivity + \delta_6 Density + \delta_7 Deprivation + \varepsilon_i,$$

where L is a predefined maximum distance where we assume the association between the presence of BE features and health outcomes no longer exists. For the current study the distance of 3.5 km was chosen. In order to examine if there were any differences by sex, the interactions between the lagged covariates and participants' sex were included in the model.

Following Zanobetti (2000) and Baek (2016), a *penalized splines smoothing* and *QR-decomposition* based approach was applied in order to estimate smoothing coefficients. The estimates for the mixed model were calculated using R package dlmBE.

To be able to compare estimations obtained with DLM and linear regression models, results must be expressed in similar scales, and for this purpose Baek (2016) suggests that the average buffer effect up to a required distance should be calculated. For example, if for a linear model of the form

$$Y_i = \beta_0 + \beta X_i(0; r_k) + \varepsilon_i,$$

we consider buffer of fixed size r_k, the average buffer effect for DLM model for the same area could be calculated using estimated coefficients for all lags from the point of location up to distance r_k as weighted summation:

$$\bar{\beta}(0; r_k) = \frac{\sum_{l=1}^{k} \beta(r_{\ell-1}; r_\ell)\ \pi(r_\ell^2 - r_{\ell-1}^2)}{\pi r_k^2}. \tag{8}$$

3.7 Statistical analysis

Statistical analysis for this study included descriptive statistics, statistical modelling (with OLS and DLMs), followed by the comparison of model fit and assumptions of these two methods were examined. All methods were previously described in detail in the Methods section. All models were adjusted for individuals' and neighbourhoods' characteristics: age, sex, whether at least one parent had a bachelor's degree, adjusted household income, population density, Pampalon Deprivation index and number of intersections (defined as weighted values for 1000 m circular buffers) as previously described. BE features included the (1) Retail Food Environment: defined as the (1a) number of fast-food restaurants, cafes and bakeries, and (1b) the number of convenience stores, and (2) Recreational Facilities Environment: defined as the number of parks, recreational areas, playgrounds, sport fields and stadiums, arenas, picnic areas and swimming pools, fitness and recreational sport centres, sport teams and clubs open for public use within relevant spatial scale (circular buffers of fixed size or 100 m ring-shaped areas). Analyses were conducted with

SAS (SAS Institute Inc., Cary, NC, USA) version 9.1 and R software (R Core Team, 2019) version 3.5.1.

3.7.1 The Spatial Autocorrelation (Global Moran's I)

When analyzing datasets that contain observations on geographical areas, assessment for the presence of spatial autocorrelation is necessary. The fundamental concepts of spatial dependence, suggested by Waldo Tobler is that, "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970). When such relations are present in a dataset, additional analytical tools should be applied. Moran (1950) proposed a spatial autocorrelation tool for continuous data in order to measure how one object is similar to others surrounding it (Moran, 1950), commonly referred as Global Moran's I. However, in practice, there is no standard regarding which proximity measure should be used to quantify "nearness", and the most commonly used options are the inverse distance methods.

The observed Moran's index can be calculated as:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}s_{ij}}{\sigma^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sigma^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}},$$

where σ^2 is the population variance, or $\sigma^2 = \sum_{i=1}^{n}(x_i - \bar{x})^2/n$,

$\boldsymbol{x_i}$ is the value of the attribute at point i, with $\boldsymbol{n}$ – total number of points,
$\boldsymbol{s_{ij}}$ – represents the similarity of attributes in point i's and j's,
$\boldsymbol{w_{ij}}$ – represents the proximity of locations, with $\boldsymbol{w_{ii}} = 0$ for all points.

Or in a more efficient way:

$$I = \frac{n \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} \sum_{i=1}^{n}(x_i - \bar{x})^2}. \tag{9}$$

The Expected value of Moran's index can be calculated as: $E(I) = -\frac{1}{n-1}$, and the standardized Z-score: $Z = \frac{I - E[I]}{\sqrt{VAR(I)}}$.

As an inferential statistic, Moran's I has the interpretation within the context of its null hypothesis, which states that the observed pattern of values is random chance and no spatial autocorrelation is observed. If both the observed and expected indexed are not significantly different (p-value > 0.05), we conclude the random pattern. Statistically significant positive z-scores suggest a clustered pattern where nearby points may show similar characteristics, while statistically significant negative z-scores suggest a dispersed pattern and nearby points may show different characteristics. As it was shown by Baek (2016), DLM provided better inference for all types of the spatial clustering settings in the simulation study. In the presence of a dispersed spatial pattern, DLM could also demonstrate the advantageous ability to capture correctly the true association between the BE features and outcome. As the count of BE features can differ significantly within every next lag, it's important to continue evaluation up to theoretical maximum distance, as every next lag will add more information for analysis.

In order to test the significance of spatial autocorrelation measures, one must make an assumption about the distribution of various point locations. We adopt a *randomisation* or *nonfree sampling* option as we assume that the observed distribution is one of many possible outcomes with the given set of values. Alternatively, if we consider infinite possible sets and each value is independent, we opt for *normality* of *free sampling* assumption. Since our analysis is limited to 233 neighbourhoods (participants living in the Montreal Metropolitan Area), the randomness assumption seems to be more appropriate.

When examining the distribution of buffers, it was noticed that the majority of buffers overlapped with at least one other buffer. In this context in order to examine for spatial auto-correlation in the dependent variable, Moran's I was computed, using (1) the inverse Euclidean distance matrix, based on participants' locations and weight status values and MVPA values simultaneously, with fixed distance of 1000 m from participants' locations. To assess the spatial autocorrelation for neighbourhood-level measures for the current study, observed and expected Moran's I values were calculated for participants living in the Montreal Metropolitan Area (n=233) using data of the 1st follow-up.

3.7.2 The Akaike Information Criterion

Given a set of nested models, the Akaike Information Criterion (AIC), introduced by the statistician Hirotugu Akaike (Akaike, 1974), is a widely used estimator to select the best one. AIC assesses the relative quality of model through estimation of the lost information. Suppose k is the number of estimated parameters and $\hat{L}$ is the maximum value of the likelihood function. The AIC value of the model is calculated as:

$$AIC = -2log(\hat{L}) + 2k. \tag{10}$$

As AIC is a relative measure of model parsimony, the number itself is not meaningful and should be interpreted only when comparing different models of the same data. The smallest AIC suggests the best model fit.

4 Results

4.1 Sample characteristics

The current study was based on the sample of children living in the Quebec province who participated in the QUALITY cohort. The data from baseline and two follow-up visits were used for the analysis. The sample size was restricted to 281 participants – the families who did not change their address during study follow-up (see ***Table 1***).

Among the participants, 150 were males (53%) and 131 were females (47%). The mean age (SD) at baseline was 9.6 (0.9) and was 11.7 (0.9) and 16.8 (1.0) at 1st and 2nd follow-ups respectively. The majority of participants (64.5% to 67.3%) at all three time points were considered to be at a healthy weight. At baseline, only 26% of the sample had initiated puberty, but all had initiated puberty by the second follow-up.

In almost 2/3 of the families, at least one parent had at least a university degree. Significant changes were observed in the distribution of the annual adjusted household income - while almost 40% of families were below the low-income cut-off at the baseline (defined as annual adjusted household income < $40,000), only 22% remained in this category by 2nd follow-up.

The distribution of quantiles of Pampalon Deprivation index suggested that our sample does not contain extreme groups in terms of social deprivation. The descriptive statistics of all five quantiles are presented in the Appendix (***Table 8***). The mean non-adjusted household income varied from $65,000 for the most deprived quantile to $108,807 in the least deprived quantile, while level of unemployment ranged from 4% to 7%. Less deprived quantiles were also characterised with lower population density of 1,755 person per square km versus 2,376 in more deprived quantiles.

Table 1: Demographic and built environment characteristics for QUALITY study participants at baseline, 1st and 2nd follow-ups (n=281, females = 47%, 2005-2016).

	Baseline 2005-2008	**1st Follow-up 2007-2011**	**2nd Follow-up 2012-2016**
Characteristic, mean (SD)[1]			
Age, years	9.6 (0.9)	11.7 (0.9)	16.8 (1.0)
BMI percentile	66.2 (26.8)	66.7 (27.1)	65.9 (27.3)
BMI z-score	0.59 (1.0)	0.60 (1.0)	0.58 (1.0)
Puberty initiated, (%)	26.0%	72.0%	100.0%
1 or 2 parents with university degree	57.0%		
Annual adjusted household income, (%)			
<$20,000	7.9%	6.8%	4.0%
$20,000-39,999	31.2%	22.2%	18.5%
$40,000-59,999	38.7%	40.5%	28.7%
≥$60,000	22.2%	30.5%	48.7%
Neighbourhood Environment Characteristics			
Density of population (per km^2)		2146.6	2302.6
Connectivity (# of junctions per km^2)		50.4	50.4
BE features of interest*			
Fast-foods, bakeries, cafes		6.8 (9.8)	6.4 (9.6)
Convenience stores		3.9 (6.4)	4.0 (6.4)
Parks, Sport fields, open swimming pools		2.4 (2.1)	2.4 (2.1)

*Number in 1000m circular buffer

[1]Presented as mean (SD) unless otherwise indicated

Some differences in neighbourhood characteristics were noticed. Density of population was on average 2,147 person per square km at 1st follow-up and increased by 7% up to 2,303 person per square km at 2nd follow-up. Measures of BE features of interest also demonstrated some changes over time. At 1st follow-up, the average number of fast foods, bakeries and cafes in a 1000 m circular buffer centered at residential location was 6.8, while 5 years later it slightly decreased to an average of 6.4 fast foods in the buffer. In contrast, the number of convenience store showed a slight increase over time, changing from 3.9 to 4.0 convenience stores per 1000 m circular buffer on average. As for Recreational Facilities Environment, 2.4 PA related neighbourhood attributes were identified on average in a 1000 m circular buffer. Detailed data are available in ***Table 9***. The maps which indicated distribution of (1) Retail Food Environment facilities (***Figure 8***) and Recreational Facilities Environment related neighbourhood attributes (***Figure 9***) are included in the Appendix.

The results of Moran's I calculations (***Table 2***) suggest that for the majority of variables, the spatial autocorrelation is not observed within the current QUALITY dataset. In other words, in terms of weight status, level of MVPA, SES neighbourhood characteristics and connectivity, study locations are spatially equally distributed. However negative z-scores for population density and Retail Food Environment suggest that spatial distribution of nearby neighbourhoods is more spatially dispersed than would be expected. These results can be explained by the diverse Montreal urban planning, where the mix of neighbourhoods with urban, suburban and rural characteristics can be observed in a relatively small area. Note that for Retail Food Environment, the spatial autocorrelation is observed for fast foods, but not for convenience stores. The rationale behind this is the reasonable difference in their points of locations. Fast food restaurants are mainly located in commercial places (plazas), often grouped within food courts, while convenience stores, often based in pharmacies/gas stations, etc. tend to fill the gaps in the commercial retail market, thus their locations are usually found to be at some distance from each other.

Table 2. Observed Moran's I for dependent variables and neighbourhood-level measures. The QUALITY study participants living in the Montreal Metropolitan Area (n=233)

Outcomes of interest and neighbourhood characteristics*	1st follow-up		2nd follow-up	
	Observed Moran's I	**p-value**	**Observed Moran's I**	**p-value**
BMI z-score	-0.0329	0.074	-0.0122	0.627
MVPA per day	-0.0059	0.944	-0.0303	0.304
Deprivation Index	-0.0042	0.446	-0.0047	0.150
Density of Population	**-0.0051**	**0.001**	**-0.0050**	**0.007**
Connectivity	-0.0046	0.276	-0.0046	0.276
Retail Food Environment: Fast foods	**-0.0049**	**0.021**	**-0.0048**	**0.042**
Convenience stores	-0.0046	0.273	-0.0047	0.169
Parks/Sport Fields	-0.0047	0.166	-0.0047	0.166

**Number of features within 1000m Circular Buffer*

4.2 Linear regression model

Retail Food Environment: presence of (a) fast foods, cafes and bakeries, (b) convenience stores in the neighbourhood.

Compared to a bivariate model, regression models that were adjusted for covariates demonstrated higher significance of Retail Food Environment features and better performance in terms of amount of explained variance. Coefficient of associations and level of significance were higher for models with smaller buffer size, for both crude and adjusted models (results presented in ***Table 3***). Although many confounders were not found to be significant, their inclusion provided better overall model fit, supporting the variables selected for these models. Variance inflation factors (VIF) did not exceed 2 (most were around 1), suggesting that multicollinearity was not an issue. At 1^{st} follow-up the bivariate model suggested a significant association for the smallest (500 m) buffer only, and no significant associations for 750 m and 1000 m buffers. The adjusted model showed higher level of significance and increase in the estimate of association and model fit (R^2 = 0.071 versus 0.013 for bivariate model). In contrast, for the 2^{nd} follow-up, the presence of Retail Food environment features demonstrated significant associations on the BMI z-score at all considered buffer sizes ***(Table 4)***.

The interaction term between the presence of BE features and sex was not significant in all models. Nevertheless, we tested it with the DLM model, as the DLM provides a potential opportunity to get a better understanding of possible sex and BE interactions.

The residuals plots for all linear models were examined and the results suggest that the assumptions were justified, see (***Figure 10***) in Appendices.

Table 3. Crude and covariate adjusted association between measure of the Retail Food Environment and BMI z-score at 1st follow-up, QUALITY study.

	Fast foods, Betas			Convenience stores, Betas		
Buffer size	500 m	750 m	1000 m	500 m	750 m	1000 m
(1) Crude model						
# of Food Env features	0.041*	0.011	0.001	0.024	0.006	0.003
R-squared	0.013	0.003	0.000	0.002	0.000	0.000
(2) Adjusted to covariates model						
# of Food Env features in the buffer	0.087**	0.029	0.016	0.101*	0.052	0.038
R-squared	0.071	0.050	0.045	0.052	0.045	0.048
Covariates						
Intercept	1.880	2.100	2.139	2.167	2.261	2.261
Age (years)	-0.082	-0.101	-0.104	-0.104	-0.114	-0.114
Sex (female)	-0.226	-0.226	-0.236	-0.263	-0.237	-0.237
Household income (in 10,000)	-0.004	-0.001	0.000	-0.002	0.001	0.002
Parents Education	-0.087	-0.075	-0.081	-0.077	-0.070	-0.078
Built Environment variables[1]						
Connectivity (# of Junctions)	-0.022	-0.026	-0.028	-0.013	-0.016	-0.01615
Density of population	-0.097*	-0.067	-0.068	-0.099	-0.089	-0.115
Deprivation Q1 (least deprived)	Ref	Ref	Ref	Ref	Ref	Ref
Deprivation Q2	0.259	0.220	0.206	0.216	0.218	0.221
Deprivation Q3	0.400	0.303	0.306	0.310	0.296	0.275
Deprivation Q4	0.429	0.425	0.436	0.396	0.409	0.392
Deprivation Q5	0.272	0.303	0.297	0.241	0.263	0.249

*** <0.01;* <0.05;*

[1] Calculated as number of BE features or weighted value within 1000 m circular buffer

Table 4. Crude and covariate adjusted association between measure of the Retail Food Environment and BMI z-score at 2nd follow-up, QUALITY study.

	Fast foods, Betas			Convenience stores, Betas		
Buffer size	500 m	750 m	1000 m	500 m	750 m	1000 m
(1) Crude model						
# of Food Env features	0.051*	0.015	0.006	0.058.	0.019	0.016
R-squared	0.018	0.006	0.003	0.012	0.003	0.007
(2) Adjusted to covariates model						
# of Food Env features	0.091**	0.040*	0.028*	0.158**	0.066*	0.068**
R-squared	0.066	0.051	0.048	0.070	0.046	0.068
Individual variables						
Intercept	1.961	1.999	2.068	2.233	2.117	2.439
Age (years)	-0.069	-0.071	-0.073	-0.081	-0.076	-0.093
Sex (female)	-0.173	-0.185	-0.174	-0.219	-0.185	-0.157
Household income (in 10,000)	-0.008	-0.003	-0.004	-0.013	-0.010	-0.012
Parents Education	-0.092	-0.099	-0.111	-0.083	-0.069	-0.082
Built Environment variables[1]						
Connectivity (# of Junctions)	-0.029	-0.037	-0.042	-0.018	-0.026	-0.027
Density of population	-0.072	-0.066	-0.083	-0.116*	-0.082	-0.157*
Deprivation Q1(least deprived)	Ref	Ref	Ref	Ref	Ref	Ref
Deprivation Q2	0.452*	0.439*	0.423*	0.449*	0.416	0.402
Deprivation Q3	0.350	0.335	0.313	0.270	0.274	0.267
Deprivation Q4	0.296	0.241	0.268	0.190	0.213	0.173
Deprivation Q5	0.292	0.312	0.287	0.290	0.307	0.251

*** <0.01; * <0.05;*

[1] *Calculated as number of BE features or weighted value within 1000 m circular buffer*

Recreational Facilities Environment: the number of parks, sport fields, swimming pools, or fitness facilities open for public use.

Three fixed buffer sizes (500 m, 750 m and 1000 m) were tested. The analytical sample contained only 214 observations, as accelerometry data were used for statistical analysis only if the requirements of a minimum of 4 days with accelerometer wear-time >10 hours per day were met (R. Colley et al., 2010). Accelerometry data were only collected at baseline and 1st follow-up thus no analyses for 2nd follow-up were conducted. The results of bivariate and adjusted regression models demonstrated no significant association between the level of MVPA and presence of recreational facilities in the neighbourhood (***Table 5***). However, the adjusted model demonstrated better performance with 26% of explained variance for buffers of all sizes. Many confounders like age, sex, having overweight or obesity, and seasonality were found to be highly significant.

Table 5. Crude and covariate adjusted association between measure of the Recreational Facilities Environment and Moderate and Vigorous Physical Activity (MVPA) at 1st follow-up.

Buffer size	Beta 500 m	Beta 750 m	Beta 1000 m
Crude model			
# of Fitness Facilities in the buffer	-0.161	1.252	0.700
R-squared	0.000	0.006	0.004
Adjusted to covariates model			
# of Fitness Facilities in circular buffer	-1.5329	0.916	0.6557
R-squared	0.262	0.261	0.261
Individual variables			
Intercept	98.005	99.888	98.927
Age (years)	-4.678**	-4.834**	-4.761**
Sex (female)	-17.239***	-17.349***	-17.495***
Overweight	-8.152**	-8.187**	-8.195**
Household income (in 10,000)	0.206	0.343	0.321
Parents Education	2.503	2.3063	2.420
Built Environment variables[1]			
Connectivity (# of Junctions)	1.261	0.616	0.6062
Density of population	-0.4406	-0.500	-0.5779
Summer	5.303	5.091	5.230
Deprivation Q2 (least deprive)	Ref	Ref	Ref
Deprivation Q2	5.4668	6.222	6.143
Deprivation Q3	6.147	6.852	6.790
Deprivation Q4	-1.5793	-1.2682	-1.2293
Deprivation Q5	-1.168	-0.516	-0.605

*** <0.01;* <0.05;*

[1] *Calculated as number of BE features or weighted value within 1000 m circular buffer*

4.3 Cross-sectional association between Retail Food Environment and BMI z-score using DLM models

4.3.1 Retail Food Environment: (1) number of fast-foods, cafes and bakeries in the residential neighbourhood

For DLM the 100 m lags were created up to 3500 m centered at the residential location, rationalized by the size of Montreal island (which is only 17000 m at its widest point) and findings from previous studies. The results of analysis demonstrated that distributed lag coefficients converged to zero after maximum 1500 m for all models considered. Models assumptions were verified, diagnostic plots presented in the Appendix (***Figure 11***).

Figure 3 shows the estimated distributed lag coefficients for the association between the BMI z-score and presence of fast foods, cafes and bakeries within a distance of 3500 m from the study locations of QUALITY study participants at 1^{st} and 2^{nd} follow-ups. Different change points for the two study periods were detected. At 1^{st} follow-up (M_{age}=11.7) the association between presence of fast foods and BMI z-score remains within the distance up to 600 m, with higher estimated coefficients of association at the first lags. In contrast, at 2^{nd} follow-up (M_{age}=16.8) for the same study population the distance where the association disappears or is no longer clinically meaningful increased to 900 meters.

For the 1^{st} follow-up no significant association was observed among males nor females despite the fact, that for the whole sample significant association was detected by both linear regression and DLM within the 500 m buffer (data not shown). The results can be explained by the lack of power for additional interaction, as our sample is limited to 281 participants. ***Figure 4*** shows estimated distributed lag coefficients by sex, showing that at 2nd follow-up the significant association between the presence of fast food in the residential neighbourhood and BMI z-score at the distance up to 900 m exists only within the female subsample. However, taking into consideration the present issue with the lack of power these results should be considered as signals and a potential direction to further explore in future studies.

Figure 3. Estimated distributed-lag coefficients. Association between measure of fast foods and BMI z-score at 1st and 2nd follow-up, QUALITY study.

1st follow-up, change point at 600 m | **2nd follow-up, change point at 900 m**

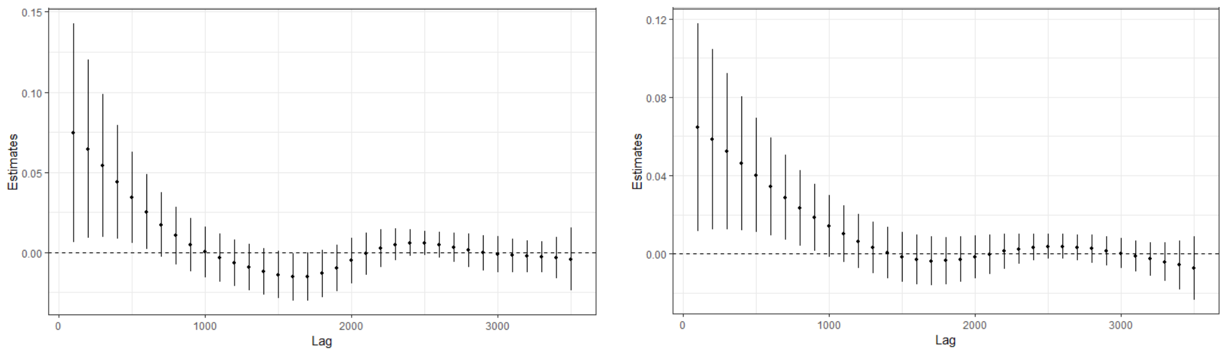
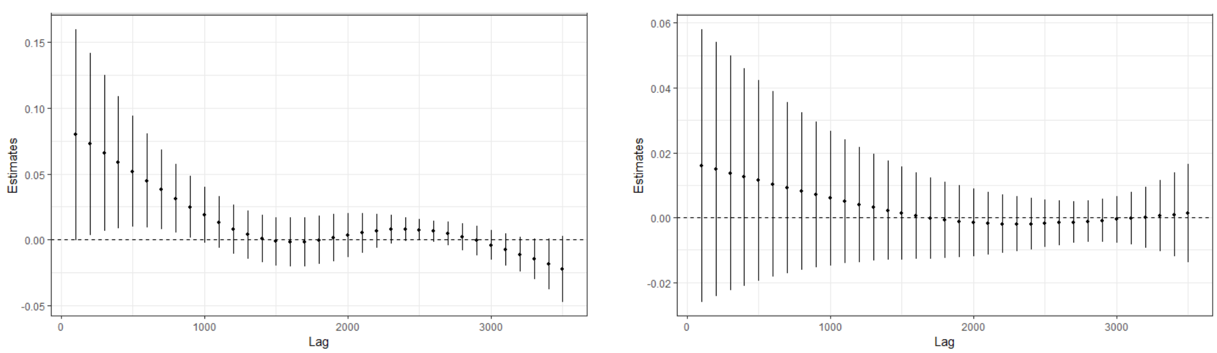


Figure 4. Estimated distributed-lag coefficients. Association between measure of Fast Foods and BMI z-score at 2nd follow-up by Sex, QUALITY study.

Females, change point at 900 m | **Males, no significant association**



4.3.2 Retail Food Environment: (2) number of Convenience stores in the residential neighbourhood

Figure 5 shows estimated distributed lag coefficients for the association between the BMI z-score and presence of convenience stores within distance of up to 3500 m from the residential locations of QUALITY study participants. While no association was detected for 1st follow-up, 1300 m was identified as the change point for 2nd follow up for the whole sample. Interaction with sex at 2nd follow up shows that change points differ based on sex and is 600 m and 1300 m for females and males, respectively (***Figure 6***).

Figure 5. Estimated distributed-lag coefficients. Association between measure of Convenience stores and BMI z-score at 1st and 2nd follow-up, QUALITY study.

1st follow-up, no change point | **2nd follow-up, change point at 1300 m**

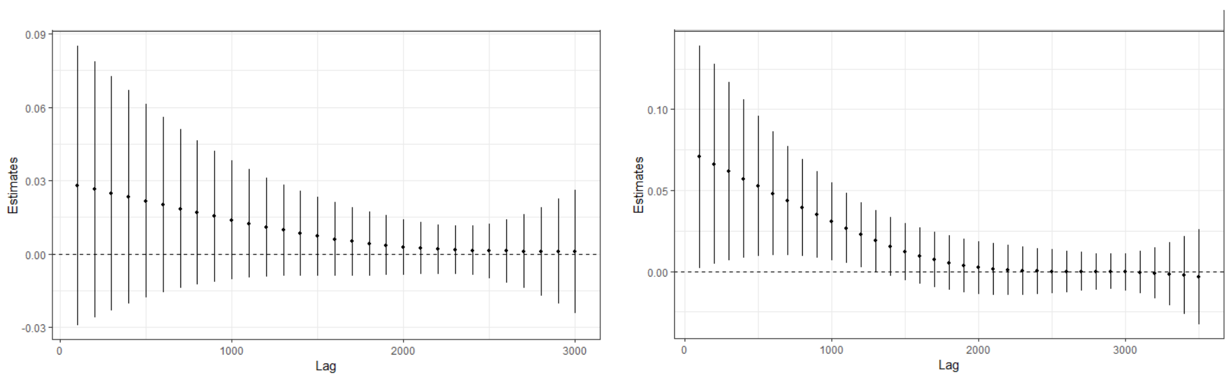
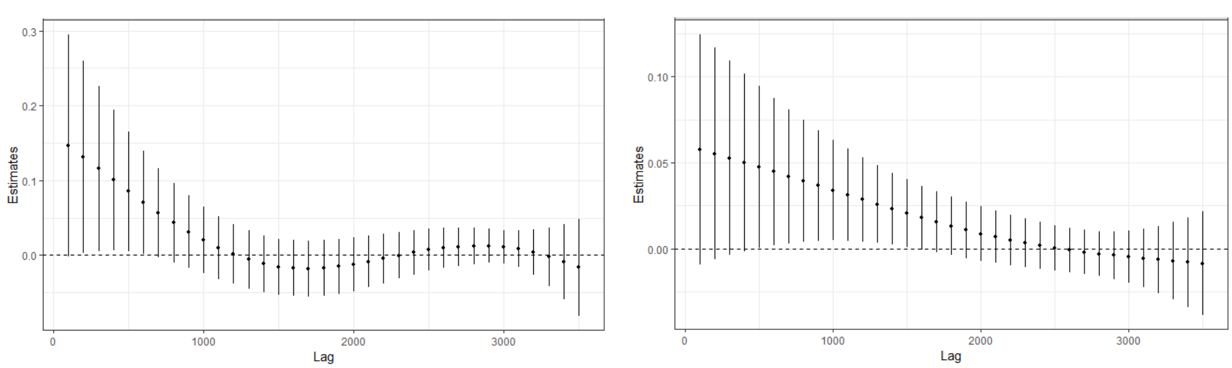


Figure 6. Estimated distributed-lag coefficients. Association between measure of convenience stores and BMIz at 2nd follow-up by sex, QUALITY study.

Females, change point at 600 m | **Males, change point at 1500 m**

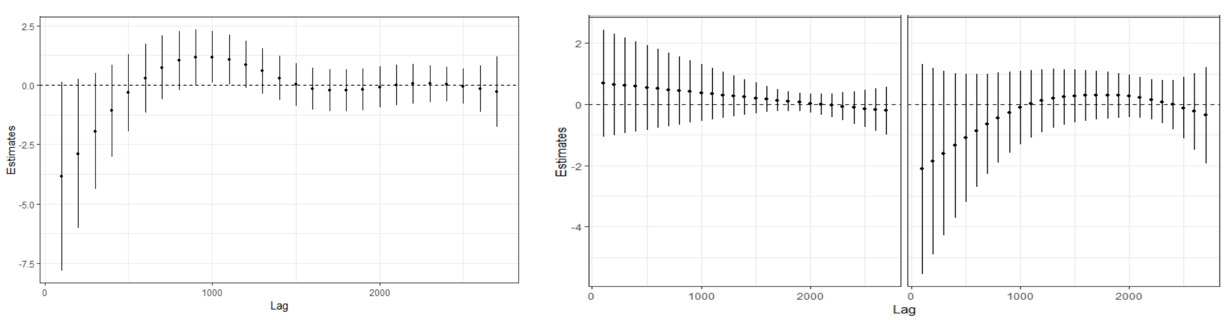


4.4 Cross-sectional association between Recreational Facilities Environment and the number of minutes of MVPA using DLM models

Figure 7 shows estimated distributed lag coefficients for the association between the daily minutes of MVPA and the Recreational Facilities Environment within a distance of 3500 m from the residential locations. DLM doesn't suggest any significant association at 1st follow-up, however the results may be affected by a lack of power. Interactions by sex did not detect any significant associations.

Figure 7. Estimated distributed-lag coefficients. Association between measure of Recreational Facilities Environment and MVPA at 1st follow-up, QUALITY study.

n=214 **Males (n=116) Females (n=98)**



4.5 Comparison of the results using DLM and linear regression models

As a secondary objective of our study, we compared the results obtained with linear regression and DLM. For this purpose, the estimated area-averaged coefficients of association for three predefined circular buffers were calculated using DLM lag coefficients according to formula (8). For the comparison of two methods, the estimations for 500 m, 750 m and 1000 m buffer sizes, as well as relevant SEs, p-values and AIC are presented in ***Table 6***. According to the linear regression model, every additional fast food in the 500 m circular buffer was associated with 0.087 (95% CI: 0.0321,0.1415) increase in participant's BMI z-score, while DLM method suggested half the strength of association (Beta=0.040) with narrower confidence intervals (95% CI: 0.0047,0.0753) and this tendency was kept for all buffer sizes.

Overall comparison of model performance based on AIC suggested that for this study OLS regression models fit the data better, when examining the presence of fast foods, especially in the buffers of smaller sizes.

However, for convenience stores, inconsistent results were observed for OLS regression models when applied to different spatial scales (***Table 7)***. More specifically, a significant association was observed between the presence of convenience stores and BMI z-score within the smallest buffer (500 m), marginal association for a slightly larger buffer (750 m) and a significant association within the largest buffer (1000 m). This inconsistency could be explained by bias possibly caused by the nature of convenience stores locations - by definition, they tend to fill the gaps in the retail market and distance between them could exceed 250 m. As a result, the buffers of 500 m and 750 m could have the same number of convenience stores and the linear regression model failed to capture the effect of association correctly.

In contrast, DLM can provide a more fair evaluation for every lag up to the maximum distance. Observed AIC of DLM was comparable with the AIC for linear regression models, suggesting equal fit. In addition, DLM provides us with the additional information about the maximum distance where the coefficient of association becomes very close to zero, suggesting that the effect of the presence of BE features on health could vanish beyond this distance.

Table 6. Covariate adjusted association between the presence of one additional fast food within fixed buffer and BMI z-score at 1st and 2nd follow-up, comparison of the linear regression models and DLM, QUALITY study.

		1st follow-up Age (mean)=11.6				**2nd follow-up** Age (mean)=16.8			
	Buffer size (m)	**Beta**	**SE**	***p-value***	**AIC**	**Beta**	**SE**	***p-value***	**AIC**
Linear Regression Model	500	0.087	0.028	*0.002*	**894.7**	0.091	0.029	*0.002*	**897.1**
	750	0.029	0.016	*0.065*	901.1	0.040	0.017	*0.020*	901.5
	1000	0.016	0.012	*0.172*	902.7	0.028	0.013	*0.034*	902.4
Distributed Lag Model	500	0.040	0.018			0.047	0.018		
	750	0.024	0.014	*600*m*	907.9	0.030	0.015	*900*m*	907.54
	1000	0.019	0.010			0.029	0.011		

**Change point*

Table 7. Covariate adjusted association between the presence of one additional convenience store within fixed buffer and BMI z-score at 1st and 2nd follow-up, comparison of the linear regression models and DLM, QUALITY study.

		1st follow-up Age (mean)=11.6				**2nd follow-up** Age (mean)=16.8			
	Buffer size (m)	**Beta**	**SE**	***p-value***	**AIC**	**Beta**	**SE**	***p-value***	**AIC**
Linear Regression Model	500	0.100	0.051	*0.049*	**900.6**	0.158	0.048	*0.001*	**896.0**
	750	0.052	0.036	*0.151*	902.5	0.066	0.033	*0.050*	903.1
	1000	0.039	0.023	*0.091*	901.7	0.068	0.021	*0.001*	896.5
Distributed Lag Model	500	0.018	0.015			0.040	0.018		
	750	0.013	0.014	*N/A*	905.9	0.035	0.012	***1300*m***	899.35
	1000	0.016	0.013			0.031	0.010		

**Change point*

5 Discussion and Conclusion

5.1 Summary

In this study we compared the use of OLS and DLM methods to investigate the environmental determinants of childhood obesity and PA. We followed the methodology introduced by Baek (2016). In that previous study, Baek (2016) compared DLMs to circular buffers based on school BE features. As the child's home is their primary environment, this study investigated the residential neighbourhood of the QUALITY cohort participants.

For this purpose, we firstly performed a traditional approach by testing commonly used fixed-size buffers with OLS models. Three fixed sized buffers of 500 m, 750 m and 1000 m were created for these OLS regression models. Note that fixed-size buffer assumes the presence of the constant effects up to the bound only (in other words the association is assumed to be constant, and to exist only within the predefined fixed-size buffer).

In contrast, DLM enabled us to estimate average association up to any defined distance, for example 1000 m, without this assumption. The DLM method only required a specification of a maximum possible distance for the presence of association which provided the opportunity to examine the pattern of association up to this limit. Thus, the distance where the association is no longer significant can be identified, provided that the effect completely disappears within the maximum limit chosen for the model. Notably this assumption is more flexible than for the predefined circular buffers (Baek et al., 2016).

For this analysis 100 m ring-shaped areas up to 3500 m centered on the residential locations were constructed. Within these settings, we assumed that no association between presence of BE features and health outcomes of interest existed beyond the 3500 m. We defined a lag of 100 m (approximately the size of 1 block in Montreal), to be considered as a reasonable lag distance in an urban environment.

Applying the DLM approach, different distances of association between the Retail Food Environment and BMI z-score were detected for different ages, demonstrating the dynamics of behaviour changes in youth. The estimated coefficients of the first few DLM lags had wider confidence intervals. This higher uncertainty may have been due to the majority of these first lags containing zeros for all BE features, reflecting a lack of information.

Comparison of OLS and DLM models indicated that DLM-estimated associations and SE were smaller than with the OLS models. AIC tended to select a regression model with the smallest buffer size needed as the best fit. However, based on our results of convenience stores at 2nd follow-up, the limitations of selecting the smallest buffer is clear: the three linear regression models with different buffer sizes showed inconsistent results. In this case where there is a potential spatial clustering presence, the AIC suggested that DLMs were generally better model fit. Results were consistent with that of the simulation study by Baek et al. (2016) which demonstrated DLM had better performance over linear regression models, smaller bias, and better coverage rates of true effects. Indeed, in our real-data study, the DLM approach demonstrated better results when examining the association between the presence of convenience stores and BMI z-scores.

Additionally, as the change points for 1st and 2nd follow-up were detected at different distances, it may be appropriate to incorporate this information to improve the analysis when choosing the spatial scale in future studies. Results of dietary recall data from the recent Canadian Community Health Survey shows that, relative to other age categories, Canadian male and female teenagers have the highest level of daily energy intake (248 kcal and 175 kcal, respectively) consumed from fast food which contributes around 9% and 8% of usual energy intake respectively, vs the Canadian average of 6.3% (Black & Billette, 2015). The patterns of nutrition behaviour in teens is an important research question for epidemiologists (Bryan et al., 2016; Duma-Kocan et al., 2017; Zalewska & Maciorkowska, 2017) and improvements in the identification of spatial scale for analysis could be immensely beneficial.

In this current study circular buffers and ring-shaped lags were used due to their relative simplicity of data collection. Future research should investigate the use of the DLM model with lags in the form of network buffers, which could potentially improve the precision of the estimation of association and better capture the complexity of the neighbourhood BE.

The maximum distance of 3500 m and lag of 100 m were chosen for this study, rationalized by the reality of the urban environment of the study population and in favor of better interpretability of the results. However, future work should explore different amounts and size of lags.

5.2 Strengths and Limitations of the study

Strengths

The main advantage of the DLM method is that it does not require a pre-specification of the buffer size. Only the maximum distance that an association is assumed to exist needs to be specified. By the DLM coefficients following a smooth association over distance, a more accurate and precise estimation of association strength can be calculated. Additionally, the distance at which the association disappears can also be identified, which can help to better design future studies.

Limitations

By design, the QUALITY cohort was restricted to Caucasian children with a parental history of obesity, thus it cannot be considered as a representative sample of the Quebec youth population. However the prevalence of children with overweight/obesity is comparable with the Canadian average (StatCan, 2015, 2017) and results may be representative of the association between weight status and PA and BE among youth at risk for overweight/obesity.

To be able to apply the DLM method, validated databases of relevant BE features are required. In this study we used data from DMTI Spatial Inc. (2008 and 2012), a Canadian digital map products company. Its products and solutions are commonly used in the field of location analytics. However, the DMTI database had previously shown only a moderate capacity to detect the presence of food stores (sensitivity and PPV of 65.5% and 77.3% respectively), with an estimated representativity of 77.7% (Clary & Kestens, 2013). Thus misclassification of BE features is likely to have occurred.

Measurement error may have biased our study results to the null. For instance, the accelerometry data were available only for a small subsample (n=214), and this study did not account for actual participants' eating behaviours or use of recreational facilities. This could explain the non-significant results between the presence of Recreational Facilities Environment features and

MVPA, which are aligned with recent reviews (Ding et al., 2011). Indeed parks and recreation facilities are inconsistently associated with PA in children, for instance, 8 out of 15 papers reported non-significant associations (Ding et al., 2011). In addition, the low R-squared, ranged from 5% to 7% was expected, as the BE variables of interest investigated in this study were human behaviour related. Nevertheless, as this study aimed to compare analytic methodologies in detecting these associations, this measurement error would be non-differential and would not likely affect general conclusions.

5.3 Conclusions

Different distances of association between Retail Food BE features and health outcomes for 1st and 2nd follow-ups were detected, suggesting the change in dietary behaviours for children based on age and sex. As DLMs do not require pre-specified fixed buffer sizes, their use can help build empirical evidence of the most appropriate spatial scale to be used in BE related studies for participants over time. These results highlight instances in which DLM may be preferable to OLS. The inconsistent OLS results for different spatial scales suggest that additional research in different populations, age and PA indicators groups is warranted. As an extension to the current analysis, future work should examine use of DLM on network-buffers centred at the residential address. The use of DLM and network-buffers is likely to provide a more precise estimation of the association between the presence of BE and health outcomes.

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Appendices

Table 8. Pampalon deprivation index (Material component): quantiles characteristics, QUALITY participants at 1st follow-up, based on Census 2006.

	Index Range	Population density/km2	Mean Household Income	Unemployment (%)
Q1 (less deprive)	[-0.064,-0.025]	1,755	108,807	4.0%
Q2	(-0.025,-0.009]	2,475	91,042	4.8%
Q3	(-0.009,0.002]	2,773	80,016	4.9%
Q4	(0.002,0.017]	2,790	76,141	5.3%
Q5 (more deprive)	(0.017,0.070]	2,376	65,000	7.0%

Calculated based on the Quebec provincial data from the Census 2006

Table 9. Distribution of Built Environment features within 1000 m circular buffer centered at study locations.

	Min	1Q	Median	Mean	3Q	Max
Fast-foods, Bakeries, Cafes	0	0	2	6.4	9	50
Convenience stores	0	1	2	4	4	34
Park/Sport fields, Pools, Recreational facilities	0	1	3	3.2	6	16

DMTI Spatial Inc. [computer file]. Enhanced Point of Interest. Markham: DMTI Spatial Inc., 2008

Figure 8. Retail Food Environment: convenience stores and fast-food restaurants (DMTI Spatial Inc.).

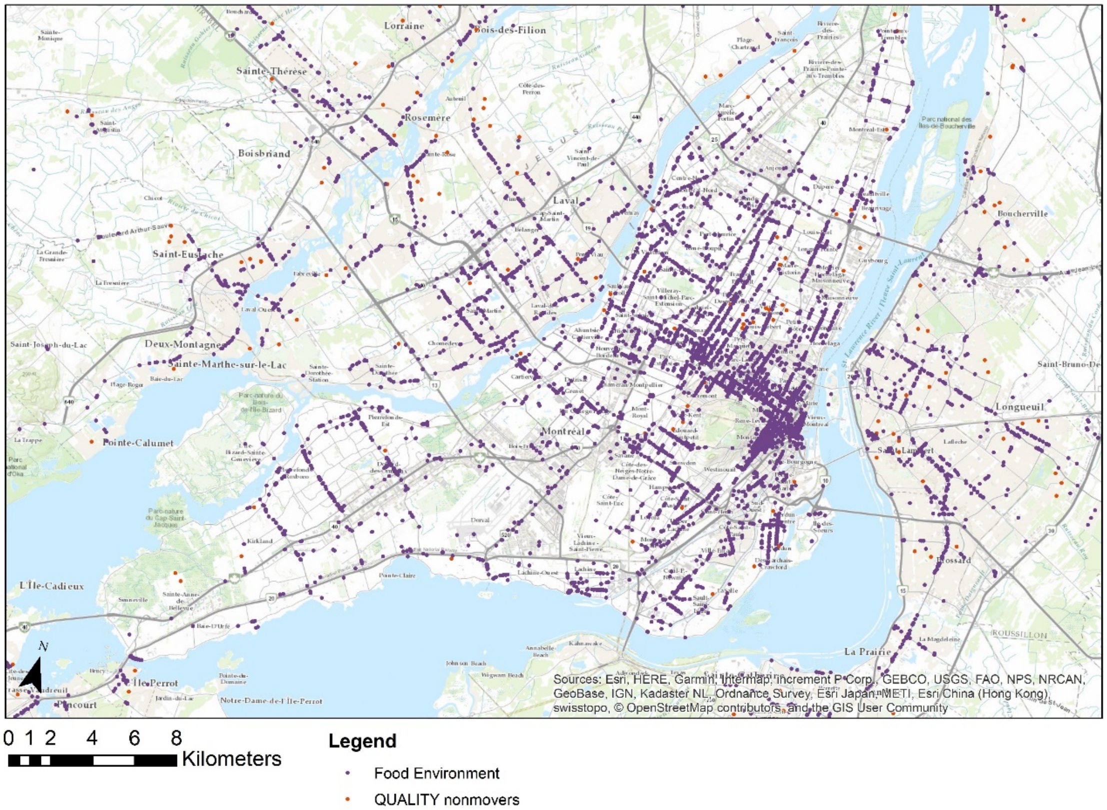


Figure 9. Recreational Facilities Environment: parks/sport fields, swimming pools, sport and recreational facilities (DMTI Spatial Inc.).

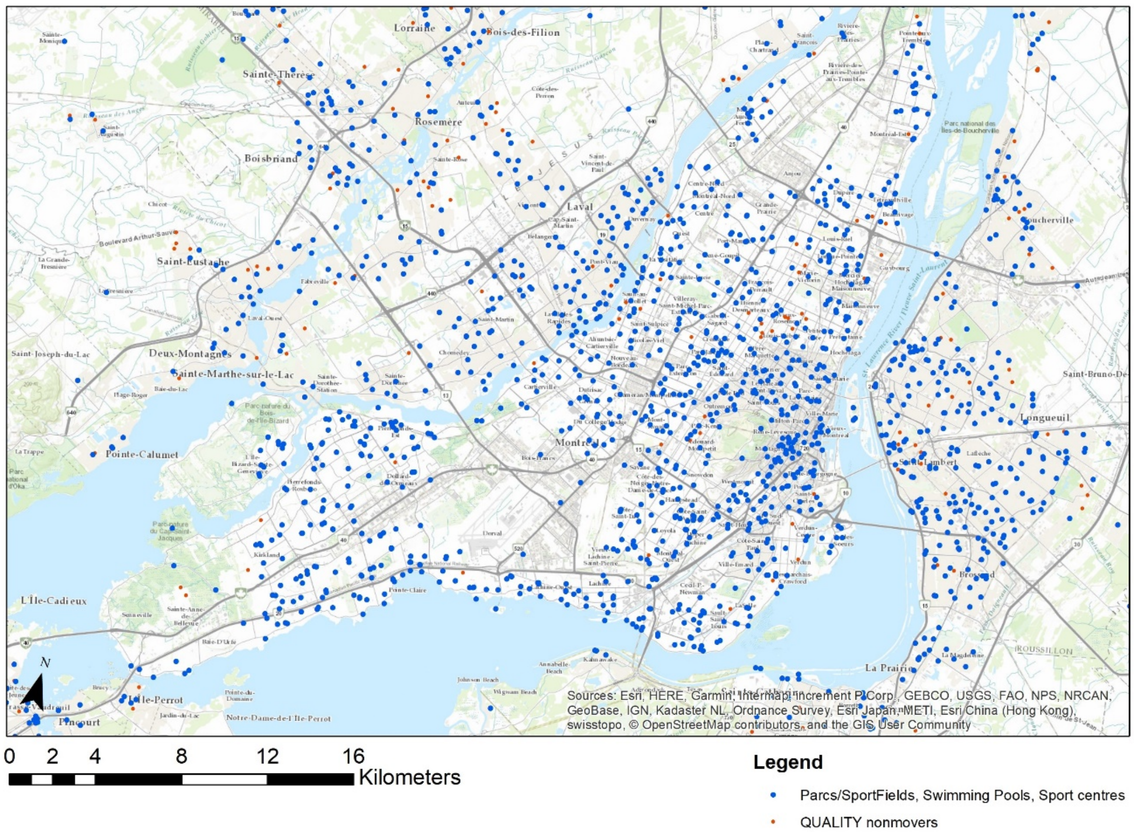
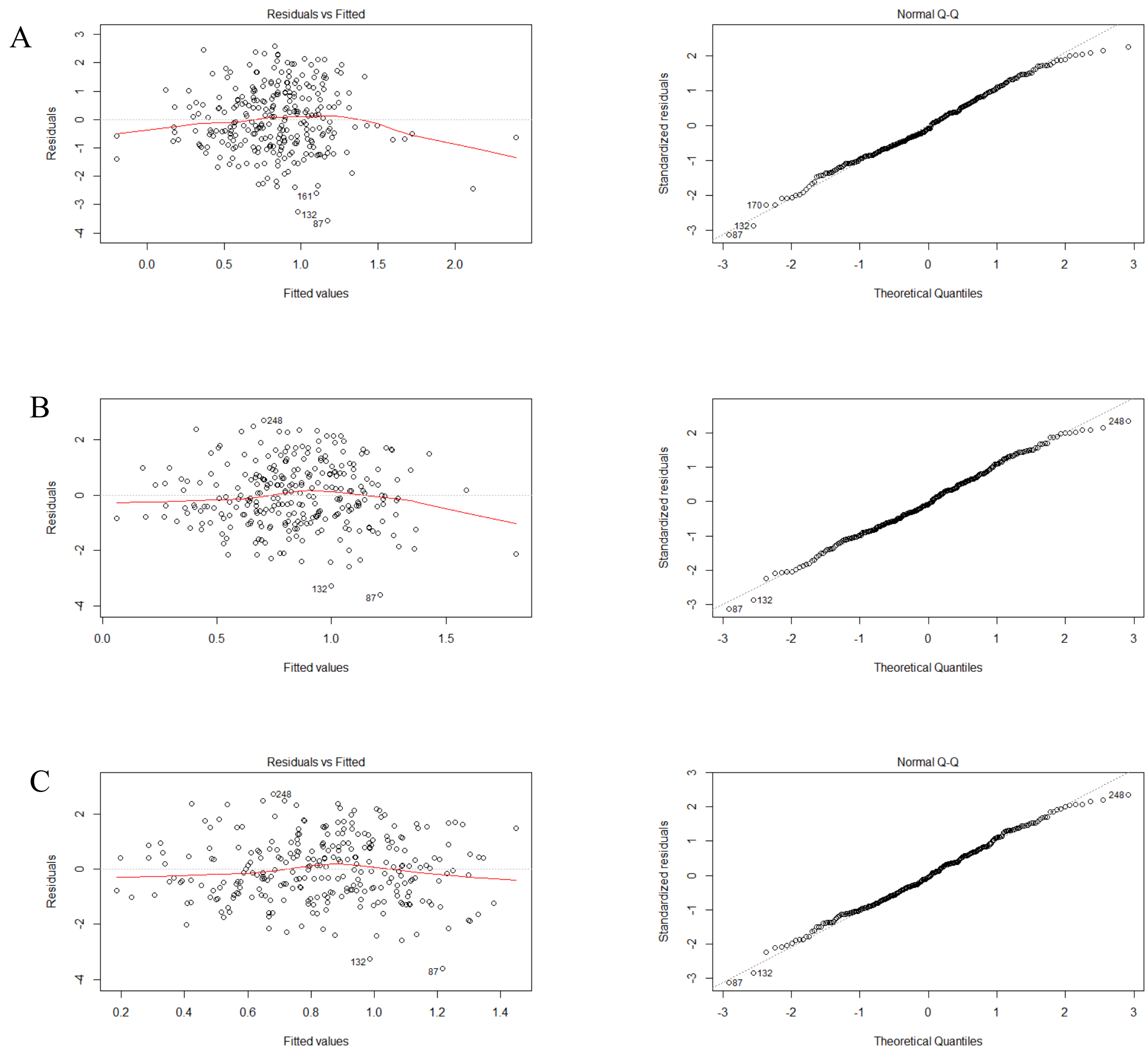
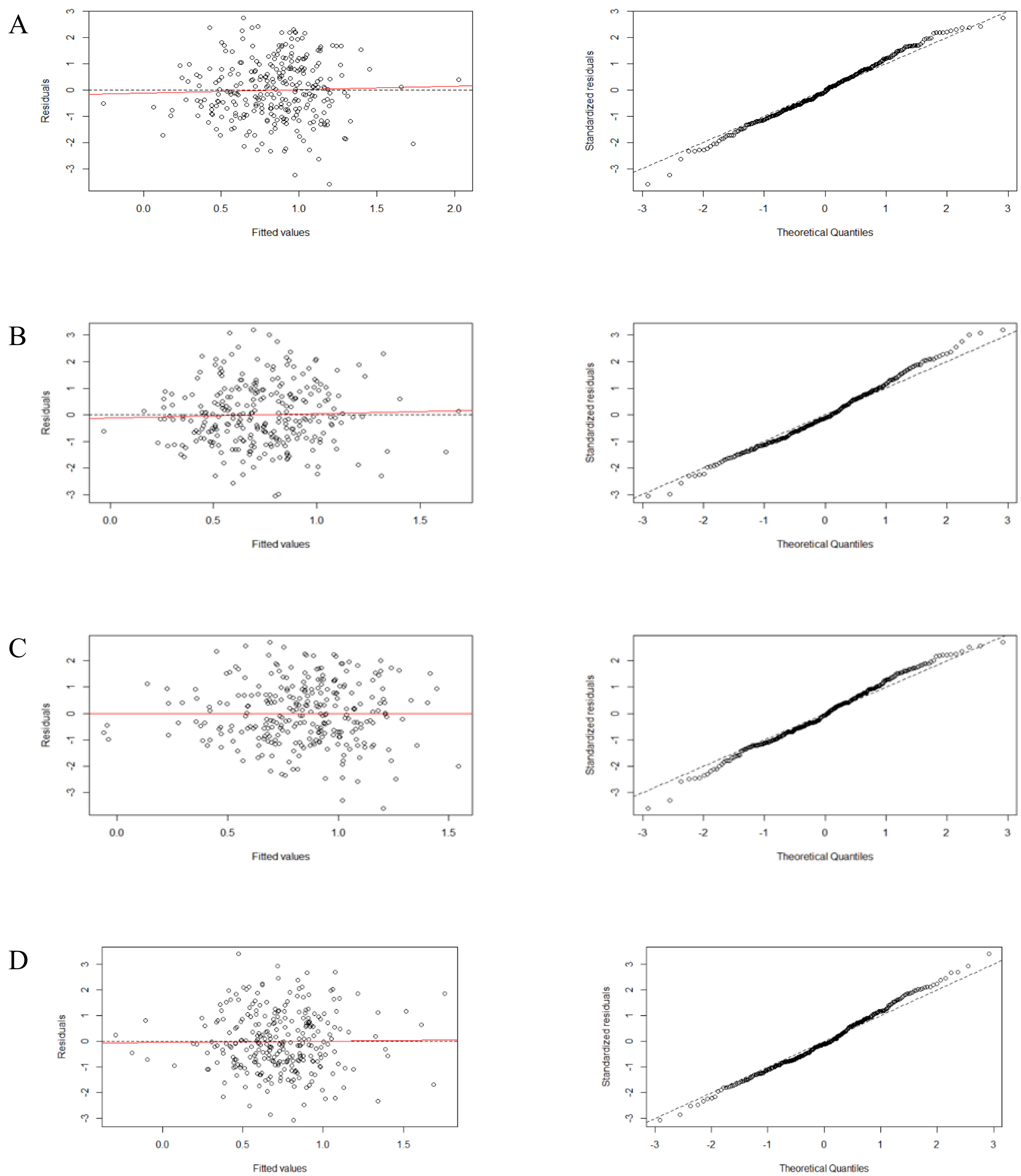


Figure 10. Residuals plots for linear regression models (association between measure of Fast Foods within fixed-size circular buffers and BMI z-score at 1st follow-up), QUALITY study.



(A) Model with 500 m circular buffer, (B) – 750 m circular buffer, (C) – 1000 m circular buffer.

Figure 11. Residuals plots for DLM, association between measure of Retail Food Environment and BMI z-score at 1st and 2nd follow-up, QUALITY study.



Association between Retail Food Environment features and BMI z-scores: (A) Fast foods at 1st follow-up, (B) Fast foods at 2nd follow-up, (C) Convenience stores at 1st follow-up, (D) Convenience stores at 2nd follow-up.